ABSTRACT

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Social interactions in a community influence perceptions and values of members of the community. Recently Web 2.0 technologies have stimulated rapid growth of online communities, where communications between participants are made much easier. It is important to study how participants' behaviors and preferences are affected by their communities. In my dissertation, I develop quantitative marketing models to empirically study perceptions and attitudes of participants in online and offline communities.

Essay 1 examines an offline community, distributor community in multi-level marketing organizations. We propose a spatial model to understand the determinants of distributor satisfaction and simultaneously account for biases in measures in the context of cross-country marketing operations. We define an attribute-space using measures such as sales momentum and effort expended on business by distributors. The relationship between distributor satisfaction and its drivers varies within this attribute-space and across markets. Based on survey data from a large multi-national multilevel marketing firm, we empirically illustrate how marketing control variables impact distributor satisfaction scores across countries after controlling for biases. We also discuss the resource allocation implications based on the study.

Essay 2 studies an online community, online bargain hunting forum. We investigate whether and how online discussions posted by active participants affect the interest and preference of the silent majority. We collect data from a major bargain hunting forum. Our analysis of the online discussions goes beyond measures of volume and valence, and delves into the specific contents of discussions posted in the forum. We classify the contents into a range of specific categories, and develop a Bayesian Poisson-Binomial model to examine how silent viewers' interest in and preference for a featured deal are influenced by the discussions, while controlling for many other factors. Our results show that the content of discussions posted by active participants indeed affects the silent viewers' interest in and preference for a featured deal, and that the effects are different across the specific categories of content. Our findings demonstrate that marketers can benefit from monitoring activities in online bargaining hunting forums, and suggest ways for them to participating in these forums.

ESSAYS ON MARKETING MODEL APPLICATIONS FOR ONLINE AND OFFLINE COMMUNITIES

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Chapter 1: Introduction

Traditionally, a community is defined as a group of interacting people that are organized around common values within a shared geographical location, generally in social units larger than a household (Hillery 1955). A community can be a student group in a university, group of people who work in the same company, group of people who attend a cycling club, or even a group of people who share common history and culture, etc. Since the invention of Internet, communities are no longer limited by geographical locations. Recently, Web 2.0 technologies have stimulated rapid growth of online communities, where communications between participants are made much easier. People meet virtually in online communities and share common interests regardless of their physical locations. For example, an online community can be a group of users at myspace.com, a group of users at facebook.com, or a group of users in an online discussion forum, etc.

Social interactions in a community influence perceptions and values of members of the community. Each member's opinion and behavior are shaped not only by their own dispositions and situations, but also by their peers in the community. It is important to study how participants' behaviors and preferences are affected by their communities. Online communities make interactions between consumers much easier. At the same time, they also create new opportunities for firms to interact with consumers. Online communities provide firms a new and cost efficient way to get consumers' feedback and new ways for firms to influence potential consumers. With this as the background, the goal of my dissertation is to develop quantitative marketing models to empirically study perceptions and attitudes of participants in online and offline communities, and provide better understanding of social influence in these communities.

The first essay of my dissertation examines an offline community, distributor community in multi-level marketing organizations. The success of multi-level marketing organizations depends to a significant extent on the rapid and word-of-mouth-driven growth of their distributor networks. Because sales generated by the distributors and their retention rates and positive word-of-mouth depend significantly on their satisfaction levels, multinational firms routinely measure their distributors' satisfaction across countries where they operate. Understanding the determinants of distributor satisfaction across countries and accounting for response biases in these satisfaction measures in cross-cultural settings are significant issues for multi-national firms, which makes the measures comparable for resource allocation and strategic decisions.

In this study, we propose a spatial model to understand the determinants of distributor satisfaction and simultaneously account for biases in measures, in the context of cross-country marketing operations. We define an attribute-space using measures such as sales momentum and effort expended on business by distributors. The relationship between distributor satisfaction and the explanatory variables varies within this attribute-space and across markets. Thus, distributors' subjective responses are inter-related within the context of their own observable outcome and behavior. Based on survey data from a large multi-national multilevel marketing firm operating in different cultural/country settings, we empirically illustrate how marketing control variables impact distributor satisfaction scores across countries after controlling for biases. We also discuss the resource allocation implications based on the study.

The second essay of my dissertation studies an online community, online bargain hunting forum. Bargain hunting forums are becoming increasingly popular among Internet users as a venue to look for good deals, post comments, exchange tips and other information. They are also attracting the attention of retailers in search for creative ways to disseminate promotion information and to influence consumers' attitudes. Despite their widespread popularity, only a small proportion of users actively participate in these discussion forums by posting comments, while most users look for information in the forums without contributing to the discussions. To assess the influence of such social discussion platforms, one must look at the impact of active participants on the silent majority, because the latter represents a much greater contributor to the customer base and sales of a company or product.

In this study, we investigate whether and how online discussions posted by active participants affect the interest and preference of the silent majority. We collect data from a major bargain hunting forum, which allow us to infer attitude of a sample of silent viewers. Our analysis of the online discussions goes beyond measures used in the prior research, such as volume and valence, and delves into the specific contents of discussions posted in the forum. We classify the contents into a range of specific categories, and develop a Bayesian Poisson-Binomial model to examine how silent viewers' interest in and preference for a featured deal are influenced by the discussions, while controlling for many other factors. Our results show that the content of discussions posted by active participants indeed affects the silent viewers' interest in and preference for a featured deal, and that the effects are different across the specific categories of content. Our findings demonstrate that marketers can benefit from monitoring activities in online bargaining hunting forums, and suggest ways for them to improve the design and information dissemination of promotions via participation in these forums.

Chapter 2: Essay 1: Comparing Distributor Satisfaction Scores and Their Drivers in Cross National Multi-level Marketing Contexts

Abstract

The success of multi-level marketing organizations depends to a significant extent on the rapid and word-of-mouth-driven growth of their distributor networks. Because sales generated by the distributors and their retention rates and positive word-of-mouth depend significantly on their satisfaction levels, multinational firms routinely measure their distributors' satisfaction across countries where they operate. Understanding the determinants of distributor satisfaction across countries and accounting for response biases in these satisfaction measures in cross-cultural settings are significant issues for multi-national firms, which makes the measures comparable for resource allocation and strategic decisions. In this study, we propose a spatial model to understand the determinants of distributor satisfaction and simultaneously account for biases in satisfaction measures in the context of cross-country marketing operations. Specifically, we posit that a distributor's satisfaction score and its relationship to its drivers are functions of where the distributor is located in an attribute-space defined by distributors' sales momentum and effort expended on business. This location determines the extent of bias in satisfaction scores and helps in predicting satisfaction scores for comparison purposes. Based on survey data from a large multi-national multilevel marketing firm operating in different cultural/country settings, we empirically illustrate how marketing control variables impact distributor satisfaction scores across countries after controlling for biases. We also discuss the resource allocation implications based on the study.

2.1 Introduction

Multi-level marketing (MLM) firms with their networks of member-distributors are one of the fastest growing global phenomena in the past decade. In the U.S. alone, participation as member-distributors in such marketing grew from 9.7 million in 1998 to 15.1 million in 2008, with the annual sales growing from $23 billion to $30 billion during the same period (Direct Selling Association 2010). The global diffusion of this marketing phenomenon has been equally strong covering product categories such as home and family care, wellness and nutrition products, cosmetics and personal care with major brands such as Mary Kay, Amway, Avon, Discovery Toys etc.

MLM's business model combines direct marketing with franchising. Customers of a MLM company are associated with the company as independent contractors. Unlike regular customers, they are both buyers and sellers at the same time. Multi-level marketing businesses often call their customers as distributors, sales consultants, or sales associates. The structure of a multi-level marketing company is a pyramid. The highest-level (level 1) distributors/customers buy products from parent company and sell to customers who are one-level lower than themselves (level 2 distributors). These individuals who are on level 2 sell products to the customers who are on level 3, and so on. The distributors sponsored directly by the top level distributor, as well as those sponsored by other distributors below, are called as the "downline" of the top level distributor. The distributors are compensated based on their sales of products or services, as well as the sales of people recruited into their "downline". Since their compensations are based on sales, they act like salespersons for the firm, while playing the role of customers for "upline" distributors.

(Insert Figure 2.1 about here)

The success of MLM firms' network marketing depends significantly on distributor satisfaction and its impact on distributor retention (Rust and Zahorik 1993) and positive word of mouth. In the context of their dual roles of being customers as well as employees of the firm, distributors' satisfaction has significant impact on their retention, commitment to the business, their recommendations to improve the firm's products and services, and their effort to satisfy their downline. Satisfied, motivated, and positively influencing distributors help multi-level marketing company succeed in business. Since increases in satisfaction levels could dramatically improve a firm's sales and profitability (Hallowell 1996), multinational MLM firms routinely measure their distributors' satisfaction across countries they operate in. These satisfaction levels and the factors that impact the satisfaction levels are key input for comparing satisfaction levels across these cross-national markets, improving satisfaction levels in these markets, and appropriately allocating resources across the markets.

One of the key problems that multinational firms face in the measurement and understanding of the drivers of distributor satisfaction is the response bias that is inherent in these measures, which makes it difficult to compare these measures across markets. As a result, determining the true satisfaction levels and their drivers in each market and comparing them for resource allocation and satisfaction and retention improvement strategies become difficult. In this paper, we propose a spatial model to understand the determinants of distributor satisfaction and simultaneously account for response biases in measures in the context of cross-country marketing operations in comparing the satisfaction scores across markets.

Given the overall objective of our paper, there are relevant extant studies dealing with the biases in customer satisfaction survey (Greenleaf 1992; Baumgartner and Steenkamp 2001; Rossi *et al.* 2001; and King *et al.* 2004). These studies achieve one or more, but not all, of following objectives: (a) removing biases in customer satisfaction scores, (b) predicting individual customer satisfaction scores after controlling for biases, (c) constructing appropriate "anchors" so that the customer satisfaction scores can be compared across contexts, and (d) being easy to administer. However, these existing approaches do have some shortcomings in handling the specific application context such as ours, where managers need to have all of the objectives met, and, in addition, relate the bias to observable outcomes and effort of distributors.

In this paper, we propose a spatial framework to account for biases in cross-national satisfaction measures and render the distributor satisfaction measures across countries comparable. The key aspect of our conceptual model is that we take into account the effort expended and the sales generated by the distributors which we argue have an important impact on their survey responses. Thus, we define an attribute-space using the sales momentum and effort expended on business by distributors, and model the relationship between distributor satisfaction and the explanatory variables within this attribute-space and across markets. That is, the relationship between distributor satisfaction and other explanatory variables is dependent on where the distributors are located in the attribute-space. Thus, distributors' subjective responses are inter-related within the context of their own observable outcomes (sales) and behaviors (effort expended). We use Geographical Weighted Regression (GWR) for linking the relationship between distributor satisfaction and explanatory variables with the attribute-space and estimate the "spatial" dependence in the variables by GWR. The relationship between distributors' overall satisfaction and other explanatory variables differs from location to location in that attribute-space. It allows the firm to compare distributor satisfaction scores at the individual level from different countries/regions on the same basis. We illustrate how our model allows us to account for cross-market and individual level biases in the context of distributor satisfaction data across multiple markets of a multi-level marketing firm, and how satisfaction levels and drivers of satisfaction can be compared across markets for developing satisfaction improvement strategies and resource allocation decisions.

The remainder of the paper is as follows. In Section 2.2, we present our conceptual framework and approach and highlight the advantages of our approach compared with other existing approaches in the context of our application. In Section 2.3, we describe our spatial model specifications based on GWR. In Section 2.4, we describe the data and the empirical results. Finally, in Section 2.5, conclusions and implications for managers and academics are discussed.

2.2 Conceptual Development

The key requirement for being able to compare distributor satisfaction scores across markets and for understanding how different drivers impact the satisfaction scores is to control for the distortion in the measures of distributor satisfaction and drivers caused by biases – both due to individual factors and cross-country effects. Extant research has viewed the individual level biases as individual response traits or styles such as tendencies to acquiesce or disacquiesce, respond in extremes, etc (Baumgartner and Steenkamp 2001) or as a tendency to use portions of a scale (e.g., Rossi et al 2001) or due to individual differences in anchors each individual uses to respond to an item. We argue that, in our application context, the bias that is inherent in the distributors' responses and the resultant distortion of the measures is a function of their effort they put in and the sales outcome experience. The location of each distributor in this attribute-space of effort input versus sales outcome "colors" his/her perception of the constructs that are being measured in the satisfaction survey. Accordingly, our approach focuses on accounting for the impact of distributors' location in the attribute-space on his/her response to the items and uses them in making the satisfaction scores comparable across markets. In what follows, we present the details of conceptual development and approach and compare them to extant approaches to argue to highlight the relative advantages of our approach in the application context.

The distributors of the multi-level marketing firm are both buyers and sellers at the same time. They buy the products from their upline distributors (some consume part of their purchase for their own use). They put in effort to sell the products to their downline and are compensated on the basis of commission – a percentage of their own sales and their downline's sales. Thus, when they evaluate their overall satisfaction as distributors, they tend to use two perspectives: as regular customers and as well as a salesperson selling the firm's products to downline distributors. As regular consumers, distributors could assess how products and services supplied by the parent company meet or surpass their expectation. As salespersons, their satisfaction depends on the sales performance, their effort put in the business, and the interaction between buyers and sellers, etc. Their satisfaction is a function of various aspects of their interactions with other distributors, the firm and its products/services.

2.2.1 The Effect of Sales and Effort

From a salesperson perspective, we posit that distributor satisfaction is influenced by the total sales s/he generates and the total effort of s/he puts in. Extant research has shown that this influence is somewhat nuanced. Bagozzi (1980) concludes that satisfaction is not just related to outcomes as sales performance, but also on the value placed on the performance. Brown and Peterson (1994) show that effort has a strong direct effect on salesperson job satisfaction that is not contingent on sales performance. However, Christen, Iyer and Soberman (2006) find a negative, direct effect of effort and a positive, direct effect of sales performance on job satisfaction. In a study focused on Korean salesperson, Park and Holloway (2003) find that the type of effort expended – adaptive behavior – has positive impact on sales performance as well as satisfaction. Money and Graham (1999) in a cross-cultural study of salesperson performance, incentive and satisfaction find distinct differences between Japanese salesperson and U.S. salesperson as to how the different drivers impact satisfaction. Brown and Peterson (1993) found the causal effects of salespersons' job performance on their job satisfaction, and both their job satisfaction and job performance have a positive effect on their commitment to organization. They also found that greater job satisfaction is associated with greater amounts of participation and involvement.

The implication we derive from this extant literature for our application is that, while effort expended and sales performance impact satisfaction, their impact is nuanced and could vary across different cultures/countries. On the basis of this, we argue that the combination of the level of effort expended and the sales outcome together have a significant impact on how distributors' respond on their satisfaction surveys and to individual items. For example, if the level of effort expended is high and the sales outcome low, the resulting frustration or exhaustion may impact (bias) negatively how distributors may feel about the firm and its products/services and how satisfied they are, as compared to the case when effort expended is low and sales outcome is high, which could lead to a sense of delight and an overstatement of their satisfaction and ratings of the firms' products/services. Higher effort level could set a higher expectation for sales outcome and vice-versa and this could lead to disappointment or delight. Alternatively, effort expended could have a positive impact on satisfaction and a higher sales performance level could just enhance this effect. As a result, the relationship between satisfaction and its potential drivers in terms of the firms' products/service could be distorted depending upon where a distributor is located in attribute-space of effort expended versus sales performance. This potential bias and distortion could be further moderated by cultural/country effects.

