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# The Impact of Customer Community Participation on Customer Behaviors: An Empirical Investigation

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Many firms increasingly offer community venues to their customers to facilitate social interactions amongst them. Prior studies have shown that community participants have high engagement and loyalty toward the firm and provide useful feedback and referrals. However, it is not clear whether community participants are the firm's "fans" to begin with and self-select themselves into the community, or whether community participation leads to increased relational customer behaviors. In the current research, we employ data from a field experiment to help answer this question. The data come from a year-long study conducted by eBay Germany, and they reveal that a simple e-mail invitation significantly increased customer participation in the firm's community. Results also show that community participation had mixed effects on customers' likelihoods of participating in buying and selling behaviors. Community participation did not translate into increased behaviors, as would be commonly expected. Although there is no impact of participation on the number of bids placed or the revenue earned, there is a negative impact of participation on the number of listings and the amount spent. Together, these results suggest that the community participants become more selective and efficient sellers, and they also become more conservative in their spending on the items for which they bid. The results also show that customer community marketing programs may be targeted to a broader set of the firm's customers than just the fans.

**Key words:** customer community; online social interactions; customer relationship management; hierarchical bayes; MCMC; multivariate Tobit

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## 1. Introduction and Research Motivation

In recent years, there has been a groundswell of interest among marketers in organizing customer communities (e.g., Belk and Tumbat 2002, Johnson 2004, Nail 2005). Spurred on by the popularity of concepts such as consumer empowerment, collaboration, and customer-led marketing (e.g., Evans and Wolf 2005, Prahalad and Ramaswamy 2004, Selden and MacMillan 2006), many firms are spending more of their marketing budgets on customer community marketing programs. For example, the Italian motorcycle manufacturer Ducati replaced its marketing department with a central community group, involving its customers actively in every function from product design and marketing communications to creating the brand experience (Favier 2005). Ducati customers can join local fan communities on the firm's website, participate in "powwows"<sup>1</sup> with one

another and with company employees, post pictures and stories of their motorcycles, and help organize motorsport events and group rides. Other firms such as Harley Davidson, Hewlett-Packard, BMW, and eBay have also successfully implemented customer community marketing programs.

Supporting such anecdotal success stories, several recent research studies have provided evidence that customer communities provide substantial marketing value to firms. For example, research has shown that customer community participants have high levels of engagement with the firm's product(s) and brand(s) (McAlexander et al. 2002), are motivated to help other customers (Bagozzi and Dholakia 2006), are very loyal, and actively recruit others to the community (Algesheimer et al. 2005).

However, virtually all of the prior research has focused on studying those customers that are existing community members. Neither are behaviors of customers prior to their community participation available in these studies nor is it clearly established whether any action on the firm's part encourages community participation. Therefore, it is difficult to determine the extent to which participating in the

<sup>1</sup> Ducati used this term in designing its community events and calls gatherings of its customers where they get together to ride, have a picnic, etc., a "powwow."

customer community leads to the behaviors observed by the researchers and also whether the firm can influence participation in a community. Another limitation of the extant customer community studies is that they are usually cross-sectional or short term, covering a few days or weeks.

Consequently, a number of questions regarding the impact of customer communities remain unanswered. First, it is not clear whether a firm can increase participation in its customer communities through means such as e-mail invitations directed to its broader customer base rather than just to its smaller “fan” base. Second, it is unknown whether community participation leads to increased relational behaviors among customers or whether customers who participate tend to self-select themselves into such programs, intrinsically displaying more relational behaviors toward the firm. Third, the longer-term impact of joining and participating in the community—say, over the course of a year—on customer behaviors is unknown.

In the current research, we seek to answer these questions. To do so, we employ data collected using a field experiment with a random assignment of customers to either being invited or not invited to join the community, and then we study effects on behaviors of those who participated and those who did not participate in the customer community over a year afterward. This empirical investigation was conducted in cooperation with eBay, the leading global online auction firm. Both *buying*—the number of bids placed and total amount spent—and *selling*—the number of items listed and revenue earned—behaviors of eBay customers were studied.

The year-long study, involving 13,735 eBay customers, revealed that a simple e-mail invitation significantly increased customer participation in the firm’s community. Results also showed that community participation had mixed effects on customers’ likelihoods of initiating buying and selling behaviors. Community participation did not translate into increased behaviors as would be commonly expected. Although there is no impact of participation on the number of bids placed or the revenue earned by the customer, there is a negative impact of participation on the number of listings and the amount spent. Together, these results suggest that the community participants become more selective and efficient sellers and also become more conservative in their spending on the items for which they bid. The results also show that customer community marketing programs may be targeted to a broader set of the firm’s customers than just the fans.

The rest of this paper is organized as follows. In §2, we describe the research setting—in particular, eBay’s customer community—in detail. Section 3 describes

the data set, and §4 presents the empirical methodology used to help answer the research questions. The estimated results are given in §5. Section 6 concludes the paper with a general discussion describing the importance of customer communities, interpreting the study’s results, and considering their implications for academics and practitioners.