It is important to note that we are not specifying any specific direction or magnitude for the potential direct, indirect and interactional impact of effort expended and sales performance, given the somewhat conflicting and nuanced relationships found in the extant literature. Rather, we argue that the potential impact is a function of the location of the distributor on the attribute-space of effort and sales, which determines the specific mindset, attitude or disposition a distributor is in while responding to the survey. We let the spatial model estimate the magnitude and direction of any such effect on the satisfaction and other evaluative measures. There is both empirical and anecdotal evidence for mindset introducing biases. Babakus et al. (1999) study the antecedents and consequences of emotional exhaustion in sales force behavior and attitude context and find that emotional exhaustion lowers the salesperson's job satisfaction and the sales performance of the salesperson. Similarly, MBA students' satisfaction with their program and evaluation of program offerings is highly influenced by the mindset they are in when they respond to the survey. This mindset is affected by whether or not they have a job after graduation, and the effort and resources they have put in towards their degree. We view the distributors' location on effort versus sales attribute-space to be the definition of the mindset they are in while responding to the survey and thus let the spatial model estimate its impact.

2.2.2 The Effect of Other Aspects on Distributors' Satisfaction

Sales force research has recognized that salesperson's long term success lie in a relational approach to the buyer-seller interaction where the salesperson adjusts to the buyer's needs and decision time frame (Dwyer, Schurr, and Oh 1987). To better understand the linkage between relational selling and salesperson's job performance satisfaction, Keillor, Parker, and Pettijohn (1999) investigate the effect of four generally accepted aspects of relational selling on salesperson's satisfaction. These four aspects of relational selling are customer-orientation, service-orientation, adaptability, and professionalism. Customer-orientation means that the salespersons would like to satisfy the customer's needs. Service-orientation takes into account the sellers' willingness to engage in both selling and non-selling tasks throughout the buyer-seller relationship. Keillor, Parker, and Pettijohn (1999) found that salespersons with high levels of customer-orientation and service-orientation exhibit higher levels of performance. In order to succeed in sales, a MLM distributor wants to satisfy his/her buyers' needs in both product and service. They will assess whether the firm's product and service will help them to achieve this goal. A distributor is also a regular customer, s/he also evaluate whether firm's product and service satisfy their own needs. Therefore, product and customer service have impacts on distributor satisfaction.

Organizational structure and communication has consistently been found to have important effect on job satisfaction (e.g., Churchill, Ford, and Walker 1976). If a salesperson can see how s/he climb corporate ladder and develop his/her career in the firm, s/he will be more confident in his/her career and satisfy with the firm. Thus, the opportunities which a MLM firm provides to their distributors have effect on distributors' satisfaction.

A good firm reputation is not only help salesperson to sale the product (Ferrell and Hartline 2010), but also attract more people to work for the firm. A product from a firm with good reputation is much easier to sale than a product from a firm with poor reputation. People also prefer to work for a firm with good reputation. Thus, we posit firm's reputation has impact on distributor satisfaction.

2.2.3 Comparison Based on Spatial Framework

Our proposed spatial framework relates all distributors' satisfaction scores to their evaluative scores of a firm's products and services, within the same attribute-space of sales outcome and effort expended, regardless of which country the distributor belongs to. The relationship between the explanatory variables – satisfaction drivers – and the dependent variable – satisfaction scores – depends on the location of the distributor in this attribute-space. Since there could be multiple distributors at a given location or at nearby locations, the spatial model utilizes the information from all these observations (regardless of which country the observation comes from) to estimate the relationship between the satisfaction drivers and satisfaction scores. Thus, the geographically weighted regression (GWR) spatial framework estimates relationships which could vary from location to location in the attribute-space using information from all distributors across different countries/markets. While the attribute-space controls for the individual-level bias introduced by the mindset of distributors, country dummies in the relationships allow for differences in country baseline satisfaction scores and in the slopes for the satisfaction drivers.

The variables defining the attribute-space – sales momentum and effort expended – are variables that can be objectively verified even if obtained directly from distributors. They are measured as follows. Sales momentum is the percentage of distributors' sales change (increase or decrease) in last six months. This is verified using actual sales volume generated by each distributor[1]. Effort expended on business measures the number of hours each week distributors spent on all aspects of their business. This is verified by the number of downline distributors recruited and the number of workshops held in each month by the distributor (Sparks and Schenk 2001). The verification eliminates any common method variance that could arise in self-reports (Rindfleisch et al. 2008), and provides an objective anchor for each distributor in accounting for the bias.

Our spatial framework does not focus on obtaining the "true" satisfaction score of each distributor in each country but rather focuses on providing a common basis or a reference for comparing satisfaction scores across countries. Given the location of a distributor from a specific country, say Korea, in the attribute-space and the estimates of the spatial model for the different countries, the distributor can be "transposed" to belong

[1] In the application we use objective measures derived from actual sales figures.

to another country, such as India, and his/her equivalent score in India can be obtained using the model estimates. Thus, to compare the levels of satisfaction scores across countries after accounting for biases arising due to the location in the attribute-space, all we need to do is to predict all satisfactions scores using a specific country as the reference or datum. Thus, the framework allows us to generate comparable distributor satisfaction measures across all countries no matter which country a distributor belongs to. The spatial model also provides the relationship between satisfaction and the satisfaction drivers within each country as a function of the attribute-space location.

2.2.4 Comparison with Extant Research

Extant researchers have developed models that account for biases in measurement caused by individual response styles and cultural differences. Baumgartner and Steenkamp (2001) define response styles as tendencies to respond systematically to questionnaire items based on content-irrelevant factors other than what the items were specifically designed to measure. Common examples of response styles include agreeing or disagreeing with items regardless of content, using the middle response category, and responding with extreme response categories, etc. Response styles lead to scale usage heterogeneity and contaminate observed responses by either inflating or deflating respondents' answers and threaten the validity of empirical findings (Rossi, Gilula and Allenby 2001). Greenleaf (1992) and Baumgartner and Steenkamp (2001) focus on detecting and correcting bias components in the response styles. For example, Baumgartner and Steenkamp (2001) develop a regression model to parcel out the response style contaminations in cross-national surveys. They assume that scale scores are a linear function of the different response styles biases. After removing the biases due to response styles, the intercept term in the regression model provides the adjusted unbiased score, which is an aggregate score. This adjusted aggregate score is at the national-level and not at the individual-level.

While Baumgartner and Steenkamp's approach uses information from an individual response to other items in the survey to quantify the response style biases, our framework borrows information from other individual observations in the vicinity of a distributor in the attribute-space, regardless of the country they come from. A disadvantage of their approach in deriving an aggregate unbiased true satisfaction score is that the scale property of the customer satisfaction measure is lost. While the unbiased scores for different countries are ranked, there is no anchor to infer the true satisfaction level the unbiased score represents. For example, if a country's unbiased score is 6.8, does it indicate that customers are satisfied or less satisfied? Such questions may haunt managers who are interested in understanding the true levels of satisfaction. Our approach, on the other hand, can allow such determination by transposing other country satisfaction scores to a baseline country score, whereby scale property is maintained.

King et al. (2004) propose an anchoring-vignettes method to correct the incomparability of measurement in survey research. They first create several hypothetical situations (or products or services) described by written vignettes for which satisfaction scores are obtained. Before survey respondents answer the survey question, they ask survey respondents to assess their situation and the hypothetical situations. The assessments of those hypothetical situations act as anchors. Through stretching or shrinking the scale to make the anchors fall into the same band, the assessments of all respondents become comparable. Their basic idea is to recode the respondent's assessment of their situation relative to the assessment of set of hypothetical situations. The advantage of their method is that it makes the responses comparable by using respondent's assessment of the hypothetical situations as anchors to adjust respondents' responses. Their method assumes each individual assessment of his/her situation is consistent with the assessments of hypothetical situations and all respondents perceive the level of the variable represented in any hypothetical situations in the same way. Their method requires that the assessments of hypothetical situations should be perceived in the same order by every respondent. However, a person who uses the product for a long time may have different expectation about the product and service than a person who uses the product for the first time. Thus, their overall evaluation of the product and service may focus on different aspects. It is hard for all respondents perceive the level of variables represented in each hypothetical situation in the same way. Another disadvantage of their method is that it requires all respondents answer all the survey questions for both their situations and the hypothetical situations. Thus, it can be expensive to design and administer in the context of many applications.

Rossi et al. (2001) study scale usage heterogeneity of customers' satisfaction indexes and propose a Bayesian hierarchical approach to model ratings data in which a multivariate ordinal Probit model is coupled with a hierarchical model of respondent-level location and scale shifts. Their model is motivated by the basic view that the discrete responses provide information on underling continuous and latent preference-satisfaction. The individual latent satisfaction is multivariate normal variable. Respondent-specific location and scale shifts in latent preference variables represent scale usage heterogeneity. The advantage of their approach is that it corrects the problem of using discrete data in continuous distribution and it models individual responses to make individual measurements comparable. However, due to lack of anchors, it is hard to compare all respondents' relative satisfaction on the same basis.

Our approach provides individual-level adjustment for distributor satisfaction scores. It allows us to relate distributor satisfaction scores with their own effort expended and objective sales outcome. Measurements of distributors' own behavior and outcome – effort expended on business and sales momentum – serve as anchors and make distributor satisfaction scores comparable across different markets. It is also easy to administer our method.

2.3 Model Specification

We relate the satisfaction scores to their drivers using Geographically Weighted Regression (GWR) technique which models spatial non-stationarity by calibrating a multiple regression model that allows different relationships to exist over the attribute-space defined by sales momentum and effort expended (Brunsdon, Fotheringham, and Charlton 1996, 1998). Because of the strong effect of sales performance and effort expended on job satisfaction, the relationship of distributors' satisfaction with other explanatory variables is not constant from location to location in our attribute-space. GWR helps us to account for the dependency of satisfaction measures and their drivers on the sales performance and effort expended. The estimates of regression coefficients vary across locations after taking into account the spatial correlation among observations in the neighboring locations. An observation close to a certain location is given a heavier weight in the model than an observation far away from that location (Mittal, Kamakura, and Govind 2004). In the GWR model, the dependent variable Y is overall distributor satisfaction. We perform a factor analysis on data array $Z = \{z_{im}\}$ to obtain the explanatory variables (factor scores) X, which are used in the model as follows:

(1) $$\mathbf{Y}_{(\mathbf{u_j},\mathbf{v_j})} = \boldsymbol{\alpha}_{(\mathbf{u_j},\mathbf{v_j})} + \boldsymbol{\beta}_{(\mathbf{u_j},\mathbf{v_j})}\mathbf{X} + \boldsymbol{\gamma}_{(\mathbf{u_j},\mathbf{v_j})}\mathbf{I} + \boldsymbol{\theta}_{(\mathbf{u_j},\mathbf{v_j})}(\mathbf{X} \times \mathbf{I}) + \boldsymbol{\varepsilon}_{(\mathbf{u_j},\mathbf{v_j})} ,$$

where Y is the overall distributor satisfaction;

X are the explanatory variables – drivers of the overall distributor satisfaction;

I are the dummy variables for the different countries/markets;

(u_j, v_j) represent the coordinates for location *j*, sales momentum and effort expended on business;

ε are the disturbance terms.

Observed data near to location *j* have more of an influence (given more weight) in the estimation of the regression coefficients specific to that location than data located farther from location *j*. Weighted least squares provides a basis for GWR operations. The weighting matrix $W_{(u_j,v_j)}$ contains weights $w_{(u_j,v_j)(u_{j'},v_{j'})}$, $j, j' = 1, \cdots J$ for all locations that are used in estimating parameters in location *j*:

(2)

$$\mathbf{W}_{(\mathbf{u_j},\mathbf{v_j})} = \begin{bmatrix} w_{(u_j,v_j)(u_1,v_1)} & 0 & 0 & \cdots & 0 \\ 0 & w_{(u_j,v_j)(u_2,v_2)} & 0 & \cdots & 0 \\ 0 & 0 & w_{(u_j,v_j)(u_3,v_3)} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & w_{(u_j,v_j)(u_J,v_J)} \end{bmatrix}_{J \times J} .$$

The weighted least squares estimates for any location *j* are as follows:

(3) $$\hat{\beta}_{(u_j,v_j)} = \left(X' W_{(u_j,v_j)} X\right)^{-1} X' W_{(u_j,v_j)} Y .$$

The relative weight $w_{(u_j,v_j)(u_{j'},v_{j'})}$ decays as the distance from the focal location *j* to location *j'* increases,

(4) $$w_{(u_j,v_j)(u_{j'},v_{j'})} = \exp\left(\frac{-d^2_{(u_j,v_j)(u_{j'},v_{j'})}}{\zeta}\right), \ \ j, j' = 1, \cdots J,$$

where ζ is the distance decay parameter which is also called as optimal bandwidth; and $d_{(u_j,v_j)(u_{j'},v_{j'})}$ is the Euclidean distance[2] between locations *j* and *j'*. ζ is estimated before the weighted least squares estimates can be obtained. We determine the most appropriate bandwidth using the least square cross-validation procedure that Cleveland (1979) suggests.

Figure 2.2 shows how the comparable distributor satisfaction measures are generated in our framework.

(Insert Figure 2.2 here)

2.4 Empirical Application

2.4.1 Data

The data we used are from 6,733 distributors of a multinational multi-level marketing company who filled out the distributor satisfaction survey. 1484 of these distributors are from Korea, 2209 of them are from India, and 3040 of them are from USA. The satisfaction survey includes a question about overall satisfaction, "*Overall, how satisfied are you being a distributor?*"; and questions about various aspects of products, communication, opportunity, and service, such as, "*How strongly do you agree*

[2] Mahalanobis distance could also be used as an alternative distance measure which would account for the correlation between the variables making up the attribute-space.

or disagree with the following statements? Dynamics is bringing new products to the market that I like”. These items are measured on a ten-point scale (1=“very dissatisfied/strongly disagree”, 10=“very satisfied/strongly agree”). The survey also asks respondents about their sales, time spent on business, and the number of people they recommend products to, such as “*Think about the products you purchase from Dynamics, is that amount in the last 6 months increasing/decreasing.”, and “On average, about how many hours each week do you spend as a distributor on all aspects of your business?”.* The item about sales momentum is measured by a five-point scale (1=”decrease more than 10%”, 2 = “decrease between 5% and 10 %, 3 = “decrease below 5% or increase below 5%”, 4 = “increase between 5% and 10%, 5= “increase more than 10%”), and the item about effort expended on business is measure by a five-point scale (1= 1 to 9 hours/week, 2 = 10 to 19 hours/week, 3 = 20 to 29 hours/week, 4 = 30 to 39 hours/week, 5= 40+ hours/week). At the end of survey, respondents are asked about demographics – gender and age. Appendix I provides all the individual items in the survey that we used to calculate the factor scores.

2.4.2 Variables

The dependent variable of our GWR model is overall distributor satisfaction of distributor i ($OVERALLSAT_i$). The explanatory variables are four factors, reputation ($REPU_i$), product ($PROD_i$), customer service ($CUSSRV_i$), and distributor’s opportunity ($OPPTNT_i$). These four factors are determined by a factor analysis with 26 items which measure various aspects of company’s products, communication, opportunity, and service. Reliability coefficients of items in each factor are larger than 0.8. Country dummy variables are country India ($DUMIND_i$) and country Korea ($DUMKOR_i$). We also include the interaction terms between four factors and country dummy variables. Coordinates of a location in the conceptual space are sales momentum ($SALMOM_j$) and effort expended (time spent) on business ($TIME_j$) by distributors.

(Insert Table 2.1 here)

We estimated the spatial autocorrelations in the dependent and independent variables to check whether the attribute-space did have any effect on these variables. If spatial autocorrelation is not present, then attribute-space location has no impact on the satisfaction scores and their drivers and a pooled linear regression across all the locations should be sufficient. Moran's I and Geary's C statistics, indicators of the degree of spatial autocorrelation, were measured across all the locations for all five variables. The results are shown in Table 2.2. For all five variables, Moran's I are larger than $-\frac{1}{N-1}$ $(p < .01)$, and Geary's C are less than $1(p < .01)$, indicating positive spatial autocorrelations for all five variables. Values of observations from a location tend to positively correlate with other observations from locations closer to that location. The simulations in Appendix II and III further show that the GWR is very effective in recovering the "true biases" caused by attribute-space variations on the satisfaction measures.

(Insert Table 2.2 here)

2.4.3 Empirical Results

Using GWR model, we estimated the relationship between distributors' overall satisfaction with company's reputation, product, customer service and distributors' opportunity. The relationship varies across different locations that is defined by distributors' sales momentum and effort expended on business.