## 2. Research Setting

The customer community we studied is the firm-managed online community of eBay customers (<http://hub.ebay.com/community>). eBay, the world’s largest online auction website, offers its customers a number of community venues on its site, such as discussion boards and chat rooms. Its online discussion boards permit customers to communicate asynchronously (not in real time) with one another by posting messages and replying to the ones posted on the boards by others. They include general and category-specific discussion boards in which customers seek and/or provide information regarding various aspects of using eBay and conducting business on eBay. There are also social bulletin boards with names like “The Front Porch,” “Night Owl’s Nest,” and “The Soap Box,” which are primarily used by participants for socializing and entertainment.

The eBay customer community also has more than three dozen general and category-specific chat rooms where users can converse with each other in real time using text messages. Many of the chat rooms’ topics overlap with those of the discussion boards, and often the same members may participate in both venues, carrying on real-time conversations in a chat room while participating in asynchronous threads on a discussion board.

On the whole, the eBay customer community is a social organization where customers’ discussions regarding trading issues are interspersed with personal conversations, humor, social support, and helping behaviors. Surprisingly, even competing sellers within a particular category often freely joke amongst themselves in the community, share war stories of nightmarish experiences with demanding buyers, and warn each other of scams and fraudulent transactions. Although some community venues are designed to proffer and receive help, many venues are strictly for socializing, with no business conversations permitted within them. Participants are quick to enforce this norm if business-related discussions creep in.

Because of this structure and these characteristics, eBay’s customer community possesses the three markers that sociologists have deemed to be essential markers of community: (1) a *consciousness of kind* in the sense that members feel a connection not only to the brand but also toward one another, and a sense

of demarcation from those who are not community members; (2) *rituals and traditions* that bind the members together; and (3) a sense of *moral responsibility or obligation* among participants to give back to the community (Muniz and O'Guinn 2001).

Importantly, the eBay customer community supports both buyers and sellers on the site. Whereas some venues are designed exclusively for buyers (e.g., "Buyer Central" and "Bidding") or for sellers (e.g., "Seller Central"), most community venues are available to both buyers and sellers. In addition to online interactions, many participants may even meet each other regularly offline through such planned events as monthly lunches or dinners, meetings, and outings, as well as the annual "eBay Live" conventions in North America, the United Kingdom, and Germany.

eBay employees participate actively in many of the customer community venues, moderating discussions, soliciting feedback for planned changes and innovations, and providing information. When they participate, they identify themselves clearly as employees. As is the case with other customer communities (e.g., Algesheimer et al. 2005), eBay community members are diverse in every sense, with participants ranging widely in their demographic profiles, the amount of experience with eBay, and their previous trading behaviors.

In the present research, we study the effects of community participation on *new* community members, i.e., existing eBay customers who joined and participated in its customer community for the first time.

### 3. The Data

The data for this study come from a field experiment conducted in cooperation with the online auction site, <http://www.ebay.de> (the German division of eBay). Note that the structure of the German site is virtually identical to the U.S. eBay site (except that it is in German!). The firm conducted a year-long field study involving existing active users (buyers and/or sellers) on the online auction site. We call both buyers and sellers "customers" henceforth, because the firm earns revenue from the trading behaviors of both user groups. Customers were randomly selected from the "collectibles" product category for participation in the study. To be eligible for participation in the study, customers had to have (1) completed at least one transaction successfully, i.e., either won an auction or completed a sale in the category, within the three months prior to the experimental manipulation (described below); and (2) never participated in an eBay community before.<sup>2</sup> The collectibles category includes items such as stamps, coins, comic

books, art, model sets, and toys, which are known to elicit high levels of emotions and involvement in many consumers (e.g., Algesheimer et al. 2005), which in turn is conducive to joining and participating in customer communities. Furthermore, on eBay, this category is very active, with hundreds of thousands of new listings added on a daily basis, along with dozens of popular and heavily trafficked discussion boards and chat rooms. As a result, the collectibles category has a vibrant marketplace that supports customer community.

The experimental manipulation was as follows. Roughly half of the selected customers (assigned randomly) were invited to participate in one or more of the customer community venues on the eBay.de website at the beginning of May 2005 through an e-mail message. The text of the e-mail message, translated from German, is provided in Appendix A. As an incentive to encourage participation, customers who posted at least one message within three months were entered into a drawing to win one of several iPods. Additionally, e-mail reminders were sent twice to those who did not participate at two weeks and four weeks after the initial invitation. The remaining users within the category did not receive an invitation. The behavior of the entire set of customers was tracked for a period of one year after the e-mail invitations.

The data set available to us contains information on 13,735 individual customers for a period of 16 months (January 2004–April 2005) prior to the experimental manipulation, and for a period of a year afterward (May 2005–April 2006). Out of these, 6,776 customers (49.3%) had received an e-mail invitation. In particular, we have variables recording customers' bidding behavior (*number of bids placed* per month and the *total amount spent* per month buying in the collectibles product category) and selling behavior (*number of items listed* per month and the *total revenue earned* per month in the collectibles product category). Furthermore, we also have certain demographic information on each of these individuals (*Nationality*, *Age*, and *Gender*) and also the *length of membership* on the eBay site (in years) and the *total positive and negative feedback scores* received by the individual.

Table 1 provides a summary of the levels of these variables in the two groups (the 49.3% of the customers who received an e-mail invitation, and the remaining 50.7% customers who did not receive an invitation). This table contains these summary statistics for the period prior to the invitation to participate in a community. The purpose of Table 1 is simply to confirm that the two groups of customers (the invited and the noninvited) were similar on this set of variables before the intervention by the firm.

<sup>2</sup> Only those active eBay customers who had zero page views for the community pages on the eBay site were chosen for inclusion in the experiment.

**Table 1** Summary Statistics on the *Invited* and the *Noninvited* Customer Groups (for the Preintervention Time Period, January 2004 Through April 2005)

	Invited to participate	Not invited to participate
Female (%)	18.80	17.90
German (%)	82.30	82.70
Age (years)	39.60	38.90
Membership length (months)	55.56	56.40
Positive feedback <sup>a</sup>	111.90	100.80
Negative feedback <sup>a</sup>	0.50	0.43
Bids placed (per month)	3.70	3.70
Items listed (per month)	3.80	4.20
Amount spent (per month, euros)	21.10	19.00
Revenue earned (per month, euros)	62.70	58.30

<sup>a</sup>The feedback scores have been adjusted for membership length. The numbers shown are the feedback scores divided by the membership length (in years).

*t*-Tests conducted on these summary statistics across the two groups do not yield any significant differences on these variables. For the time period after the invitations, aggregate behavioral data at the individual customer level were available from the firm across three time periods: for the first three months after the intervention (June–August 2005), the next four months (September–December 2005), and the final four months (January–April 2006) of the one-year period.<sup>3</sup> Along with these data we also have data on whether or not an individual participated in a community during any of these postinvitation periods;<sup>4</sup> in all, 6.6% of the total sample of customers participated in the community. Therefore, we have data on behaviors across four time periods  $T_1$  (January 2004 through April 2005),  $T_2$  (June 2005 through August 2005),  $T_3$  (September 2005 through December 2005), and  $T_4$  (January 2006 through April 2006). The intervention on the part of the firm (sending e-mail invitations) was carried out in May 2005, and then during time periods  $T_2$  through  $T_4$  the behavior of the entire group of customers was monitored. Table 2 contains some summary statistics on key behaviors after the intervention period (i.e., aggregate behaviors across time periods  $T_2$  through  $T_4$ ). These have been presented across the two groups of customers, those who *participated* and those who *did not participate* in the community.

<sup>3</sup> Because the e-mail invitations (and reminders) to participate in the customer community were sent in the beginning, middle, and end of May 2005, this month is excluded from the analysis.

<sup>4</sup> Participation was defined as either having a page view of the customer community Web page or posting a message on it during anytime June 2005 through August 2005. Also, recollect that none of the individual customers had ever participated in any community prior to May 2005.

**Table 2** Summary Statistics on the Community *Participants* and the *Nonparticipants* (for the Postintervention Time Period, June 2005 Through April 2006)

	Participated in a community			Did not participate in a community		
Female (%)	21			18.20		
German (%)	72.90			83.20		
Age (years)	42.70			39		
Membership length (months)	46.92			56.64		
Positive feedback <sup>a</sup>	290.40			93.40		
Negative feedback <sup>a</sup>	1.26			0.41		
Time period	$T_2$	$T_3$	$T_4$	$T_2$	$T_3$	$T_4$
Bids placed (per month)	17.9	27.7	24.2	8.3	18.4	17.2
Items listed (per month)	51.6	149.9	141.6	9.5	34.5	35.3
Amount spent (per month, euros)	73.7	215.1	177.7	27.7	131.5	119.7
Revenue earned (per month, euros)	605.6	2,014.0	1,990.9	163.8	437.5	395.8

<sup>a</sup>The feedback scores have been adjusted for membership length. The numbers shown are the feedback scores divided by the membership length (in years).

A cursory examination of Table 2 reveals that all behaviors, across participants as well as nonparticipants, increased during time periods  $T_2$  (June 2005 through August 2005) and  $T_3$  (September 2005 through December 2005). However, more importantly, there is a substantial difference in the increase in behaviors across the *participants* relative to the *nonparticipants* across all the three time periods. The four outcome behaviors (bids placed, items listed, amount spent, and revenue earned) appear to be positively correlated to participation in the community. Therefore, one question that is important from the firm's standpoint is whether customers *who participate* tend to intrinsically display these increased behaviors (i.e., are predisposed towards increased behaviors), or is it that community participation *causes* these increased behaviors?