(5) $$\mathrm{OVERALLSAT_i} = \alpha_j + \beta_{1j}\mathrm{REPU_i} + \beta_{2j}\mathrm{PROD_i} + \beta_{3j}\mathrm{CUSSRV_i} + \beta_{4j}\mathrm{OPPTNT_i} + \gamma_{1j}\mathrm{DUMIND_i} + \gamma_{2j}\mathrm{DUMKOR_i} + \theta_{1j}\mathrm{DUMIND_i} \times \mathrm{REPU_i} + \theta_{2j}\mathrm{DUMIND_i} \times \mathrm{PROD_i} + \theta_{3j}\mathrm{DUMIND_i} \times \mathrm{CUSSRV_i} + \theta_{4j}\mathrm{DUMIND_i} \times \mathrm{OPPTNT_i} + \theta_{5j}\mathrm{DUMKOR_i} \times \mathrm{REPU_i} + \theta_{6j}\mathrm{DUMKOR_i} \times \mathrm{PROD_i} + \theta_{7j}\mathrm{DUMKOR_i} \times \mathrm{CUSSRV_i} + \theta_{8j}\mathrm{DUMKOR_i} \times \mathrm{OPPTNT_i} + \varepsilon_i ,$$

where ε_i is i.i.d. normal disturbances.

Table 2.3 is the summary of estimates of coefficients across all locations of GWR model with the last column in Table 2.3 providing the estimates of coefficients of global OLS (OLS Model 1) which has the same explanatory variables, country dummy variables, and interaction terms. For global OLS model, only Product, Opportunity, Customer service, dummy variable for India, and interaction terms between Reputation, Product, Opportunity and dummy variables for India are significant at $\alpha < 0.001$ level. However, for GWR model, except for dummy variable for Korea and interaction terms between Opportunity, Customer Service and dummy variable for Korea, all other variables and interaction terms are significant at $\alpha < 0.001$ level.

(Insert Table 2.3 here)

The ranges of the estimates for almost all coefficients are quite large, ranging from negative to positive. For example, for variable Product, the minimum of estimates is -0.21 and the maximum of estimate is 0.17; and for Opportunity, the minimum of parameter estimates is 0.10 and the maximum of estimates is 0.27. These large ranges indicate that the relationship between overall distributor satisfaction and explanatory variables varies significantly across the attribute-space, and the combination of sales momentum and effort expended on business has a significant impact on this relationship.

From the OLS estimates in the last column of Table 2.3, we infer that for the base country (USA), reputation (of the firm and its products) has no impact on distributor satisfaction, but the coefficients of interaction between reputation and country dummies indicate that reputation has significant impact on distributor satisfaction in both India and Korea. While products (new market-focused products) have a significant and moderate (in terms of magnitude) impact on satisfaction in U.S. and Korea, the magnitude of impact is much higher in India. On the other hand, customer service (service provided by the firm) seems to have a much lower impact on satisfaction across all markets.

However, when the spatial correlations are taken into account – that is, the impact of the attribute-space of sales momentum and effort expended is considered – the GWR indicates that there could be a significant variation, even within countries, in the coefficients indicating the impact of drivers across distributors depending on their location in the attribute-space. Examples of such variations are shown in Figures 2.3 and 2.4. Darker (lighter) color indicates a lower (larger) value for the regression coefficient, that is, lower (higher) impact of the company's reputation, and customer service on overall satisfaction. In Figure 2.3, we observe that while reputation impacts are high for distributors in U.S. markets with sales momentum and effort expended coordinates (5, 1) – high sales and low effort, (1, 1) – low sales and low effort, or (5, 5) – high sales and most effort, it tends to be lower in the middle coordinates (3, 3) – moderate sales and moderate effort and nearby. However, for India, reputation impacts generally tends to be higher all over except for coordinates (1, 3 – low sales and moderate effort) and nearby. For Korea, reputation effects are associated with higher values of sales momentum. Similarly, Figure 2.4 indicates that while customer service has a high magnitude impact on distributor satisfaction scores for those with high sales momentum in the U.S. market, it has a uniform impact in other markets (India and Korea) except for coordinates (1, 5) – low sales and high effort and nearby. The GWR results therefore provide useful insights into how the satisfaction drivers vary in impact across distributors whose sales performance and effort expended vary. This has useful segmentation implications for improving distributor satisfaction.

(Insert Figures 2.3 & 2.4 here)

Figure 2.5 provides the plot of the observed distributor satisfaction scores for U.S. distributors as a function of the location in the attribute-space, along with the predicted distributor satisfaction scores using the GWR model. The first observation on these plots is that the plot of predicted satisfaction scores is very close to the plot of observed satisfaction scores indicating a good fit of the GWR model. The second observation is that satisfaction scores do vary significantly over the attribute-space – the satisfaction scores are generally lower with lower sales momentum except for the case when effort level is at the highest (this is based on fewer observations in that region). The satisfaction scores are the highest when sales momentum and effort level are at their highest level, with satisfaction scores being generally high when sales momentum is at the highest level, regardless of the level of effort. It is interesting to note that satisfaction levels are higher when effort levels are high – this could be due to the fact that higher effort levels put the distributors in more contact and interaction with the firm and the customer service could be leading to higher satisfaction levels. In general, distributor satisfaction scores change appreciably over the attribute-space indicating that the attribute-space of sales momentum and effort expended does contribute to understand the variation in satisfaction scores as posited in our conceptual model. This is also the case in other markets – India and Korea – as seen in Figure 2.6. In addition, the GWR model incorporating the attribute-space is able to predict the satisfaction scores very well tracking the observed satisfaction scores closely. Next, we measure this performance quantitatively.

(Insert Figures 2.5 & 2.6 here)

2.4.4 Model Performance and Comparison

We compares three models – the GWR model, the OLS Model 1, which has all the explanatory variables and interactions as the GWR model, and OLS Model 2, which has all the variables in OLS Model 1 and sales momentum and effort expended (and all their interactions with other independent variables). Two criteria were used to evaluate model performances of the comparative models: 1) the variance explained by the models, and 2) model's predictive ability in a hold-out sample.

The Residual Sum of Squares (RSS) of OLS Model 1 is 22,718.71, and RSS of GWR model is 19,999.12. GWR model improvement of RSS is 2719.591. Leung et al. (2000) F(1) test and F(2) test, and Brunsdon, Fotheringham & Charlton (1999) ANOVA test show that RSS of GWR is significantly less than RSS of OLS Model 1, and GWR has a significant improvement on RSS (p-value = 6.48e-06, 2.2e-16, 2.2e-16, respectively). R-square for OLS model is 0.42 and R-square for GWR model is 0.50, which shows GWR model has better explanatory power. AIC for GWR model is 26,549.43. The RSS of OLS Model 2 is 20879.76, which is still much larger than RSS of GWR model. R-square of OLS Model 2 is 0.47, which is smaller than the R-square of GWR model. Thus the proposed spatial framework has much better performance than benchmark models.

(Insert Table 2.4 here)

The hold-out sample consisting of 900 observations was used to evaluate predictive ability of the models. Although GWR can estimate coefficients even for locations with no observed data, we would like to duplicate the real situation in which every country has at least one observation for each location. Thus, 6 observations were added to randomly drawn observations. The hold-out sample included 906 observations. In Table 2.5, the mean and median of absolute prediction error for linear regression model (OLS Model 2) are about twice as much as those for GWR model. In Table 2.6, the mean of predicted distributor satisfaction are quite close to the mean of original distributor satisfaction for both the calibration dataset and the hold-out sample, indicating the superior performance of the GWR model.

(Insert Tables 2.5 & 2.6 here)

2.4.5 Comparable Scores

In order to obtain comparable distributor satisfaction scores, we use U.S. market as the baseline. Given a specific set of independent variables for a distributor in a non-U.S. market, say Korea, the equivalent set of independent variables for this distributor in the U.S. space is first determined. This determination involves the following steps: (1) given the location in the attribute-space, the multivariate distributions of the independent variables in the U.S. space and the Korean space are determined – this procedure involves borrowing information from nearby locations using the spatial model; (2) given the mean and variance-covariance of the estimated distributions, the independent variables for the distributor in Korea is transformed to the equivalent set of independent variables in the U.S. space. This set of equivalent independent variables is used along with U.S. specific coefficients to predict the equivalent satisfaction score in the U.S. space. For example, suppose there are a U.S. distributor and a Korean distributor at location A. For the U.S. distributor, the expected satisfaction score is:

(6) $$\widehat{Y}_{US} = \alpha^{A}{}_{US} + \beta^{A}{}_{US} X_{US} \ ,$$

and for the Korean distributor, the comparable distributor satisfaction score in the U.S. space is

(7) $$\widehat{Y}_{KOREA \to US} = \alpha^{A}{}_{US} + \beta^{A}{}_{US} X_{KOREA \to US} \, .$$

It is to be noted that the individual response biases are accounted for through the attribute-space. For the same location, distributors from different countries are on the same datum, which allows us to get the comparable satisfaction measures across different countries with the location-specific coefficients for each distributor. If the comparable scores in the U.S. space are determined for all distributors in Korea, then averaging those scores produces the comparable overall mean score. These are presented in Table 2.6 column 3 and column 6. The comparable satisfaction scores for India and Korea are also plotted in the attribute-space in Figure 2.6. It is easy to see that the distribution of the comparable satisfaction scores in the U.S. space is somewhat different the predicted satisfaction scores in their own market (India or Korea) space.

In Table 2.6, we find that the average of comparable distributor satisfaction scores of India is actually lower than average of the original distributor satisfaction, and the average of comparable distributor satisfaction of Korea is actually higher than average of the original distributor satisfaction.

2.5 Managerial Implications and Conclusions

In multinational multi-market contexts where satisfaction scores – either distributor/salesperson satisfaction as in our case or customer satisfaction as in other cases – are important metrics for firms for purposes of resource allocation and development of satisfaction enhancement strategies, our study and methodology provide very useful insights and helpful mechanisms. In many multi-level marketing firms such as Avon International, Amway, and others, the relative values of satisfaction scores in each market are used for resource allocation purposes. For example, a market where satisfaction scores are very low might require infusion of additional funds to enhance the satisfaction levels as it has important implications for distributor/customer retention and positive word-of-mouth. Likewise, if a market has high satisfaction scores, then the resources needed may not be that significant. However, if the absolute satisfaction measures from each market are not directly comparable because of individual level and country-level biases, resource allocation strategies based on such satisfactions scores may fail. Our framework overcomes this problem by making the satisfaction scores comparable. In our empirical illustration it is seen that when Korean average score is compared to U.S. average score on the same basis, it is adjusted upwards (from 6.35 to 6.96), while Indian average score is adjusted downwards (from 8.35 to 8.16). This indicates that the Korean situation may not be as dire as it may seem to be, while the Indian scores may not be as rosy as they may seem to be. In the Indian case, the implication could be that there is still a lot of room for improvement. Thus, the adjusted comparable scores provide a better and more justifiable basis for resource allocation of marketing budget across these markets. The anchoring of the scores on the basis of distributors' sales momentum and effort expended provides an objective basis for comparing these scores.

A more important implication from our study is how the marketing resources allocate to a specific market to be used to enhance distributor satisfaction. Our results show that satisfaction drivers are indeed different in different markets – in India, new, market-driven product introductions are much more important in impacting satisfaction, while in Korea and India, firm and product reputations play a much more important role than in the U.S. market. However, what is more important is that our framework provides useful insights into how the impact of the different drivers varies across the attribute-space in each of these markets. Since sales momentum and effort expended by distributors are variables that the firm can easily measure and track, they can be used as powerful segmentation tools to focus on appropriate actions for satisfaction improvement programs by identifying groups of distributors who are located differently on the attribute-space based on their sales momentum and effort expended. Understanding how the different drivers impact satisfaction of each of these groups can be very useful in developing customized marketing programs for distributor segments. An argument could be made that distributors' effort expended, sales momentum and satisfaction scores are all endogenous. If this indeed the case, then firm really does not have a direct control on the effort expended and sales outcome of each distributor. Thus, segmenting distributors on the basis on the attribute-space coordinates allows the firm to understand how the coordinates impact the relationship between drivers and satisfaction scores.

An alternative formulation to our model is to include sales momentum and effort expended as additional independent variables in the model. However, as our model comparisons show that the OLS Model 2 formulation does not perform as well as GWR in model fit and in prediction. Additionally, given that sales momentum and effort expended could be endogenous, treating them as coordinates rather than independent variables would be more desirable from a conceptual viewpoint. Of course, it is important to note that these coordinates that have been chosen are very specific to our application. In other applications, say involving customer satisfaction, the coordinates could be externally verifiable measures such as total purchase, share of wallet, or average price paid, etc. Future research could focus on how our framework compares with alternative methods of controlling biases in an empirical setting.

Chapter 3: Essay 2: Peeking into Online Bargain Hunting Forums: How Active Participants Influence the Silent Majority

Abstract

Bargain hunting forums are becoming increasingly popular among Internet users as a venue to look for good deals, post comments, exchange tips and other information. They are also attracting the attention of retailers in search for creative ways to disseminate promotion information and to influence consumers' attitudes. Despite their widespread popularity, only a small proportion of users actively participate in these discussion forums by posting comments, while most users look for information in the forums without contributing to the discussions. To assess the influence of such social discussion platforms, one must look at the impact of active participants on the silent majority, because the latter represents a much greater contributor to the customer base and sales of a company or product.

In this study, we investigate whether and how online discussions posted by active participants affect the interest and preference of the silent majority. We collect data from a major bargain hunting forum, which allow us to infer attitude of a sample of silent viewers. Our analysis of the online discussions goes beyond measures used in the prior research, such as volume and valence, and delves into the specific contents of discussions posted in the forum. We classify the contents into a range of specific categories, and develop a Bayesian Poisson-Binomial model to examine how silent viewers' interest in and preference for a featured deal are influenced by the discussions, while controlling for

many other factors. Our results show that the content of discussions posted by active participants indeed affects the silent viewers' interest in and preference for a featured deal, and that the effects are different across the specific categories of content. Our findings demonstrate that marketers can benefit from monitoring activities in online bargaining hunting forums, and suggest ways for them to improve the design and information dissemination of promotions via participation in these forums.

3.1 Introduction

According to a recent survey by guidance.com, nearly 30 percent of online shoppers believe that the best way to find promotion deals is through some form of online social interactions (Guidance 2008), such as online bargain hunting forums and social network websites. In recent years, bargain hunting forums (such as dealcatcher.com, dealofday.com, dealsea.com, fatwallet.com, gotapex.com, gottadeal.com, slickdeals.net, and wireddeals.com) are becoming increasingly popular among Internet users. They attract numerous web surfers who look for deal information, post comments, and exchange tips and other information on a wide range of goods and services.

Discussion forums in these bargain hunting websites offer the media and software support for user-generated contents. The forum format differentiates them from conventional shopping websites (such as Travelocity.com, PriceGrabber.com, and PriceScan.com), which are aimed at providing users with firm-generated price comparisons of goods and services. In contrast, contents in bargain hunting forums are generated by the users. In these forums, extensive information on special deals as well as personal opinions about them are communicated in a vast social community and shared by a large number of users. Table 3.1 presents the traffic information of several popular bargain hunting forums, which illustrates their popularity among Internet users.

[Insert Table 3.1 here]

With the rising popularity of online bargain hunting forums, they are also attracting the attention of retailers in search for creative ways to disseminate promotion information and to influence consumer attitudes. These online forums provide not only a platform for consumers to post deal information and to comment on the promoted products, but also a low cost channel for retailers to inform consumers of their promotion offerings. In addition, they allow marketers to monitor online discussions, get direct feedback from consumers, and create an opportunity for retailers to even actively engage in online discussions. By peeking into online bargaining hunting forums, marketers can gather valuable information to design and adjust their promotion offerings.

Despite the widespread popularity of online bargain hunting forums, only a small portion of users actively participate in these discussion forums by posting their comments and questions and providing product or company information, while the vast majority look for information in these forums without actively contributing to the content of discussions. This phenomenon exists in most online communities. Research shows that in websites primarily relying on user-generated contents, about 1% of users contribute to the contents on a regular basis, 9% of users contribute occasionally, while 90% of users never contribute (Nielsen 2006). These users who simply lurk in the background are the silent majority. In order to assess the influence of social discussion platforms in general, and online bargain hunting forums in particular, one must look at how discussions posted by active participants affects the silent majority, because the latter represents a much greater contributor to the customer base and sales of a company or product.

Although there has been extensive research on social network websites and Internet word-of-mouth, not many studies have focused on online bargain hunting forums. In addition to gaining domain-specific managerial insights, these forums offer a good opportunity to study the influence of online discussions in shaping the viewers' attitudes, because discussions in these forums are centered around special deals available only in limited timeframe, and thus data of fairly short time span would serve the purposes.

With the rapid development of online communities and research on these topics, academics and practitioners alike are emphasizing the need for more in-depth content analyses and more nuanced understanding of the nature of online discussions. While prior research has suggested that viewers do read and are influenced by the content of online reviews (Chevalier and Mayzlin 2006), little is known yet about how specific contents of online discussions, beyond their valence, may affect the viewers' attitudes. This will be a focus of our study.

We intend to achieve three main objectives in this research: 1) to investigate how discussions in bargain hunting forums affect the silent majority's interest in and preference for the featured deals; 2) to distinguish and examine the effects of different categories of discussion contents, beyond volume and valence; and 3) to provide suggestions on how to utilize online bargain hunting forums to more effectively disseminate promotion information and influence potential buyers' attitude. We will examine the impact on both interest and preference of the silent viewers. Interest refers to their level of engagement with a featured deal, and preference refers to their extent of positive attitude toward the deal. While both are important determinants of a product's sales, the impact of online discussions on them may be quite different. It is important for marketers to understand what kind of online discussions may influence interest vis-à-vis preference, and whether they can and how to utilize online bargain hunting forums to stimulate interest of and to foster positive attitude toward their promotions among potential buyers.

We collect data from a major bargain hunting forum, which allow us to infer attitudinal information of a sample of silent viewers, in addition to detailed information of all discussions posted by active participants. We conduct a detailed content analysis of those posts, and investigate how silent viewers' interest in and preference for a featured deal are influenced by the content of online discussions, while controlling for other factors such as the type of deal and size of the merchant. The specific issues that we intend to address in this study include: 1) Whether and how discussions posted by active participants in online bargain hunting forums affect the level of interest and preference of the silent viewers? 2) What types of discussion contents are more effective in influencing the viewers' interest and preference, respectively? For example, comments on which aspect of a featured deal tend to have the strongest impact: the product, price, or retailer? 3) How do the patterns differ by types of deals, size of the merchant, status of the posters, etc? 4) What are the implications for marketers in terms of effectively disseminating promotion information and influencing potential buyers' interest and preference?

The rest of the paper is organized as follows. We first provide a brief review of the relevant literature and highlight the intended contributions of this study, and then describe the research methodology, followed by the model estimation results and follow-up analyses. We conclude with discussion of the key findings and managerial implications of this research.

3.2 Literature Review and Intended Contributions

Prior research has shown that interpersonal influence and word-of-mouth (WOM) communication have a significant impact on consumers' evaluations of products and purchase decisions (e.g., Katz and Lazarsfeld 1955; Hugstad et al. 1987). The emerging

Internet technology has enabled an individual to share opinions and experiences with others across the globe and no longer be limited to one-on-one communications (Dellarocas 2003). Unlike traditional WOM communications that are effective in limited social contact boundaries (Ellison and Fudenberg 1995), online WOM can reach a large number of consumers quite rapidly. Consumers' desire for social interactions, economic incentives, concerns for others, and willingness to enhance their own self-worth motivate them to participate in online discussions (Hennig-Thurau et al. 2004).

There has been extensive research on how online WOM or reviews impacts product sales (see Zhu and Zhang 2010 for a comprehensive review of empirical studies on this topic), which has investigated the effects of various characteristics of online reviews or WOM. In the context of the movie industry, Liu (2006) finds that the volume of online WOM is the most significant predictor of movie box-office revenue, while the valence does not seem to have an effect. Duan, Gu, and Whinston (2008) show that the volume of online WOM increases movie box-office revenue and is also influenced by the latter in turn. Dellarocas and colleagues (2007) find that online movie ratings significantly improve the predictive power of their movie revenue forecasting model. In other product contexts, Godes and Mayzlin (2004) show that the dispersion of online WOM positively affects TV show viewership. Chevalier and Mayzlin (2006) demonstrate that the valence of online book reviews affects book sales. In addition, they find a positive relationship between the length of reviews and book sales, suggesting that the contents of reviews do affect consumers' purchase decisions. The moderating effect of product and consumer characteristics (Zhu and Zhang 2010) and product quality (Moe 2009) on the impact of online WOM on sales has also been studied.

In spite of the extensive prior research, how the specific contents of online discussions influence viewers' perceptions remains largely unexplored. For example, online discussions about featured deals usually involve information on the following aspects: the product, price, retailer, and how to get the promotion. It is unclear yet discussions on which aspects are more impactful on viewers. An investigation based on more in-depth analyses of these specific contents can provide valuable new insights for marketers, and will be a focus of this study. Thus, an intended contribution of our research is to go beyond the volume and valence of online discussions and to analyze the effects of a variety of specific contents.

Prior research on online WOM or reviews has primarily focused on their impact on product sales. Another under-explored topic is their influence on the intermediate steps leading toward purchase decisions: *interest* in and *preference* for the product, two distinctive factors both important to the eventual sales of a product. A consumer's interest in a product or promotion message reflects his/her level of involvement with the object (Hupfer and Gardner 1971; Mittal and Lee 1988). Highly involved consumers devote more attention to product- and store-related information, are more engaged in understanding their advertisements and learning about the products (Solomon 2006), which in turn increases their purchase intention (Swinyard 1993). Increasing consumers' involvement may potentially increase marketing effectiveness and efficiency for companies (O'Cass 2000). Nonetheless, high-involvement does not necessarily lead to positive attitude toward a product. Highly-involved consumers may generate negative attitudes toward the product and decide against purchasing it, if they are exposed to negative information or evaluations about it. Only when highly-involved consumers have positive attitudes toward a product, are they likely to make a purchase and even develop brand commitment or store loyalty (Warrington and Shim 2000). By examining the distinct effects of online discussions on potential buyers' interest and preference, respectively, our study will provide insights to help retailers develop potentially different strategies to stimulate consumers' interest and/or to foster their preference, which in turn affects sales or other behavioral outcomes.

Prior research suggests that firms may benefit from taking part in consumer generated discussions. Some firms even routinely monitor online forums and strategically manipulate online reviews in order to influence consumers' purchase decisions (Dellarocas 2006). Dellarocas (2006) offers a theoretical analysis of the impact of strategic manipulation of online forum on firm profits and consumer surplus. Chen and Xie (2008) look into firm's strategies to provide consumer reviews on their websites, and show that helping consumers create and broadcast their own opinions about the firm's products is a new and potentially powerful opportunity for firms. Mayzlin (2006) find that when firms spend more resources promoting inferior products, online WOM is persuasive despite the promotional chat activity by competing firms. In addition, Godes and Mayzlin (2009) find that, besides WOM generated from consumers' personal experiences with a product, firm-created WOM can also affect product sales. An important question remains largely unanswered: what kinds of messages should firms use, if they choose to participate in online discussions? In this study, we intend to provide guidance for retailers on this issue, in the context of bargain hunting forums. More broadly speaking, we intend to offer insights on how to utilize online discussion forums to effectively disseminate promotion information and proactively influence potential buyers' attitudes.

3.3 Research Methodology

3.3.1 Data Description

Our data were collected from a major online bargain hunting forum during a two-month period (October – December 2009). We analyze data on deals of digital cameras posted during this period, which include 104 threads. We choose to analyze the digital camera category for several reasons. First, this category is one of the most frequently promoted categories on the website. Second, there are substantial variations in the model, price, and brand quality among digital cameras, and consumers also have quite different needs and thus tend to seek input from others before making purchase decisions. And third, digital cameras are primarily consumer products, so the data are unlikely to include institutional buyers whose preference formation process may be quite different from that of individual consumers.

In online bargain hunting forums, a set of posts related to the same featured deal grouped together as a conversation among users are called a "thread". A thread represents one and only one featured deal. The post in a thread that announces a deal is called the "original post", which often includes detailed information about the deal, such as the product, price, and retailer. The user who posts the original post is called an "original poster". Other users can posts comments and/or vote positive or negative on the featured deal. Each user has a unique username, which allows us to identify who have posted and/or voted in a forum. We classify users in a forum into several groups (see Figure

3.1): all users coming to visit a forum are “viewers”; those viewers who post any comments on the featured deal are called “active participants”; those viewers who vote on a featured deal are called “voters”, who are further divided into “active voters” – those who post and vote, and “silent voters” – those who vote but do not post.

[Insert Figure 3.1 here]

We use 10 days of data for each thread, because there was hardly any activity after 10 days for nearly all threads. We have the following information about each thread: (a) topic, posting date, and the original poster of a thread; (b) daily number of posts; (c) date and content of each post; (d) user name of each poster; (e) daily number of votes on the featured deal in a thread; (f) user name of each voter; and (g) the direction of each vote (positive vs. negative).

The votes on a featured deal reflect viewers’ attitudes toward it. To study how the contents of online discussions may influence their viewers’ attitudes, we focus on analyzing the votes casted by silent voters, i.e., those who have never posted comments. Besides the managerial importance of studying the silent majority, as motivated in the Introduction section, there is also a methodological reason for removing vote data of the active participants in our analysis. Viewers who post positive comments about the featured deal are likely to cast positive votes on it, and vice versa, and thus there is likely a spurious correlation between the content of posts and votes by the same participants, which does not represent a casual relationship. Therefore, one needs to look at the effects of the active participants’ posts on votes casted by silent voters in order to get a cleaner assessment of the relationship between discussion contents and viewers’ attitudes.

3.3.2 Model Specification

We develop a Bayesian zero-inflated Poisson-Binomial model to examine the impact of online discussions on the silent viewers' interest and preference. Two key components in our model are: 1) interest of the silent viewers, which is defined as the level of engagement with a featured deal expressed by silent viewers, and is measured by the number of their votes on the featured deal[3], and 2) preference of the silent voters, which refers to the extent of positive attitude toward a featured deal, and is measured by the number/percentage of positive votes by silent voters on the featured deal. We model these two components jointly, with the number of votes by silent viewers captured by a zero-inflated Poisson model, and the number of positive votes by silent voters formulated as a Binomial model conditional on the former quantity. We use a zero-inflated Poisson model for the interest part because there is a fairly large number of threads in our data which received no votes by silent viewers on a given day, and thus a conventional Poisson model would under-estimate the occurrence of zero votes.

Zero-inflated Poisson Model for Interest

To better fit the needs for this research, we modify the conventional zero-inflated Poisson model by re-parameterizing it. Let $\mathrm{Y}_{\mathrm{it}}^{1}$ denote the number of votes by silent viewers on the featured deal in thread *i* on day *t*. $\mathrm{Y}_{\mathrm{it}}^{1} = 0$ when the featured deal does not receive any votes from silent viewers on day *t*. π_{it} is the probability that the deal receives non-zero votes. When $\mathrm{Y}_{\mathrm{it}}^{1} > 0$, we assume that it follows a truncated Poisson distribution with mean λ_{it}. The model is specified as:

[3] Since we cannot directly measure the viewers' level of interest with a featured deal, a proxy measure that is observable is needed here. Although not perfect, the number of votes on a feature deal reflects the relative level of engagement – a deal which receives more votes is likely to have generated a higher level of interest than a deal that receives fewer votes.

$$(1)\ Y^1_{it} = \begin{cases} 0 & \text{with probability } 1\text{-}\pi_{it} \\ y^1_{it} > 0 \ \sim Truncated\ Poisson(\lambda_{it}) & \text{with probability } \pi_{it} \end{cases},$$

where

$$(2)\ \pi_{it} = \frac{e^{(\alpha_{1i} + \mathbf{Z}'\boldsymbol{\beta})}}{1 + e^{(\alpha_{1i} + \mathbf{Z}'\boldsymbol{\beta})}}\text{, and}$$

$$(3)\ \lambda_{it} = e^{(\alpha_{2i} + \mathbf{X}'\boldsymbol{\gamma})}\ .$$

In the above equations, parameters α_1 and α_2 are intercepts of the two exponential functions, respectively; the vectors Z and X contain explanatory variables (details to be described later); and β and γ are vectors of their coefficients, respectively. The difference between our model and the conventional formulation of a zero-inflated Poisson model is that we parameterize the zero and non-zero counts separately, instead of adding an adjustment parameter for the zero counts to an un-truncated Poisson distribution. In our formulation, the probability of getting non-zero counts is π_{it}, a function of covariates, and the non-zero counts follow a truncated Poisson distribution. The conditional probability mass function of the number of non-zero votes is:

$$(4)\ P(Y^1_{it} = y^1_{it} | y^1_{it} > 0) = \frac{(e^{-\lambda_{it}}) {\lambda_{it}}^{y^1_{it}}}{(1 - e^{-\lambda_{it}}) y^1_{it}!},\ Y^1_{it} = 1, 2, 3, \ldots$$

Binomial Model for Preference

Let Y^2_{it} denote the number of positive votes by silent voters conditional on the number of votes by silent viewers (Y^1_{it}) in thread *i* on day *t*. We assume that Y^2_{it} follows a Binomial distribution with the base Y^1_{it} and probability p_{it}. The model is specified as:

$$(5)\ Y^2_{it} \sim \text{Binomial}\ (Y^1_{it}, p_{it})\text{ , with}$$

(6) $p_{it} = \frac{e^{(\alpha_{3i} + \mathbf{W}'\boldsymbol{\theta})}}{1 + e^{(\alpha_{3i} + \mathbf{W}'\boldsymbol{\theta})}}$,

where α_{3i} is the intercept of the exponential function, the vector W contains explanatory variables corresponding to thread *i*, and the vector θ consists of its corresponding coefficients. The conditional probability of the featured deal in thread *i* getting y_{it}^{2} positive votes by silent voters conditional on the number of their votes y_{it}^{1} is:

(7) $P(Y_{it}^{2} = y_{it}^{2} | y_{it}^{1} > 0) = \binom{y_{it}^{1}}{y_{it}^{2}} (p_{it})^{y_{it}^{2}} (1 - p_{it})^{y_{it}^{1} - y_{it}^{2}}$,

and the unconditional probability is:

(8) $P(Y_{it}^{2} = y_{it}^{2}) = \left[P(Y_{it}^{2} = y_{it}^{2} | y_{it}^{1} > 0) \times P(Y_{it}^{1} = y_{it}^{1} | y_{it}^{1} > 0) \times \pi_{it}\right]^{I_{it}} + [1 -$

$\pi it1 - Iit$,

where I_{it} = 1 if $y_{it}^{1} > 0$, and I_{it} = 0 otherwise.

The likelihood function of the data is:

(9) $L = \prod_{i} \prod_{t} \left\{ \left[P(Y_{it}^{2} = y_{it}^{2} | y_{it}^{1} > 0) \times P(Y_{it}^{1} = y_{it}^{1} | y_{it}^{1} > 0) \times \pi_{it}\right]^{I_{it}} + [1 - \pi_{it}]^{(1 - I_{it})} \right\}$.

3.3.3 Model Estimation

We account for heterogeneity across threads using a hierarchical Bayesian framework. We allow the intercepts $\boldsymbol{\alpha 1}$, $\boldsymbol{\alpha 2}$, and $\boldsymbol{\alpha 3}$ to correlate with each other and vary across threads. The prior distributions of these parameters are specified as:

(10) $\begin{bmatrix} \boldsymbol{\alpha_1} \\ \boldsymbol{\alpha_2} \\ \boldsymbol{\alpha_3} \end{bmatrix} \sim \text{Multivariate Normal}\ (\boldsymbol{\mu_\alpha}, \boldsymbol{\Sigma_\alpha})$,

where

(11) $\boldsymbol{\mu_\alpha} \sim \text{Multivariate Normal}\ (\boldsymbol{\mu_0},\ \boldsymbol{\Sigma_0})$,

(12) $\boldsymbol{\Sigma_\alpha} \sim \text{Inverse Wishart}\ (\boldsymbol{\Omega}, \mathrm{d})$.