This is an important question, because depending on which of the possibilities is true, the answer provides different guidance to the firm. For example, if the first possibility is true (i.e., community participants intrinsically display increased relational behaviors), then the firm should target only its fans when seeking new customers to attract to its community. In contrast, if the second possibility is verified (i.e., community participation causes increased behaviors), then the firm can try to implement interventions to attract customers to participate in a community more broadly. Indeed, it would mean that customer

community programs can be used broadly to market to more of the firm's customers than just the fans.

In the next section we describe the methodology used to help answer these questions.

#### 4. The Model

The aim of our study is twofold. First, we wish to investigate whether any firm-level action can influence participation in a customer community. Second, we also wish to investigate the impact of participation in a community on the customers' buying and selling behaviors. Because the firm-level action in this field experiment (*sending of e-mail invitations*) was randomly distributed across the participants, we could potentially study the impact of such an action on participation. However, in studying the impact of participation in a community on outcome behaviors, one is faced with a potential self-selection issue: customers may *self-select* into participation in communities. In other words, the participation may not be randomly distributed across the set of customers. This makes any attempt to link participation to outcome behaviors susceptible to the problem of self-selection or endogeneity. We attempt to statistically control for this problem in our analysis by using the two-step *instrumental variables* (IVs) approach (Heckman and Navarro-Lozano 2004, Angrist and Krueger 2001, Vella and Verbeek 1999, Vella 1998, Staiger and Stock 1997).

Accordingly, we first specify a "participation model" wherein we link participation in a community to the intervention (e-mail invitation by the firm) and the customer's demographic and other characteristics (*Nationality, Age, Gender, Membership Length, Positive and Negative Feedback*). Subsequently, we specify an "outcome model" that investigates the impact of customer community participation on the four outcome behaviors of customers (*bids placed, items listed, amount spent, and revenue earned*).

The following subsections discuss these models in greater detail.

##### 4.1. The Participation Model

For a binary outcome variable such as participation in a community, a probit model is commonly used. Therefore, we model a customer's participation in the community as a probit process specified as a function of explanatory variables.

We observe a dummy variable  $P_h$  that equals 1 if the customer participated in the community during any time from June 2005 through August 2005 (i.e., time period  $T_2$ ); else it equals 0.

Furthermore, we assume

$$\begin{aligned} P_h &= 1 & \text{if } P_h^* > 0, \\ P_h &= 0 & \text{if } P_h^* \leq 0, \end{aligned} \quad (1)$$

where  $P_h^*$  is a latent participation variable for customer  $h$ . Furthermore, we assume that this  $P_h^*$  is distributed per a Normal distribution:

$$P_h^* \sim \text{Normal}[\rho_h, 1], \quad (2)$$

where  $[\rho_h, 1]$  are the mean and variance of the distribution.

This leads to a "probit" model of choice where the *probability of participation*,  $\text{Prob}_h$ , is specified as  $\int_0^\infty P_h^* dP_h^*$ .

We further specify  $\rho_h$  in Equation (2) as follows:

$$\begin{aligned} \rho_h &= \rho_0 + \rho_1 \text{German}_h + \rho_2 \text{Age}_h + \rho_3 \text{Gender}_h \\ &\quad + \rho_4 \text{Memlength}_h + \rho_5 \text{PosFB}_h + \rho_6 \text{NegFB}_h \\ &\quad + \rho_7 \text{Invite}_h. \end{aligned} \quad (3)$$

$\text{German}_h$  is an indicator variable and equals 1 if the nationality of the customer is German; else it equals 0.  $\text{Age}_h$  is the age (in years) of customer  $h$  as of May 2005, and  $\text{Gender}_h$  is an indicator variable that equals 1 if customer  $h$  is a female (0 otherwise). The variable  $\text{Memlength}_h$  is the membership length (in months)<sup>5</sup> of customer  $h$  as of May 2005.  $\text{NegFB}_h$  is the number of negative feedback that the customer received until time period  $T_1$  (the first time period), normalized by the membership length (in years).  $\text{PosFB}_h$  is the number of positive feedback received by the customer until time period  $T_1$ , normalized by membership length (in years). Finally,  $\text{Invite}_h = 1$  if an e-mail invitation was sent to customer  $h$  to join a community (0 otherwise).

This model gives us the answer to our first research question, i.e., whether or not an e-mail invitation to participate in the customer community has any impact on such participation.

##### 4.2. The Outcome Model

In the "outcome model," we attempt to link the outcome behaviors of the customer with participation in a community. The four outcome behaviors we observe and study are as follows:<sup>6</sup>

- $\text{Bids}_{ht}$  the average number of bids placed in the product category per month by customer  $h$  during time period  $t$  ( $t = T_1, T_2, T_3$ , or  $T_4$ ).
- $\text{Listings}_{ht}$  the average number of product listings for auctions placed in the product category per month by customer  $h$  during time period  $t$ .
- $\text{Amnt}_{ht}$  the average amount (in euros) spent buying in the product category per month by customer  $h$  during time period  $t$ .