The prior distributions of the other parameters are specified as:

(13) $\boldsymbol{\beta} \sim \text{Multivariate Normal}\left(\boldsymbol{\mu}_{\boldsymbol{\beta}}, \boldsymbol{\Sigma}_{\boldsymbol{\beta}}\right)$,

(14) $\boldsymbol{\gamma} \sim \text{Multivariate Normal}\left(\boldsymbol{\mu}_{\boldsymbol{\gamma}}, \boldsymbol{\Sigma}_{\boldsymbol{\gamma}}\right)$,

(15) $\boldsymbol{\theta} \sim \text{Multivariate Normal}\left(\boldsymbol{\mu}_{\boldsymbol{\theta}}, \boldsymbol{\Sigma}_{\boldsymbol{\theta}}\right)$.

We use uninformative priors for the estimation: $\boldsymbol{\mu}_{\mathbf{0}} = [0 \quad 0 \quad 0]'$, $\boldsymbol{\Sigma}_{\mathbf{0}} = 1.0\text{E} - 6 \times \text{I}_{\text{k}\times\text{k}}$, $\boldsymbol{\mu}_{\boldsymbol{\beta}} = \boldsymbol{\mu}_{\boldsymbol{\gamma}} = \boldsymbol{\mu}_{\boldsymbol{\theta}} = [0 \quad \cdots \quad 0]_{\text{m}\times 1}{}'$, $\boldsymbol{\Sigma}_{\boldsymbol{\beta}} = \boldsymbol{\Sigma}_{\boldsymbol{\gamma}} = \boldsymbol{\Sigma}_{\boldsymbol{\theta}} = 1.0\text{E} - 6 \times \text{I}_{\text{m}\times\text{m}}$, $\boldsymbol{\Omega} = 100 \times \text{I}_{\text{k}\times\text{k}}$, k = 3, and d = 114. In our empirical analysis, 19 covariates are included in each vector of explanatory variables, and thus m=19.

We estimate the proposed model using the software WinBugs. The first 100,000 iterations are used as burn-in. The large number of burn-in is due to the slow convergence of the random-effect component in the model. We obtain inferences of the parameters based on their posterior samples from the next 10,000 iterations.

3.3.4 Explanatory Variables

Table 3.2 lists the explanatory variables included in each component of the proposed model (**X**, **Z**, and **W)**. We use two binary variables for the types of promotions, *Free Shipping* and *Price Drop* (including instant rebate/coupon), because they are the two most frequently available deal types for digital cameras. The baseline is all other forms of promotions combined. Since all merchants in our data (i.e., retailers offering the featured deals) have online stores and most of them are private pure-play e-tailers for which company revenue information is unavailable, we measure their size (*Size of Merchant*) by the volume of their website traffic, specifically, the three-month (November 2009- January 2010) average of the percentage of global Internet users who have visited the merchant's website, provided by Alexa.com. The variable *Expressive*

Member refers to the status of the original poster of a featured deal, which equals 1 if the original poster is an expressive member and 0 otherwise. We define an expressive member as someone who has changed his/her default membership status ("new member", "member", or "senior member") to self-customized names which are often expressive in nature (such as "Stimulating Economy", "OnlyDealPlz", or "Happy Member", etc.)[4]. The variable *Total Previous Posts* represents the total number of posts in thread *i* up to day *t-1*. The variable *Total Previous Positive Votes* represents the total number of positive votes by all voters (active and silent) in thread *i* up to day *t-1*. This variable is included to account for the possibility that a viewer's vote may be influenced by others' votes that he/she has observed. The variable *Days* represents the number of days since the original post of thread *i* was first posted. The most important explanatory variables are the *Categories of Discussion Contents*, each of which is measured as the percentage of posts of a given category up to day *t-1*.

We have conducted a detailed content analysis of all discussions posted in the 104 threads, with a total of 974 posts. We classify the discussion contents into 12 categories according to their evaluative or informational nature. The evaluative categories include positive and negative evaluations of the price, product, or retailer (focal and competitors) of a featured deal, respectively, with seven of them used in the model[5]. The informational categories refer to those that seek or provide information without explicit evaluations or judgments, and include those for 1) seeking information about the featured deal

[4] We have tested the model that includes categorical variables for the original membership status and found no significant differences between "new members", "members", and "senior members". Therefore, these distinctions were dropped from the final model.

[5] We eliminated the category of "positive retailer evaluation" in the final analysis, because it occurred only a few times in the entire data and thus this variable has very low variation.

("Seeking Information"), 2) describing information about how to get the featured deal ("How-to Information"), 3) describing features of the promoted product ("Product Features"), 4) expressing purchase intention ("Purchase Intention"), and 5) confirming having made a purchase of the promoted product ("Purchase Confirmation"). Table 3.3 shows the name, definition, and examples of each category.

Three coders carefully read each post and classified them into the content categories independently. After all coders finished categorization of posts, they got together to compare the result. The initial agreement rate among the three coders was 89%. For the remaining posts with any disagreement, they discussed each and reconciled the differences.

Table 3.4 presents descriptive statistics of the data, and Table 3.5 reports the correlation matrix of all covariates in the model.

[Insert Tables 3.2, 3.3, 3.4 & 3.5 here]

3.4 Empirical Analyses

3.4.1 Model Estimation Results

Table 3.6 reports the posterior coefficients for the proposed model. We summarize the posterior distributions of the parameters of the proposed model by reporting their means, standard deviations, and the 95% and 90% credible intervals. Recall that parameters in the zero-inflated Poisson model (Equations 1, 2, and 3) capture the effects on silent viewers' level of interest in the featured deal, and those in the Binomial model (Equations 5 and 6) reflect the effects on the silent voters' preference for it. “Significant”[6] parameter estimates in the zero-adjustment component of the Poisson model show that the chance of a feature deal receiving any votes from the silent viewers on a given day increases with the total number of previous posts in a thread , (posterior mean of *Total Previous Posts* = .06), and it appears to decline with the number of days since the original post, reaching the lowest point on the last day in the data (Day 10) (posterior mean of *Days* = -1.45, $Days^2$=.07). In terms of the effects of discussion contents, the chance of a featured deal receiving any votes from the silent viewers increases with the percentage of previous posts with positive price evaluations (posterior mean of *Positive Price Evaluations* = 1.89). Interestingly, a featured deal is more likely to get any votes from silent viewers, if there has been a higher percentage of previous posts with negative evaluations on either the focal retailer or its competitors (posterior mean of *Negative Retailer Evaluation* and *Negative Competing Retailer Evaluation* = 5.42 and 4.45, respectively). This indicates that negative news about the focal retailer can attract attention and generate interest, just like negative news on its competitor, but such interest is unlikely to translate into preference, as we will see in the next model component. In addition, silent viewers are more likely to cast any votes, if there is a higher percentage of previous posts seeking information about the deal (posterior mean of *Seeking Information* = 1.62).

Conditional on a featured deal getting any votes on a given day, the number of votes it receives is positively and significantly affected by the *Expressive Member*, indicating that featured deals posted by members using expressive names can generate a

[6] We use the term “significant” hereafter to denote that the 95% credible interval does not contain zero.

higher level of interest among viewers (Posterior mean of *Expressive Member* = .76). In addition, there appears to be a nonlinear trend in the number of silent votes received per day as time goes by, increasing initially, reaching the peak around the 3rd day, and then declining afterwards (Posterior mean of *Days* = .48 and $Days^2$ = -.09). We also find that *Price Drop*, as compared to other forms of promotions, has a positive and significant effect, indicating that price drops tend to attract a higher level of interest from consumers. The above results indicate that the content of posts appears to affect whether a featured deal gets any votes at all from the silent viewers, but does not play a significant role in affecting the number of votes it gets once it goes beyond zero.

The Binomial model of preference shows very different patterns with regard to the content variables, with a good number of them showing significant effects, indicating that the specific content of discussions posted by active participants indeed affects the silent viewers' preference for a featured deal. All the evaluative categories, except "Negative Product Evaluation" which is insignificant, have the expected sign in their posterior means, with the effects of "*Positive Price Evaluation*", "*Negative Retailer Evaluation*", "*Positive Competing Retailer Evaluation*", and "*Negative Competing Retailer Evaluation*" being significant. We find that the silent viewers exhibit a higher level of preference for the featured deal, if there is a greater percentage of positive price evaluations in previous posts (posterior mean = 4.99) or negative evaluations of competing retailers (posterior mean = 15.84). And the opposite holds if there is a greater percentage of negative retailer evaluations (posterior mean = -10.97) or positive evaluations of competing retailers in previous posts in previous posts (posterior mean = -13.72). Among the informational categories, "*How-to Information*" has significant and positive effect (posterior mean = 4.68). It appears that providing clarification about how to get a deal can positively influence the viewers' attitudes toward a featured deal.

In terms of the effects of other factors on preference, we find that *Free Shipping*, as compared to other forms of promotions, has a negative and "significant" effect, indicating that consumers perceive it as less attractive, perhaps because it is commonly offered by many online merchants and merely offsets the additional costs incurred for online shopping (i.e., shipping and handling). This finding suggests that online merchants should consider offering and/or emphasizing other types of promotion in order to stand out from the crowd. There also appears to be a nonlinear trend in the percentage of positive votes received per day as time goes by, decreasing initially, and starting to increase around the 4th day (Posterior mean of *Days* = -1 and $Days^2$ = .13). In summary, we find that not only the valence matters, the specific categories of post content also play different roles in influencing silent viewers' preference. The effects of evaluations on both the focal retailer and competitors are the largest in magnitude[4], which shows that comparing with price and product evaluations, online bargain hunting forum users are more affected by evaluations concerning retailers. Conventional wisdom may put more emphasis on the information about product and price in a promotion message, our findings indicate that information on retailers, both the focal one and competing retailers offering similar promotions, actually has the strongest impact on the viewers' preference.

We did not find any significant effects of the *Size of Merchant* on either interest or preference, which implies that large firms may not have much advantage over small businesses when it comes to influencing viewers' opinions in online bargain hunting forums, and these forums can be a particularly attractive venue for small businesses to disseminate promotion information due to their convenient and low-cost nature.

[Insert Table 3.6 here]

3.4.2 Counterfactual Simulation Analysis

Prior research shows that firm-created WOM can affect product sales (e.g., Godes and Mayzlin 2009). Online bargain hunting forums allow firms to get feedback from consumers quickly, and even give them the opportunity to participate in the discussion and to communicate with consumers in a timely manner. How to effectively disseminate promotion information and participate in discussions in these forums is an important managerial issue to many companies, yet much is still unknown about the specific tactics. For examples, what information should be emphasized in the original post? What kind of discussions may be most helpful, and what kind of messages is most alarming? And what is the best timing to intervene in online discussions, if any? Our model estimation results show that the content of online discussions does affect the silent viewers' interest in and preference for a featured deal, and that the effects vary by the specific categories of contents. This provides the basis for further investigation on these tactical issues.

In this section, we conduct various counterfactual simulation analyses to quantify the effects of a firm's intervention with various messages and timings. Specifically, we examine how interest and preference of the silent viewers may change if the number of posts of a given content category is increased or decreased by one and at different stages of the discussion (e.g., Day 1 vs. Day 9), while holding other activities in the data constant. Note that the total number of previous posts and the percentage of every other content category are adjusted accordingly in our simulation analysis. We choose the following five content categories as potential candidates which a firm could influence: 1)

Positive Price Evaluation, 2) Negative Retailer Evaluation, 3) Negative Competing Retailer Evaluation, 4) How-to Information, and 5) Seeking Information. The first three categories show significant effects in influencing viewers' interest as well as preference, and the latter two have significant impact on either interest or preference. In addition, they are the types of messages, among those examined here, that firms are likely to be able to influence. The simulations are carried out using Monte Carlo simulations based on posterior distributions of the parameters, and thus take into account uncertainties in the parameter estimates (see Appendix A for details of the procedure).

Results of the counterfactual simulation analysis are reported in Table 3.7. The average predicted number of votes and average predicted percentage points of positive votes from the silent viewers (called "silent votes" and "percentage points of positive silent votes" hereafter for convenience) by Day 10 in current practice are 3.81 and 79.2%, respectively. If the number of posts of the positive price evaluation category is increased by one on *Day 1*, these numbers would rise to 4.09 and 85.4%, respectively, representing a 7.3% and 7.8% relative increase compared to the current practice. If the number of posts of the same category is increased by one on *Day 9*, the silent votes and percentage of positive silent votes by Day 10 would be 3.81 and 79.2%, respectively, making no difference over the current practice. The same pattern of the timing effect exists in every category that we have tested. This is mainly due to the fact that changes in the corresponding content category and the total number of previous posts occur in all subsequent days, which affect silent viewers' interest, as well as the positive carry-over effect of the number of previous positive votes on preference (see Table 3.6). This result suggests that early timing is critically important, if firms choose to participate in discussions in online bargain hunting forums.

[Insert Table 3.7 here]

We now focus on the effects when intervention occurs on Day 1. If the number of posts of the negative retailer evaluation category is increased by one on Day 1, the silent votes would rise from 3.81 to 5.97, representing a 56.7% increase. It suggests that negative retailer evaluations can effectively attract consumers' attention and generate more votes on the featured deal. Such a surge, however, would lead to a substantial decrease in the percentage of positive silent votes, from 79.2% to 43.0% --- a 45.7% drop. If the number of posts of the negative retailer evaluation category is decreased by one on Day 1, the silent votes would decline to 3.75 (or by 1.6%), but the percentage of positive silent votes would increase from 79.2% to 83.3% (or by 5.2%).

Influencing the negative competing retailer evaluation category also shows substantial effects. The silent votes and the percentage points of positive silent votes would be 11.35 (+197.9%) and 95.5% (+20.6%), respectively, if the number of post in this category increases 1 on Day 1. The effectiveness of information on competitors has also been documented in the marketing literature. Urban (2004) argues that consumers will trust a firm more, if the firm provides unbiased competitive information to them. Providing competitive information to consumers might enlarge the pool of consumers who will consider a firm's product because consumers are more likely to consider a product if the cost of searching and evaluating different products is lowered (Hauser and Wernerfelt 1990). Liberali, Urban, and Hauser (2010) suggest that if a firm has products that are much better than consumer perceive them to be, making competitive information available will increase consumers consideration and purchase of the firm's products.

Obviously, it is unethical to smear competitors. If a firm disseminates negative information about competitors, it should be based on solid facts.

We now look at the effects of intervening with the two most significant informational categories. If the number of posts of the seeking information category is decreased by one, the number of silent votes would increase by 11.0%, and the percentage of positive silent votes would increase by 2.8%. These comparisons show that what may attract consumers' attention and interest may not translate into positive attitudes, and firms need to pay careful attention to the roles that various discussion contents play at the different stages of shopping and purchase decision process. This reinforces the importance of distinguishing and monitoring online discussions by their specific contents. If the number of posts of the How-to Information category is increased by one on Day 1, the predicted number of silent votes and percentage points of positive votes would increase by 7.6% and 7.2%, respectively. These two results indicate the importance of providing clarification information and doing so at an early time. Retailers should offer clear and detailed information about the deals and feature products upfront, facilitate clarification about how to obtain them as they monitor the discussions and see questions arisen, and reduce viewer confusion and posts seeking information preemptively, if they intend to utilize online bargain hunting forums to disseminate promotion information.

Comparing the parameter estimates and the counterfactual simulation results across different content categories[7], evaluations about retailers (the focal one and its competitors, positive and negative) show the strongest impact on viewers' attitudes,

[7] The content category variables are measured in percentage terms and thus the magnitude of their coefficients are comparable.

much more so than that of evaluations about the price and product or of discussions that provide information without evaluation or judgment. This implies that, when marketers monitor activities in online bargain hunting forums, they should pay special attention to comments about retailers (such as in a key word analysis). Moreover, if firms have limited resources to monitor or intervene in these discussion forums, they should prioritize their efforts to retailer-related information. In fact, among all the content categories examined here, we find that influencing the "negative retailer evaluation" and "negative competing retailer evaluation" categories have the largest effects on silent viewers' interest and preference. It indicates that firms not only should pay close attention to consumers' voices, but also be very vigilant about competitors "smear campaigns". In addition to monitoring online discussion forums about their own products/promotions, they should also keep an eye on those involving their key competitors. This would allow them to detect consumer complaints and competitors' smear actions early, and address the problems or counter false claims before incurring serious damages.