<sup>5</sup> We use natural logs of  $\text{Memlength}_h$  and  $\text{Age}_h$  in the estimation.

<sup>6</sup> We scale all the four outcome behaviors by dividing them by 100.

$Revenue_{ht}$  the average amount (in euros) earned selling in the product category per month by customer  $h$  during time period  $t$ .

Because many of these behaviors in our data have a zero value, we specify a multivariate Tobit type I model for these behaviors as follows.

Define a latent outcome vector

$$\mathbf{Outcome}_{ht}^* = \begin{bmatrix} Bids_{ht}^* \\ Listings_{ht}^* \\ Amnt_{ht}^* \\ Revenue_{ht}^* \end{bmatrix} \quad \text{such that}$$

$$\begin{aligned} Bids_{ht} &= 0 & \text{if } Bids_{ht}^* \leq 0, \\ Bids_{ht} &= Bids_{ht}^* & \text{if } Bids_{ht}^* > 0, \end{aligned} \quad (4a)$$

$$\begin{aligned} Listings_{ht} &= 0 & \text{if } Listings_{ht}^* \leq 0, \\ Listings_{ht} &= Listings_{ht}^* & \text{if } Listings_{ht}^* > 0, \end{aligned} \quad (4b)$$

$$\begin{aligned} Amnt_{ht} &= 0 & \text{if } Amnt_{ht}^* \leq 0, \\ Amnt_{ht} &= Amnt_{ht}^* & \text{if } Amnt_{ht}^* > 0, \end{aligned} \quad (4c)$$

$$\begin{aligned} Revenue_{ht} &= 0 & \text{if } Revenue_{ht}^* \leq 0, \\ Revenue_{ht} &= Revenue_{ht}^* & \text{if } Revenue_{ht}^* > 0. \end{aligned} \quad (4d)$$

Furthermore,

$$\mathbf{Outcome}_{ht}^* \sim \text{MV Normal}(\boldsymbol{\beta}_{ht}, \boldsymbol{\Sigma}), \quad (5)$$

where

$$\begin{aligned} \boldsymbol{\beta}_{ht} &= \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 P_h + \boldsymbol{\beta}_2 T_{2t} + \boldsymbol{\beta}_3 T_{3t} + \boldsymbol{\beta}_4 T_{4t} + \boldsymbol{\beta}_5 German_h \\ &+ \boldsymbol{\beta}_6 Age_h + \boldsymbol{\beta}_7 Gender_h + \boldsymbol{\beta}_8 PosFB_h \\ &+ \boldsymbol{\beta}_9 NegFB_h + \boldsymbol{\beta}_{10} Memlength_h, \end{aligned} \quad (6)$$

and  $\boldsymbol{\Sigma}$  is a  $4 \times 4$  variance-covariance matrix. The off-diagonal elements of the  $\boldsymbol{\Sigma}$  matrix specify the structure of covariance across the four dimensions of the latent outcome vector. As described earlier,  $P_h$  is a dummy variable equal to 1 if customer  $h$  participates in the community, and 0 otherwise. Also, because of customer self-selection into participation,  $P_h$  is potentially endogenous. Therefore, we use an IV approach to account for the endogeneity of  $P_h$  in the outcomes model. We use a linear probability model to predict the participation propensity (i.e.,  $Propen_h$ ) for each customer in the first stage of model estimation and then use this predicted  $Propen_h$  instead of  $P_h$  in Equation (6) in the second stage to estimate the effect of community participation on the outcomes

studied. Therefore, we estimate Equation (6) specified as follows:

$$\begin{aligned} \boldsymbol{\beta}_{ht} &= \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 Propen_h + \boldsymbol{\beta}_2 T_{2t} + \boldsymbol{\beta}_3 T_{3t} + \boldsymbol{\beta}_4 T_{4t} \\ &+ \boldsymbol{\beta}_5 German_h + \boldsymbol{\beta}_6 Age_h + \boldsymbol{\beta}_7 Gender_h \\ &+ \boldsymbol{\beta}_8 PosFB_h + \boldsymbol{\beta}_9 NegFB_h \\ &+ \boldsymbol{\beta}_{10} Memlength_h. \end{aligned} \quad (6a)$$

Note that the estimation of  $Propen_h$  in the first stage can be done in several ways (e.g., using a probit or a logit probability). However, a linear probability model for this purpose is recommended in the literature even if the endogenous variable is a dummy variable, as in our case (Grootendorst 2007, Angrist and Krueger 2001, Angrist 2001, Vella and Verbeek 1999). Please see more details of the first-stage estimation in Appendix C. We refer to  $Propen_h$  as the *propensity to participate* in a community for customer  $h$ .  $T_{2t}$ ,  $T_{3t}$ , and  $T_{4t}$  are dummy variables representing the respective time periods, and the remaining variables are as described earlier.

Equations (4a) through (6a) specify the model for the four outcome behaviors. The parameter  $\boldsymbol{\beta}_1 = [\beta_1^{(Bids)}, \beta_1^{(Listings)}, \beta_1^{(Amnt)}, \beta_1^{(Revenue)}]'$  is the impact of participation in a community on the four behaviors. Positive signs on these coefficients would imply increased behaviors with participation.

In the IV model, identification requires exclusion restrictions in the outcome model. In our decision to exclude variables for identification, we considered our prior knowledge about the likely relationship between the outcomes and the covariates, our desire to minimize the number of exclusion restrictions for identification, and the formal tests for validity and strength of instruments. We include all the covariates in the participation model and exclude two of them, i.e.,  $Invite_h$  and  $Memlength_h$ , from the outcome model. The variable  $Invite_h$  represents the e-mail invitation to randomly selected customers to participate in the customer community and is not expected to have any direct impact on the outcomes studied. However, it can have an impact on the likelihood of participation in the community. Therefore, we exclude this variable from the outcome model. The variable  $Memlength_h$  was the second exclusion from the outcome model. We used the Sargan test for validity of an instrument (Kennedy 2003) and the  $F$ -test for strength of instruments (Cameron and Trivedi 2005, Staiger and Stock 1997, Stock et al. 2002) to formally test our instruments. Based on the results of the Sargan test,  $Memlength_h$  was not excluded from the  $Revenue_{ht}$  model. Therefore, in Equations (6) and (6a),  $\beta_{10}$  is specified as  $\boldsymbol{\beta}_{10} = [0, 0, 0, \beta_{10}^{(Revenue)}]'$ .<sup>7</sup>

<sup>7</sup> We thank an anonymous reviewer for guiding us in the testing of instruments.

### 4.3. Model Estimation

The Bayesian specification of the model (Equations (1)–(6)) is completed by assigning appropriate prior distributions on the parameters to be estimated. Appendix B provides the prior distributions used in the analysis. The model is estimated by a Markov chain Monte Carlo (MCMC) sampling scheme using data augmentation, details of which are provided in the electronic companion to this paper, available as part of the online version that can be found at <http://mktsci.pubs.informs.org>. The result is a set of posterior distributions on each parameter to be estimated. These posterior distributions are summarized in the next section.

## 5. The Estimated Results

The posterior distributions obtained from the sampling scheme are summarized by their means and standard deviations. This section describes and interprets the estimated coefficients. The figures in parentheses (in various tables) are the posterior standard deviations, and the shaded cells indicate the statistically insignificant estimates.<sup>8</sup>

### 5.1. The Participation Model

The participation model (the *probit* model in §4.1, Equations (1)–(3)) links the customer's participation in a community to specific demographics, customer characteristics, and the firm's action of sending e-mail invitations. Table 3 contains estimates for the various parameters of this probit model.

All nonshaded coefficients in Table 3 are significantly different from zero, indicating that the covariates (*Age*, *Memlength*, *PosFB*, *NegFB*, and *Invite*) have a significant impact on participation. Increased age is found to have a positive relation to the propensity (and hence probability) of participation; the estimated coefficient 0.514 is statistically greater than 0. This corresponds to approximately 9.9% increase in the probability of participation corresponding to a 10% increase in age.<sup>9</sup> Longer-tenure customers tend to have a lower propensity to participate in a community—a 10% increase in the membership length tends to reduce the probability of participation by 5.4%. Positive (negative) feedback has a positive (negative) impact on participation probabilities. A 10% increase in positive feedbacks tends to increase the participation probability by 0.8% and a 10% increase in negative feedback tends to reduce the participation probability by 0.2%.

Finally, the results reveal that the firm's e-mail invitation has a positive influence on participation. The

**Table 3** Parameter Estimates: Participation Model (the Estimated Coefficients for Various Covariates)

	$\rho_0$	–2.395 (0.2968)	
<i>German<sub>it</sub></i>	$\rho_1$	0.034 (0.0592)	Germans tend to have similar participation probability as non-Germans
<i>Age<sub>it</sub></i>	$\rho_2$	0.514 (0.0697)	Participation tends to increase with age
<i>Gender<sub>it</sub></i>	$\rho_3$	0.018 (0.0427)	Females tend to have similar participation probability as males
<i>Memlength<sub>it</sub></i>	$\rho_4$	–0.294 (0.0383)	Longer-tenure customers tend to have lower participation
<i>PosFB<sub>it</sub></i>	$\rho_5$	$3.56 \times 10^{-4}$ ( $0.421 \times 10^{-4}$ )	Positive feedback is <i>positively</i> correlated to the probability of participation
<i>NegFB<sub>it</sub></i>	$\rho_6$	–0.024 (0.0045)	Negative feedback is <i>negatively</i> correlated to the probability of participation
<i>Invite<sub>it</sub></i>	$\rho_7$	0.103 (0.0351)	E-mail invitation to participate increases the probability of participation