3.5 Discussion

We have conducted an empirical investigation on whether and how discussions posted by active participants in bargain hunting forums affect the silent viewers' interest in and preference for the featured deals. Our data were collected from a major bargain hunting website. Our analysis of online discussions goes beyond their volume and valence, and delves much deeper into the specific nature of the contents. We have analyzed all discussions posted in the forum of the focal product category (digital camera), and classified them into about a dozen distinct categories. We develop a Bayesian Poisson-Binominal model to jointly estimate the effects of these content categories on the number of votes from the silent viewers and the number of positive votes casted by them, while accounting for the effects of other factors such as the types of deals, size of the merchant, status of the original poster, time trend, and the volume of previous posts and positive votes. The key findings of the model estimation results are summarized in the follows.

- The content of discussions posted by active participants affects the silent viewers' interest in and preference for a featured deal, and the specific categories of content, not just its valence, play different roles in the process.
- Evaluations about retailers (the focal one and its competitors, positive and negative) show the strongest impact on viewers' attitudes, much more so than that of evaluations about the price and product or of discussions that provide information without evaluation or judgment. In addition, discussions providing information on how to get the featured deal can positively affect the silent viewers' preference.
- Deals posted by users with expressive names appear to generate a higher level of interest in the featured deals. Compared to other types of promotions, free shipping is perceived as less desirable.

We did not find evidence that the content of online discussions affects the number of votes casted by silent viewers on a featured deal, once it goes beyond zero, after controlling for the total number of previous posts in a forum and other factors. This may not be surprising, because viewers are unlikely to read through the discussion contents of deals that receive low level of general interest, and they may infer the general interest by the total number of previous posts.

Our model estimation results suggest that firms can benefit from actively participating in online bargain hunting forums. We have conducted counterfactual simulation analysis to examine and quantify the impact of a firm's intervention with various messages and timings. These analyses reveal valuable insights on how to effectively disseminate promotion information through online bargain hunting forums and how to proactively influence the viewers' attitudes. We find that: 1) Influencing the discussions at an early time is critically important, if firms choose to participate in the discussions in bargain hunting forums; 2) Evaluations about the retailer of a featured deal and its competitors have stronger impact on viewers' attitude than information about the price or product of the featured deal; and 3) Firms should provide clear and detailed descriptions of their promotions upfront, if they use online bargain hunting forums to disseminate the information.

Among the content categories examined, we find that, in general, negative evaluations have greater impact on silent viewers' interest and preference than their positive counterparts. Firms should address negative evaluations about them with an open and constructive attitude. If they can respond to consumer complaints in a timely fashion, it not only will reduce future negative evaluations, but also send a signal to potential buyers that they care about consumers and are willing to improve their products or services. This could even turn negative experience into positive attitudes toward them.

If firms see more consumers prefer competitors' deals, they may consider adjusting their current offering. These adjustments can be done in a more timely manner in online bargain hunting forums, because firms can easily observe whether and why consumers prefer competitors. Although firms are unlikely to decrease negative retailer evaluation category, if they observe more and more negative evaluations about them appearing in the forum, they should try to address the root cause immediately if there are real problems with the product or price, and to clarify the matters if the negative evaluations are caused by any misunderstanding. In addition, due to the cumulating effects of the total number of previous posts and positive votes, firms need to take actions as soon as they see negative evaluations of themselves, otherwise the negative effects will carryover and cause more negative attitude towards their featured deals.

Firms' participations in online communities of user-generated contents may bring up some ethical issues. One can argue that firms' interventions reduce the credibility of the online discussions and may mislead consumers. We do not suggest that firms give false statements about their products and promotions or to mislead viewers in other ways. What we recommend is that firms should actively monitor and learn from discussions posted in bargain hunting forums and adjust their promotion offerings or information contents accordingly. For example, if a firm notices viewers posting questions expressing confusion about their promotions, they should participate by providing more detailed or accurate information on how to get the deal. Our counterfactual simulation analysis results indicate that doing so and at an early time can lead to substantial increase in the viewers' preference for a deal.

To conclude, our study shows that, through actively monitoring discussions posted in bargain hunting forums, marketers can learn what types of online discussions have more impact on potential buyers' interest in and preference for their featured deals, and the distinct roles that various categories of discussion contents may play in the process. We hope our study has provide some valuable insights for marketers on how to effectively utilize online bargain hunting forums to disseminate promotion information and influence potential buyers' attitudes.

Chapter 4: Conclusion

An individual's perception and values are influenced not only by their own situations, but also by social interactions that s/he has in the communities. Developments in Internet technologies, especially Web 2.0 technologies, have enabled the growth of online communities. These online communities have broken the geographical boundary of the traditional communities, and let people from different locations meet and communicate with each other virtually. Individual consumers are easier to interact with other consumers, and the firms have a new way to interact with consumers.

Distributor community in multi-level marketing organizations and online bargain hunting forum are examples of the offline and online communities, respectively, and provide the contexts for my dissertation. We empirically examine how individual consumer's behavior and preference are influenced by their communities. In the first essay, we provide a framework for understanding the determinants of distributor satisfaction and simultaneously account for biases in satisfaction measures. The key underpinning of the framework is a spatial model in which the relationship between a distributor's satisfaction score and its drivers is mapped as a function of where the distributor lies in an attribute-space defined by distributors' sales momentum and effort expended on business. Our results show that the impact of the different drivers on satisfaction varies across the attribute-space in each of these markets. Firm can use sales momentum and effort expended by distributors as powerful segmentation tools to identify groups of distributors; and develop customized marketing programs for different distributor segments to improve distributor satisfaction. In the second essay, we find that the content of discussions posted by active participants affects the silent viewers' interest in and preference for a featured deal, and the specific categories of content, not just its valence, play different roles in the process. We demonstrate that, through actively monitoring discussions posted in bargain hunting forums, marketers can learn what types of online discussions have more impact on potential buyers' interest in and preference for their featured deals, and the distinct roles that various categories of discussion contents may play in the process. This study provides valuable insights for marketers on how to effectively utilize online bargain hunting forums to disseminate promotion information and influence potential buyers' attitudes.

In summary, the two essays of my dissertation provide a better understanding of how individuals are affected by their peers in their communities. These studies contribute to the growing marketing literature of empirical studies in social influence, word-of-mouth, online social networks, and customer satisfaction measurement. Findings from these studies are also beneficial to marketing practitioners who are seeking to leverage the power of these online and offline communities.

Appendices

Appendix I: Measurement Items and Factor Analysis Result

Constructs and Measurement Items	**Factor Loading**
Product (α= .894)	
1. Dynamics is bringing new products to the market that I like.	.696
2. Dynamics is bringing new products to the market that helps me build my business.	.637
3. Dynamics offers the right products that I like to purchase for myself.	.633
Customer Service (α= .842)	
1. Customer service personnel are courteous and helpful.	.712
2. Customer service executives promptly resolve any issues I have.	.705
3. I can return products to Dynamics conveniently and easily without any hassles.	.627
Opportunity (α= .892)	
1. Dynamics products are a good value compared to other competitive products.	.764
2. Dynamics products are better than other competitive products.	.673
3. Dynamics products offer good value for the money.	.671
Reputation (α= .900)	
1. The Dynamics business plan keeps my downline active and motivated.	.750
2. Dynamics reputation makes it easy for me to sponsor new distributors.	.773
3. The reputation of Dynamics coreline products makes it easy for me to sponsor new distributors.	.746

Appendix II: Performance of the GWR Model in Recovering True Parameters

We conduct a simulation exercise to check how effective GWR is in recovering true biases caused attribute-space on the satisfaction measures and in uncovering the unbiased parameters which indicate the relationship between overall satisfaction and other explanatory variables. We first simulate responses for the global distributor satisfaction survey based on normal distribution. Then we introduce different levels of scale usage into these responses. The scale usage is a function of coordinates in the attribute-space, that is, different locations will be characterized by different scale usages. We estimate our GWR model using the simulated data with these different scale usages to check how well our model performs in recovering the unbiased parameters. The simulation algorithm is provided in Appendix III and the results of our simulation are provided below. The results show that our model successfully recovers the true φ. In four cases, the median of $\hat{\varphi}$'s for all locations are close to true value of φ's.

Table A1: Simulation Results

True φ	δ_1	δ_2	ξ_1	ξ_2	$\hat{\varphi}$ by OLS	$\hat{\varphi}$ by Our Model (Median)
5	0.01	0.025	0.02	0.15	5.21	4.93
					RSS: 13341.85	RSS: 9.57
5	−0.025	−0.03	−0.01	−0.25	5.65	5.05
					RSS: 35574.67	RSS: 38.70
-5	0.015	0.035	0.02	0.15	-5.44	-4.88
					RSS: 25832.35	RSS: 23.90
-5	−0.025	−0.03	−0.01	−0.25	-5.65	-5.03
					RSS: 36443.55	RSS:49.65

Appendix III: The Simulation Algorithm

1. Generate **X** variable, **X** ~ Normal (0, 2). The number of observations is 1000. The number of exploratory variable **X** is 1 here.
2. Set the true value for φ. In case 1 and 2, we set φ as 5. In case 3 and 4, we set φ as -5.
3. Generate **Y** variable. $\mathbf{Y} = \mathbf{X}\varphi + \boldsymbol{\varepsilon}$, where $\boldsymbol{\varepsilon}$ ~ Normal (0, 1).
4. Generate spatial coordinates, $\mathbf{Z_1}$ and $\mathbf{Z_2}$. The coordinates are random combination of two integer numbers, which are between -20 and 20.
5. Generate $\mathbf{Y_{scale}}$, which are **Y** with scale usage. We add location τ and shape μ usage into the **Y**,

$$\mathbf{Y_{scale}} = \tau + \mu\widehat{\mathbf{Y}}$$

These two kinds of usage depend on the location. Thus, the τ and μ are functions of the location, respectively:

$$\tau = \delta_1\mathbf{Z_1} + \delta_2\mathbf{Z_2} \ ;$$

$$\mu = \exp(\xi_1\mathbf{Z_1} + \xi_2\mathbf{Z_2}) \ .$$

We use different values for δ_1, δ_2, ξ_1, and ξ_2.

	δ_1	δ_2	ξ_1	ξ_2
Case 1	0.01	0.025	0.02	0.15
Case 2	−0.025	−0.03	−0.01	−0.25
Case 3	0.015	0.035	0.02	0.15
Case 4	−0.025	−0.03	−0.01	−0.25

6. Estimate φ for each location by GWR with $\mathbf{Y_{scale}}$, **X,** and coordinates **($\mathbf{Z_1}$, $\mathbf{Z_2}$).**

Appendix IV: Simulation Procedure

1. For each parameter, randomly draw 5,000 samples from its posterior distributions according to our estimation results as the coefficient estimate. We have 5000 sets of coefficient estimates.

2. For each of the five content categories of interest, we increase/decrease the number of posts of the category by one on Day 1 or Day 9, while assuming all other activities are the same as in the data. We adjust the values of the total previous posts and the percentage of every other content category accordingly, because they are intrinsically related to the number of posts of the focal category.

3. For each draw of the coefficient estimates, we apply the joint Poisson-Binomial model and the modified variables to get the daily predicated number of votes and positive votes by silent voters for each thread;

4. We calculate the predicated number of votes and percentage of positive votes by silent voters by Day 10 across all 104 threads for each draw, and then take the averages across 5000 draws. The same process is repeated for changes occurring on different Days and for other focal content categories.

Tables

Table 2. 1: Summary of Dependent Variable, Explanatory Variables, and Coordinates

	Minimum	Median	Mean	Maximum
Overall Distributor Satisfaction	1	8	7.64	10
Reputation	2.27	18.90	17.82	24.96
Product	1.97	17.57	16.41	21.63
Opportunity	2.11	18.88	17.51	23.19
Customer Service	2.04	19.74	18.30	22.48
Effort Expended on Business	1	3	2.84	5
Sales Momentum	1	3	3.21	5

Table 2. 2: Spatial Autocorrelation in Variables

	Moran's I	Geary's C
Distributor Satisfaction	0.14	0.79
Reputation	0.05	0.87
Product	0.08	0.82
Opportunity	0.08	0.82
Customer Service	0.04	0.90

Table 2. 3: Summary of Estimates of Coefficient of GWR Model

Coefficient	Min.	Median	Max.	F statistic	Estimates of Global OLS Model
(Intercept)	0.04	1.46	3.97	1.18	0.81**
Reputation	-0.05	-0.01	0.16	11.54***	0.01
Product	-0.21	0.11	0.17	2.26***	0.10***
Opportunity	0.10	0.21	0.27	1.96***	0.25***
Customer Service	-0.04	0.06	0.19	2.65***	0.05**
Dummy Variable for India	-5.50	-1.27	3.03	1.57***	-1.10**
Dummy Variable for Korea	-6.62	-0.68	1.83	1.11	-0.19
Reputation*DummyIndia	-0.05	0.06	0.17	1.84***	0.09***
Product*DummyIndia	-0.02	0.10	0.43	1.79***	0.10***
Opportunity*DummyIndia	-0.16	-0.02	0.16	3.89***	-0.07***
CustomerService*DummyIndia	-0.18	-0.02	0.11	1.49***	-0.04.
Reputation*DummyKorea	-0.10	0.05	0.26	2.82***	0.04*
Product*DummyKorea	-0.23	-0.06	0.36	1.31***	-0.03
Opportunity*DummyKorea	-0.13	0.004	0.19	1.40*	-0.03
CustomerService*DummyKorea	-0.23	-0.03	0.15	1.11	-0.02

Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’

Table 2. 4: Residual Sum of Squares and R^2 of GWR and OLS Model

	GWR Model	OLS model 1	OLS model 2
Residual Sum of Squares	19,999.12	22,718.71	20879.76
R^2	0.50	0.42	0.47

OLS model 1: Using the same explanatory variables as GWR model
OLS model 2: Using the same explanatory variables, as well as coordinates in GWR model as explanatory variables

Table 2. 5: Absolute Prediction Error with Hold-out Sample for Two Models

Model	Mean	Median
GWR Model	1.25	0.96
OLS Model 2	2.19	2.43

Table 2. 6: Mean of Original, Predicted, and Comparable Distributor Satisfaction Scores

Country	Full Dataset			Hold-out Sample		
	Mean of original distributor satisfaction scores	Mean of predicted distributor satisfaction scores	Mean of comparable distributor satisfaction scores	Mean of original distributor satisfaction scores	Mean of predicted distributor satisfaction scores	Mean of comparable distributor satisfaction scores
India	8.33	8.35	8.16	8.36	8.39	8.20
Korea	6.35	6.35	6.96	6.82	6.54	7.12
USA	7.76	7.75	7.75	7.87	7.76	7.76

Table 3. 1: Traffic Information of Sample Bargain Hunting Websites

Website	Traffic Rank in U.S.	Percent of Global Internet Users Who Have Visited	Daily Pageviews per User	Sites Linked in
Slickdeals.net	168	16.32%	4.69	2,255
Fatwallet.com	438	7.86%	3.71	2,524
Techbargains.com	1,102	3.39%	2.74	1,259
Dealsea.com	2,098	2.02%	1.69	252

Source: Alexa.com (accessed on April 15, 2010).

Table 3. 2: Explanatory Variables in the Model

Variable	Definition	Used in
Day (t)	The number of days since the original post of thread *i* was first posted	Z, X, W[a]
Type of Deal	Free shipping, Price drop (including Instant Rebate/Coupon), vs. all others	Z, X, W
Size of Merchant	The three-month average of percentage of global Internet users who have visited the merchant's website	Z, X, W
Expressive Member	The status of the original poster of a featured deal, vs. other members	Z, X, W
Total Previous Posts	The total number of posts in the thread *i* by day *t-1*	Z, X
Total Previous Positive Votes	The total number of positive votes by all voters in thread *i* up to day *t-1*	W
Categories of Discussion Content	The percentage of posts of a given category up to day *t-1* (see Table 3 for details).	Z, X, W

[a] Z = covariates for getting any votes; X = covariates for number of votes; W = covariates for preference.