Note. Shaded cells indicate statistically insignificant estimates.

estimated coefficient  $\rho_7$  ( $=0.103$ ) translates to a 22.7% higher probability of participation for customers who were invited to participate via e-mail compared with those not sent the e-mail invitation. This last result sheds light on the important question of whether firms can target their customer base for participation in customer communities. Our results reveal that in the present case, eBay received a significant increase in participation in its customer community on account of inviting its customers with e-mail messages, rather than simply building the community and waiting for its fans to register voluntarily.

### 5.2. The Outcome Model

The outcome model (see §4.2) links the four outcome behaviors of customers (*Bids<sub>it</sub>*, *Listings<sub>it</sub>*, *Amnt<sub>it</sub>*, and *Revenue<sub>it</sub>*) to participation in the customer community and various other covariates. Tables 4(a) and 4(b) provide the parameter estimates of the model specified in §4.2 (Equations (4a)–(6a)). Table C.1 in Appendix C provides estimates of the first-stage linear probability model.

Interestingly, the results indicate that the impact of community participation on the four behaviors is *either a null effect or a negative impact* (the parameter  $\beta_1$  in Table 4(a)). Participation in the community does not translate into increased behaviors. Although there is no impact of participation on the number of bids placed or the revenue earned, there is a negative impact of participation on the number of listings and the amount spent. A 10% increase in the propensity to participate from its median value of

<sup>8</sup> “Insignificance” in our context implies that the 95% posterior estimated interval contains a zero.

<sup>9</sup> Calculated using the estimated coefficients and the average values of the covariates observed in the data set.



**Table 4(a) Parameter Estimates: Outcome Model (the Estimated Coefficients for Various Covariates)**

	$Bids_{it}$	$Listings_{it}$	$Amnt_{it}$	$Revenue_{it}$
$\beta_0 =$	$\begin{bmatrix} -0.432 \\ (0.0287) \end{bmatrix}$	$\begin{bmatrix} -4.598 \\ (0.4068) \end{bmatrix}$	$\begin{bmatrix} -2.711 \\ (0.1923) \end{bmatrix}$	$\begin{bmatrix} -55.834 \\ (4.4248) \end{bmatrix}$
$Propen_{it}$	$\beta_1 = \begin{bmatrix} -0.049 \\ (0.1075) \end{bmatrix}$	$\begin{bmatrix} -7.132 \\ (1.4957) \end{bmatrix}$	$\begin{bmatrix} -1.014 \\ (0.6125) \end{bmatrix}$	$\begin{bmatrix} -2.557 \\ (10.254) \end{bmatrix}$
$T_{2t}$	$\beta_2 = \begin{bmatrix} 0.0007 \\ (0.0057) \end{bmatrix}$	$\begin{bmatrix} -0.893 \\ (0.0718) \end{bmatrix}$	$\begin{bmatrix} -0.285 \\ (0.0329) \end{bmatrix}$	$\begin{bmatrix} -13.145 \\ (0.9108) \end{bmatrix}$
$T_{3t}$	$\beta_3 = \begin{bmatrix} 0.178 \\ (0.0056) \end{bmatrix}$	$\begin{bmatrix} 0.999 \\ (0.0655) \end{bmatrix}$	$\begin{bmatrix} 1.337 \\ (0.0330) \end{bmatrix}$	$\begin{bmatrix} 11.959 \\ (0.8946) \end{bmatrix}$
$T_{4t}$	$\beta_4 = \begin{bmatrix} 0.162 \\ (0.0058) \end{bmatrix}$	$\begin{bmatrix} 0.875 \\ (0.0652) \end{bmatrix}$	$\begin{bmatrix} 1.182 \\ (0.0335) \end{bmatrix}$	$\begin{bmatrix} 9.683 \\ (0.8207) \end{bmatrix}$
$German_{it}$	$\beta_5 = \begin{bmatrix} -0.052 \\ (0.0070) \end{bmatrix}$	$\begin{bmatrix} 2.717 \\ (0.0937) \end{bmatrix}$	$\begin{bmatrix} -0.315 \\ (0.0399) \end{bmatrix}$	$\begin{bmatrix} 31.261 \\ (1.3086) \end{bmatrix}$
$Age_{it}$	$\beta_6 = \begin{bmatrix} 0.134 \\ (0.0091) \end{bmatrix}$	$\begin{bmatrix} -0.172 \\ (0.1271) \end{bmatrix}$	$\begin{bmatrix} 0.824 \\ (0.0597) \end{bmatrix}$	$\begin{bmatrix} -9.902 \\ (1.1705) \end{bmatrix}$
$Gender_{it}$	$\beta_7 = \begin{bmatrix} -0.017 \\ (0.0050) \end{bmatrix}$	$\begin{bmatrix} -0.028 \\ (0.0675) \end{bmatrix}$	$\begin{bmatrix} -0.183 \\ (0.0319) \end{bmatrix}$	$\begin{bmatrix} -1.080 \\ (0.7727) \end{bmatrix}$
$PosFB_{it}$	$\beta_8 = \begin{bmatrix} 9.3 \times 10^{-6} \\ (1.3 \times 10^{-5}) \end{bmatrix}$	$\begin{bmatrix} 0.006 \\ (1.64 \times 10^{-4}) \end{bmatrix}$	$\begin{bmatrix} 5.6 \times 10^{-5} \\ (8.0 \times 10^{-5}) \end{bmatrix}$	$\begin{bmatrix} 0.059 \\ (0.0014) \end{bmatrix}$
$NegFB_{it}$	$\beta_9 = \begin{bmatrix} -0.001 \\ (0.0011) \end{bmatrix}$	$\begin{bmatrix} -0.280 \\ (0.0125) \end{bmatrix}$	$\begin{bmatrix} 0.001 \\ (0.0068) \end{bmatrix}$	$\begin{bmatrix} -1.122 \\ (0.1267) \end{bmatrix}$
$Memlength_{it}$	$\beta_{10} = \begin{bmatrix} 0.0 \\ (0.0) \end{bmatrix}$	$\begin{bmatrix} 0.0 \\ (0.0) \end{bmatrix}$	$\begin{bmatrix} 0.0 \\ (0.0) \end{bmatrix}$	$\begin{bmatrix} 5.763 \\ (0.9615) \end{bmatrix}$