Table 3. 3: Categories of Discussion Contents

Category	Definition	Examples
Positive Price Evaluation	A post that gives a positive evaluation of the price of the promoted product.	*"This is the lowest price I have ever seen for the 5D Mark 2."*
Negative Price Evaluation	A post that gives a negative evaluation of the price of the promoted product.	*"$400 for a P&S? You people are getting ripped off. This is not a deal."*
Positive Product Evaluation	A post that gives a positive evaluation of the promoted product.	*"If you are looking for a new compact camera, I highly recommend this one."*
Negative Product Evaluation	A post that gives a negative evaluation of the promoted product.	*"We were sadly disappointed with the photos."*
Positive Competing Retailers Evaluation	A post that mentions competing retailer(s) having better deal(s) of the same product.	*"Might as well wait a couple weeks and get it with the 55-200 VR lens for $599 at Best Buy." (in the discussion of a Wal-Mart deal)*
Negative Competing Retailers Evaluation	A post that mentions the focal retailer offering a better deal of the same product than competing retailers.	*"I consider this is a much better deal than Best Buy because in Best Buy we have pay $40 tax and total will comes to around $640." (in the discussion of a Wal-Mart deal)*
Negative Retailer Evaluation	A post that gives a negative evaluation of the retailer.	*"The website sucked, couldn't cancel online, finally successful canceling over the phone after being handed off a number of times."*
Seeking Information	A post that asks for information about the featured deal or promoted product.	*"Where do I get the "30 off 150" coupon?"* *"Does this have the speed of a dslr?"*
How-to Information	A post that describes information about how to get the featured deal, *without evaluations*.	*"You can get the coupons from ejunkie, just search for it."*
Product Features	A post that describes features of the promoted product, *without evaluations*.	*"It has a flash, and has an SD expansion slot."*
Purchase Intention	A post that expresses purchase intention of the promoted product.	*"I would like to have one."*
Purchase Confirmation	A post that confirms having made a purchase of the promoted product.	*"Ordered one from Dell."*

Table 3. 4: Descriptive Statistics

Variable	Mean	St. Dev.
Number of threads without any votes[a] on a given day	86.30	20.97
Number of threads with votes on a given day	17.70	20.97
Number of threads that never got any votes	19	N/A
For threads with any votes:		
Daily number of votes	.36	.95
Daily number of positive votes	.29	.87
Cumulative number of votes by day 10	3.59	3.23
Cumulative number of positive votes by day 10	3.40	3.24
Free Shipping (vs. others)	.62	.49
Price Drop (vs. others)	.91	.28
Size of Merchant	125.53	159.24
Expressive Member	.23	.42
Total Previous Posts	6.48	10.19
Total Previous Positive Votes	2.55	3.99
Positive Price Evaluation	16.1%	21.4%
Negative Price Evaluation	7.7%	19.5%
Positive Product Evaluation	12.6%	20.9%
Negative Product Evaluation	6.5%	16.3%
Negative Retailer Evaluation	2.1%	6.7%
Positive Competing Retailers Evaluation	3.9%	13.2%
Negative Competing Retailers Evaluation	1.2%	5.4%
Seeking Information	10.6%	18.3%
How-to Information	17.3%	25.4%
Product Features	5.1%	12.1%
Purchase Intention	4.2%	12.6%
Purchase Confirmation	12.9%	20.4%

[a] “votes” refers to votes by silent viewers.

Table 3. 5: Correlation Matrix of Variables

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
A	1																					
B	.91	1																				
C	-.15	-.21	1																			
D	.05	.07	-.21	1																		
E	-.10	-.03	.41	-.02	1																	
F	.10	.11	.08	-.10	.23	1																
G	-.13	-.08	.06	.06	.10	.06	1															
H	-.14	-.09	.06	.06	.09	.04	.96	1														
I	.11	.18	-.10	.14	.08	.18	.59	.56	1													
J	-.04	.06	-.06	.12	.09	.21	.64	.59	.86	1												
K	-.06	.05	.10	.12	.04	.06	.17	.09	.17	.22	1											
L	-.06	-.15	.07	.05	.10	-.03	.13	.10	-.05	-.10	-.02	1										
M	-.09	-.05	.03	.09	.13	-.07	.12	.05	.02	.09	.39	.13	1									
N	.02	.04	.02	.01	-.04	.01	.01	-.04	.06	.09	.19	-.06	.03	1								
O	-.04	-.04	.05	.08	-.03	.07	.15	.12	2E-3	-.02	.10	.39	-.08	-.07	1							
P	-3E-3	-.16	.04	.06	-.15	-.01	.02	.01	-.04	-.12	.2E-3	.52	-.12	-.08	.32	1						
Q	-.05	-.12	.09	.08	.14	.14	.12	.07	.10	.06	.09	.11	.01	-.03	.48	.20	1					
R	-.02	.01	-.03	.04	.06	.02	.17	.12	.24	.18	.11	-.12	.08	.15	-.02	-.05	-.02	1				
S	.07	.17	-.11	-.06	.08	.08	.15	.10	.28	.23	2E-3	-.11	.01	-.09	.01	-.11	.08	.08	1			
T	-.05	-.01	-.05	.05	2E-3	.07	.04	1E-3	.02	.06	.29	-.08	.35	.11	-.08	-.07	-.09	.03	-.10	1		
U	-.02	.02	.06	-.11	.04	-.07	.10	.07	.16	.22	.13	-.05	.01	.02	-.03	-.02	.02	-.07	.01	.02	1	
V	.02	.13	-.07	.10	.11	.10	.41	.35	.49	.48	.42	-.11	.29	-4E-3	9E-3	-.13	.14	.16	.10	.36	.03	1

A: Daily Votes by Silent Viewers
B: Daily Positive Votes by Silent Voters
C: Free Shipping (vs. others)
D: Price Drop (vs. others)
E: Size of Merchant
F: Expressive Member
G: Days
H: Days^2
I: Total Previous Posts
J: Total Previous Positive Votes
K: Positive Price Evaluation
L: Negative Price Evaluation
M: Positive Product Evaluation
N: Negative Product Evaluation
O: Negative Retailer Evaluation
P: Positive Competing Retailers Evaluation
Q: Negative Competing Retailers Evaluation
R: Seeking Information
S: How-to Information
T: Product Features
U: Purchase Intention
V: Purchase Confirmation

Table 3. 6: Model Estimation Results

Parameters/Variables	Posterior Mean	Posterior S.D.	Percentiles (2.5%, 97.5%)	Percentiles (5%, 95%)
Interest: Zero-inflated Poisson Model				
Getting any Votes (β and α_1):				
Free Shipping (vs. others)	.05	.33	-.60, .70	-.49, .59
Price Drop (vs. others)	.06	.60	-1.09, 1.19	-.94, 1.06
Size of Merchant	1E-3	1E-3	-6E-4, 3E-3	-3E-4, 3E-3
Expressive Member	.21	.36	-.50, .92	-.40, .81
Days	**-1.45**	**.23**	**-1.89, -1.01**	**-1.83, -1.08**
Days^2	**.07**	**.02**	**.03, .11**	**.03, .10**
Total Previous Posts	**.06**	**.01**	**.03, .09**	**.04, .09**
Positive Price Evaluation	**1.89**	**.72**	**.50, 3.30**	**.70, 3.08**
Negative Price Evaluation	.90	.98	-1.10, 2.78	-.74, 2.52
Positive Product Evaluation	.59	.80	-1.03, 2.19	-.75, 1.88
Negative Product Evaluation	.32	.91	-1.50, 2.04	-1.20, 1.79
Negative Retailer Evaluation	**5.42**	**2.07**	**1.41, 9.68**	**1.95, 8.88**
Positive Competing Retailers Evaluation	-.51	1.46	-3.33, 2.28	-2.95, 1.86
Negative Competing Retailers Evaluation	**4.45**	**2.07**	**.16, 8.39**	**.99, 7.82**
Seeking Information	**1.62**	**.80**	**.05, 3.16**	**.30, 2.91**
How-to Information	.75	.64	-.50, 2.04	-.29, 1.81
Product Features	1.34	1.25	-1.10, 3.76	-.70, 3.37
Purchase Intention	1.70	1.17	-.65, 3.92	-.25, 3.60
Purchase Confirmation	-.48	.84	-2.15, 1.16	-1.86, .87
Mean of Getting any Votes Intercept	.81	.69	-.44, 2.21	-.23, 2.03
Variance of Getting any Votes Intercept	**1.02**	**.14**	**.78, 1.33**	**.81, 1.27**
Number of Votes (γ and α_2):				
Free Shipping (vs. others)	-.46	.37	-1.20, .26	-1.1, .15
Price Drop (vs. others)	**1.20**	**.62**	-.07, 2.29	**.08, 2.14**
Size of Merchant	-6E-4	1E-3	-3E-3, 2E-3	-2E-3, 1E-3
Expressive Member	.76	.39	-.02, 1.50	**.12, 1.37**
Days	.48	.35	-.16, 1.12	-.11, 1.04
Days^2	**-.09**	**.04**	**-.18, -.01**	**-.17, -.02**
Total Previous Posts	4E-3	.02	-.03, .04	-.02, .03
Positive Price Evaluation	-.40	.86	-2.15, 1.34	-1.79, 1.01
Negative Price Evaluation	-1.53	1.66	-5.25, 1.32	-4.43, .92
Positive Product Evaluation	-.53	.99	-2.50, 1.31	-2.23, 1.02
Negative Product Evaluation	.52	1.02	-1.57, 2.43	-1.23, 2.11
Negative Retailer Evaluation	-.52	1.61	-3.98, 2.47	-3.31, 1.91
Positive Competing Retailers Evaluation	1.32	1.71	-2.03, 4.77	-1.31, 4.30
Negative Competing Retailers Evaluation	.22	2.20	-4.38, 4.57	-3.46, 3.69
Seeking Information	-.64	.90	-2.51, 1.04	-2.22, .74
How-to Information	.45	.59	-.75, 1.54	-.53, 1.39
Product Features	-.55	1.31	-3.40, 1.86	-2.88, 1.47
Purchase Intention	-1.28	1.72	-4.93, 1.82	-4.25, 1.42
Purchase Confirmation	-.36	.99	-2.35, 1.55	-2.03, 1.23
Mean of Number of Votes Intercept	**-1.84**	**.75**	**-3.05, -.35**	**-2.92, -.60**
Variance of Number of Votes Intercept	**.94**	**.13**	**.72, 1.21**	**.75, 1.16**
Covariance of Getting any Votes and Number of Votes Intercepts	-3E-3	.09	-.19, .19	-.16, .15

The Bold font indicates that the 90% or 95% credible interval does not contain zero.

Table 3. 6: Model Estimation Results (continued)

Parameters/Variables	Posterior Mean	Standard Deviation	Percentiles (2.5%, 97.5%)	Percentiles (5%, 95%)
Preference ($\boldsymbol{\theta}$ and α_3):Binomial Model				
Free Shipping (vs. others)	**-1.17**	**.62**	-2.43, .04	**-2.21, -.17**
Price Drop (vs. others)	.69	.95	-1.29, 2.47	-.94, 2.15
Size of Merchant	3E-3	2E-3	-1E-3, .01	-4E-4, 6E-3
Expressive Member	.09	.64	-1.17, 1.36	-.96, 1.17
Days	**-1.00**	**.60**	-2.19, .14	**-1.98, -.03**
Days^2	**.13**	**.07**	**2E-3, .29**	**.02, .26**
Total Previous Positive Votes	-.03	.12	-.26, .23	-.23, .19
Positive Price Evaluation	**4.99**	**2.34**	**.85, 9.90**	**1.38, 8.96**
Negative Price Evaluation	-3.72	2.56	-8.92, 1.20	-8.01, .42
Positive Product Evaluation	.36	1.89	-3.13, 4.26	-2.65, 3.60
Negative Product Evaluation	.33	1.81	-3.04, 4.05	-2.54, 3.36
Negative Retailer Evaluation	**-10.97**	**6.43**	**-25.07, -.50**	**-22.63, -1.62**
Positive Competing Retailers Evaluation	**-13.72**	**5.98**	**-27.33, -4.27**	**-25.02, -5.48**
Negative Competing Retailers Evaluation	**15.84**	**7.55**	**3.61, 32.7**	**5.05, 29.60**
Seeking Information	-1.06	1.32	-3.66, 1.51	-3.25, 1.09
How-to Information	**4.68**	**1.88**	**1.38, 8.78**	**1.86, 8.02**
Product Features	-1.36	2.19	-5.62, 2.94	-4.94, 2.22
Purchase Intention	1.24	2.75	-3.76, 7.00	-2.91, 6.06
Purchase Confirmation	3.43	2.59	-1.23, 9.01	-.52, 8.09
Mean of Preference Intercept	**2.02**	**1.14**	-.04, 5.14	**.22, 4.42**
Variance of Preference Intercept	**.95**	**.14**	**.72, 1.26**	**.75, 1.20**
Covariance of Getting any Votes and Preference Intercepts	-.01	.10	-.21, .18	-.17, .15
Covariance of Number of Votes and Preference Intercepts	.03	.09	-.14, .21	-.11, .18

The Bold font indicates that the 90% or 95% credible interval does not contain zero.

Table 3. 7: Counterfactual Simulation Analysis

Scenario	Average Predicted Number of Silent Votes by Day 10 (per thread)	Average Predicted Percentage Points of Positive Silent Votes by Day 10 (per thread)
Current practice	3.81	79.2%
Number of posts of **positive price evaluation** category increases by 1 on Day 1	4.09 (+7.3%)	85.4% (+7.8%)
Number of posts of **positive price evaluation** category increases by 1 on Day 9	3.81 (0%)	79.2% (0%)
Number of posts of **negative retailer evaluation** category decreases by 1 on Day 1	3.75 (-1.6%)	83.3% (+5.2%)
Number of posts of **negative retailer evaluation** category decreases by 1 on Day 9	3.81 (0%)	79.2% (0%)
Number of posts of **negative retailer evaluation** category increase by1 on Day 1	5.97 (+56.7%)	43.0% (-45.7%)
Number of posts of **negative retailer evaluation** category increase by 1 on Day 9	3.81 (0%)	78.3% (-1.1%)
Number of posts of **negative competing retailer evaluation** category increase by 1 on Day 1	11.35 (+197.9%)	95.5% (+20.6%)
Number of posts of **negative competing retailer evaluation** category increase by 1 on Day 9	3.82 (+0.3%)	79.5% (+0.4%)
Number of posts of **seeking information** category decrease by 1 on Day 1	4.23 (+11.0%)	81.4% (+2.8%)
Number of posts of **seeking information** category decrease by 1 on Day 9	3.81 (0%)	79.2% (0%)
Number of posts of **how-to information** category increase by 1 on Day 1	4.10 (+ 7.6%)	84.9% (+7.2%)
Number of posts of **how-to information** category increase by 1 on Day 9	3.81 (0%)	79.2% (0%)

Figures

Figure 2. 1: Structure of a Multi-level Marketing Company

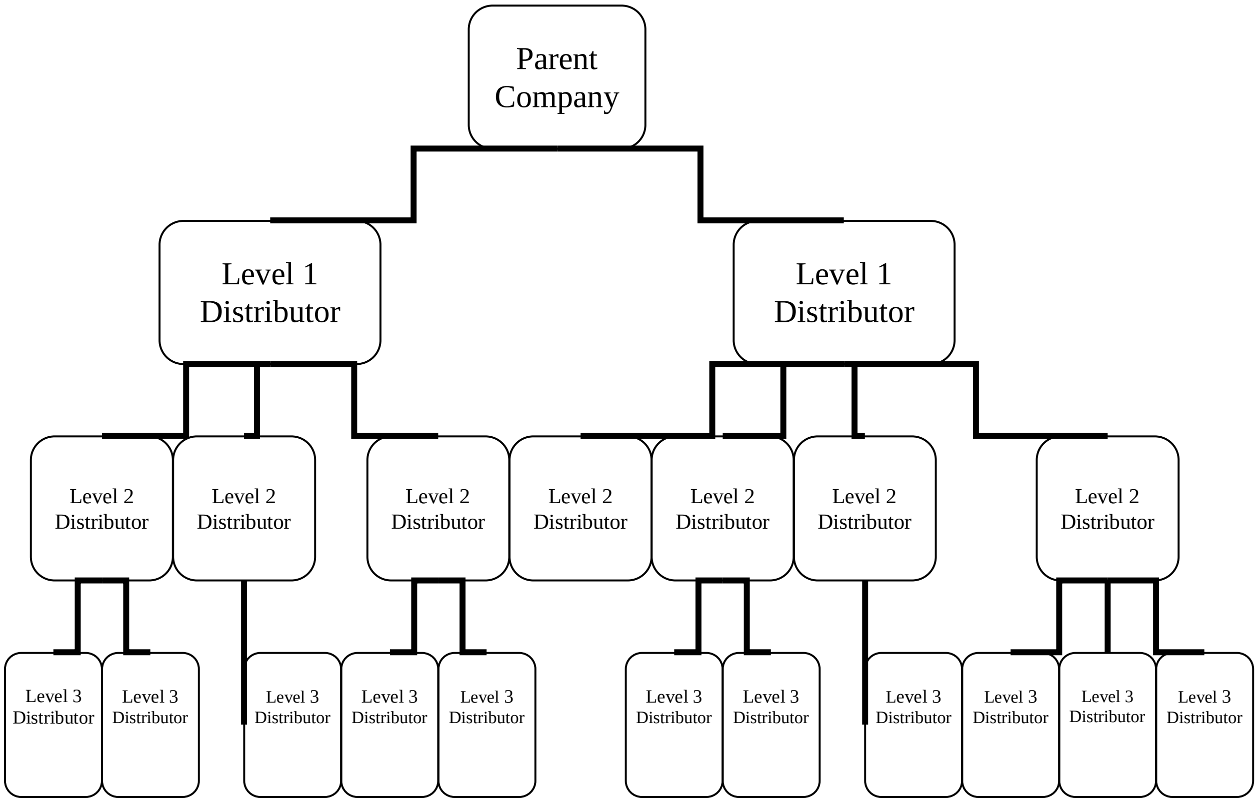


Figure 2. 2: Flow Chart for Generating the Comparable Customer/Distributor Satisfaction Measures

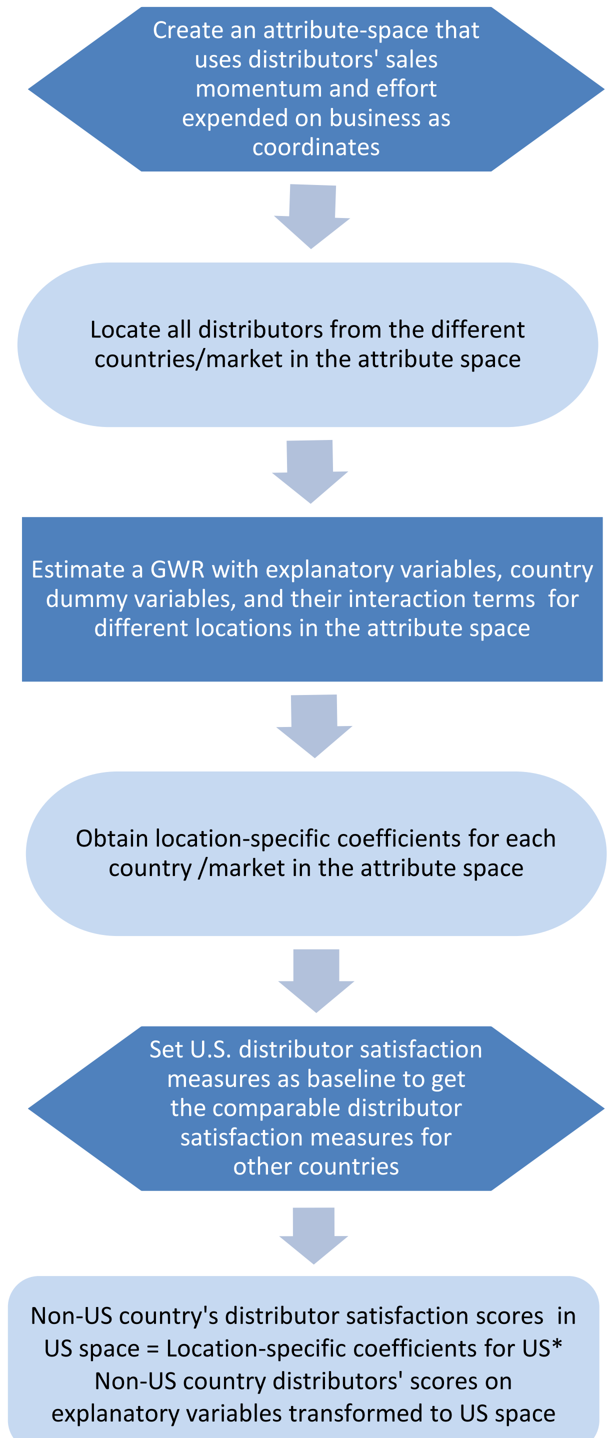
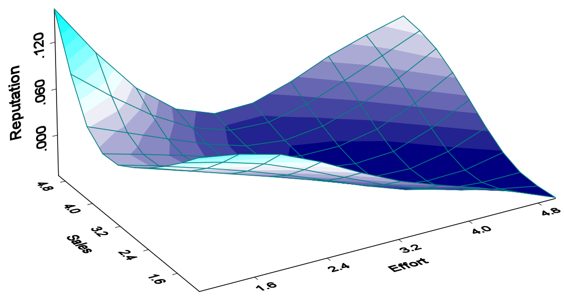
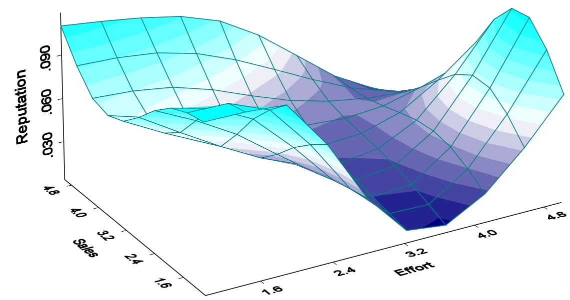


Figure 2. 3: Plots of Coefficient Estimates for Reputation in the Attribute-space:

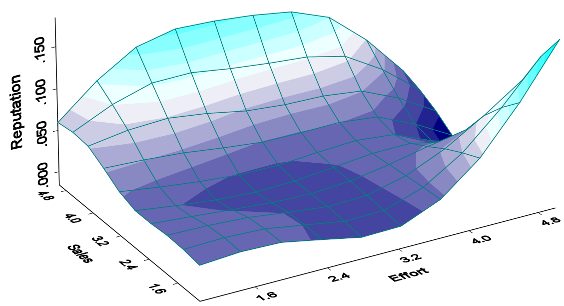
Sales Momentum vs. Effort Expended



USA

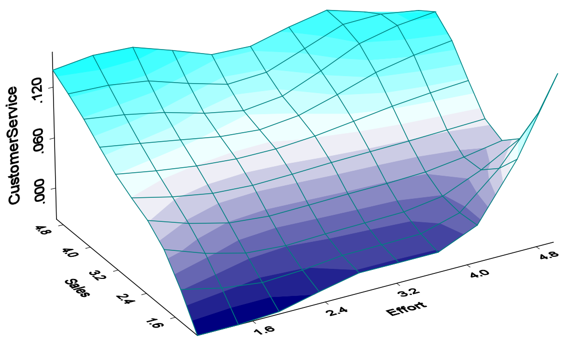


India

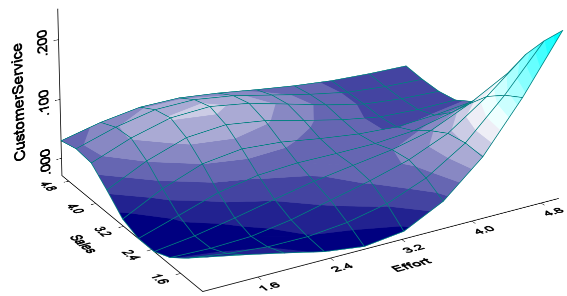


Korea

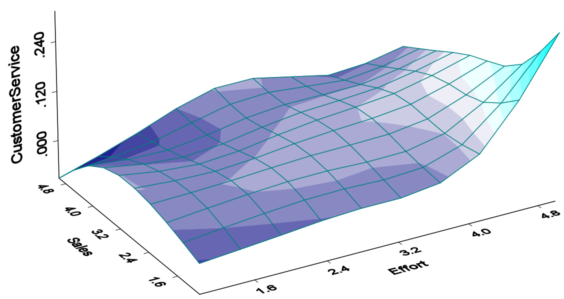
Figure 2. 4: Plots of Coefficient Estimates for Customer Service in the Attribute-space: Sales Momentum vs. Effort Expended



USA

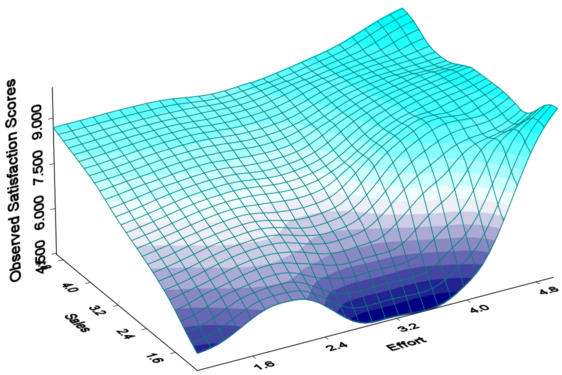


India

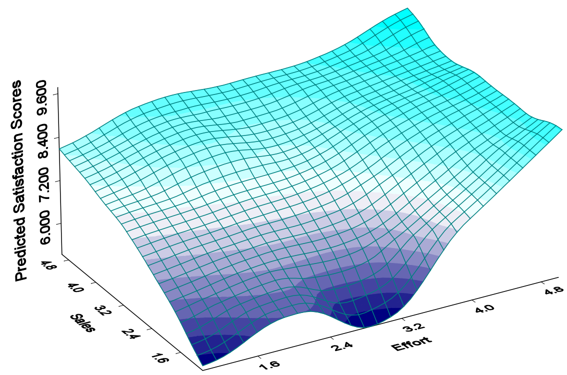


Korea

Figure 2. 5: Plots of Observed and Predicted Distributor Satisfaction Scores of USA in the Attribute-space: Sales Momentum vs. Effort Expended



Observed Distributor Satisfaction Scores



Predicted Distributor Satisfaction Scores

Figure 2. 6: Plots of Predicted and Comparable Distributor Satisfaction Scores in the Attribute-space: Sales Momentum vs. Effort Expended

Predicted Distributor Satisfaction Scores | **Comparable Distributor Satisfaction Scores**

India

Korea

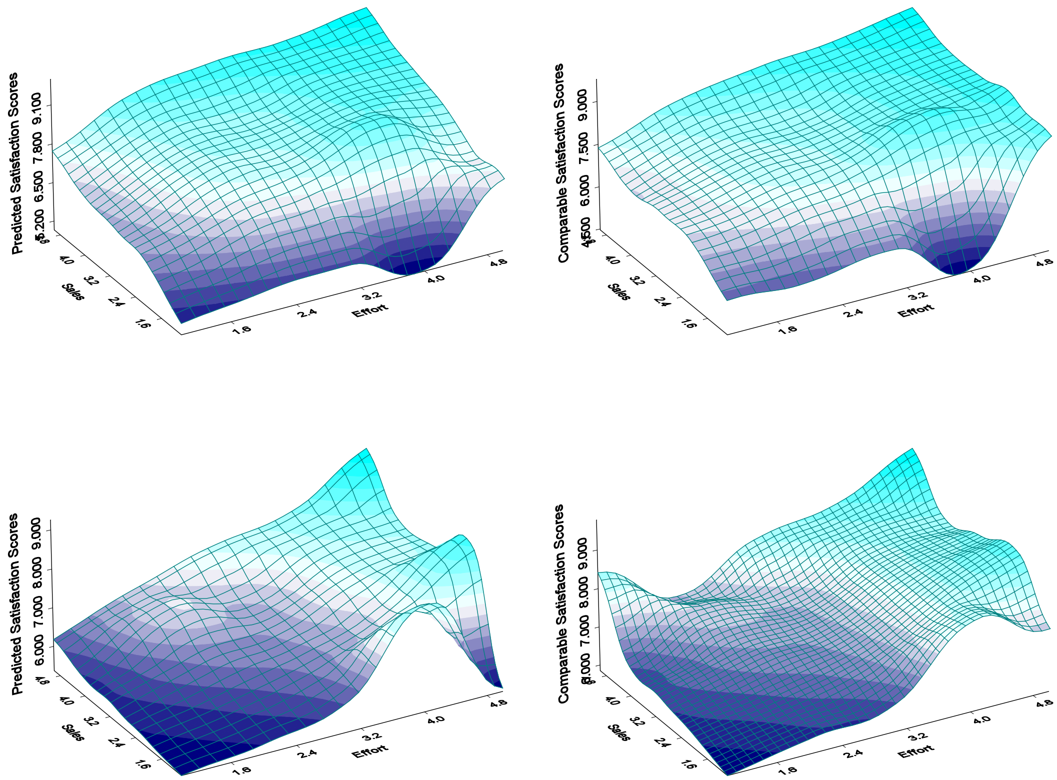
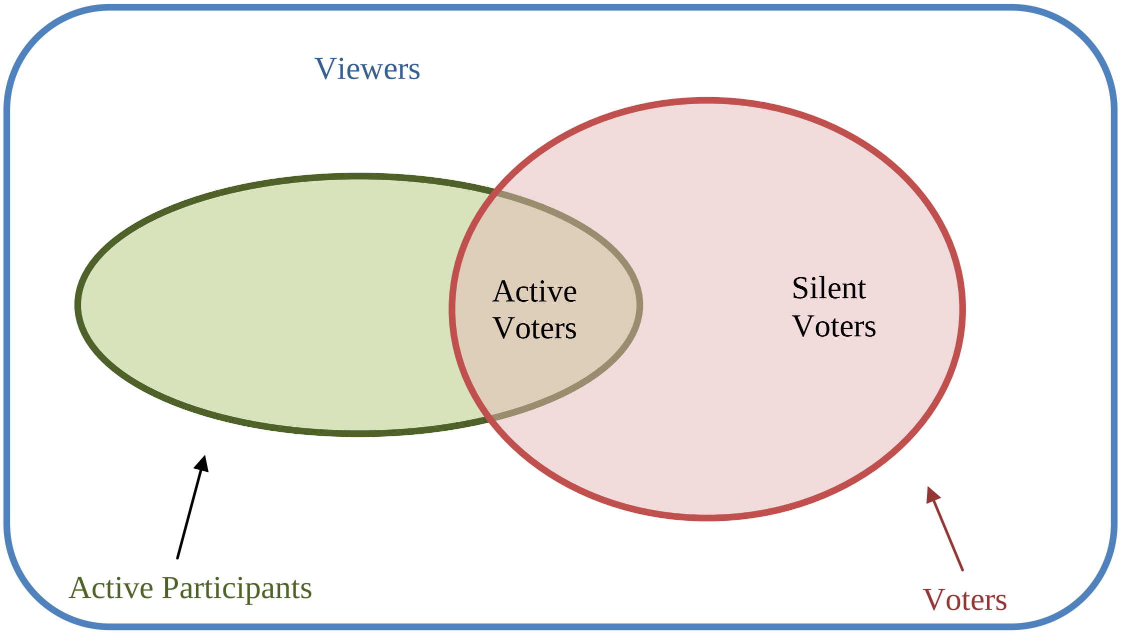


Figure 3. 1: A Classification of Users in a Discussion Forum



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