Note. Shaded cells indicate statistically insignificant estimates.

**Table 4(b) Parameter Estimates: Outcome Model (the Estimated Variance-Covariance Structure)**

$\Sigma$  (Equation (5)) in terms of variance and correlation matrix

	Variance	$Bids_{it}$	$Listings_{it}$	$Amnt_{it}$	$Revenue_{it}$	
$Bids_{it}$	$\begin{bmatrix} 0.202 \\ (0.0012) \end{bmatrix}$	<b>1.0</b>	$\begin{bmatrix} -0.011 \\ (0.0052) \end{bmatrix}$	$\begin{bmatrix} 0.345 \\ (0.0037) \end{bmatrix}$	$\begin{bmatrix} -0.020 \\ (0.0055) \end{bmatrix}$	$Bids_{it}$
$Listings_{it}$	$\begin{bmatrix} 21.558 \\ (0.2143) \end{bmatrix}$	$\begin{bmatrix} -0.011 \\ (0.0052) \end{bmatrix}$	<b>1.0</b>	$\begin{bmatrix} -0.003 \\ (0.0056) \end{bmatrix}$	$\begin{bmatrix} 0.410 \\ (0.0044) \end{bmatrix}$	$Listings_{it}$
$Amnt_{it}$	$\begin{bmatrix} 7.356 \\ (0.0477) \end{bmatrix}$	$\begin{bmatrix} 0.345 \\ (0.0037) \end{bmatrix}$	$\begin{bmatrix} -0.003 \\ (0.0056) \end{bmatrix}$	<b>1.0</b>	$\begin{bmatrix} 0.010 \\ (0.0050) \end{bmatrix}$	$Amnt_{it}$
$Revenue_{it}$	$\begin{bmatrix} 3,685.9 \\ (36.136) \end{bmatrix}$	$\begin{bmatrix} -0.020 \\ (0.0055) \end{bmatrix}$	$\begin{bmatrix} 0.410 \\ (0.0044) \end{bmatrix}$	$\begin{bmatrix} 0.010 \\ (0.0050) \end{bmatrix}$	<b>1.0</b>	$Revenue_{it}$

0.057<sup>10</sup> corresponds to a decrease of 4.0 listings per month and a decrease of about 0.58 euros per month in the amount spent.<sup>11</sup> Although it could be argued that the impact on the amounts spent is small, nevertheless, the impact is statistically significant and

<sup>10</sup> The posterior 95% interval for the propensity to participate ( $Propen_{it}$ ) across the 13,735 customers is [0.014, 0.157], the median value being 0.057.

<sup>11</sup> Calculated using the estimated coefficients and Equations (5) and (6a).

for a large customer base the total impact will be significant. These results indicate that participation in customer community seems to deter customers from listing auctions on eBay and spending bidding amounts (although the impact on bidding amounts is marginal). Interestingly, although participation tends to reduce the number of listings, it does not seem to have an effect on the revenues earned.

One possible reason for this finding could be that participating in customer communities is educational for many customers, providing them with a clearer, more accurate understanding of the complexity and risk involved in the bidding and listing of items for sale on eBay, and concluding transactions successfully. For many customers, knowing such details from the community may lead to a more selective selling behavior on eBay. This could explain fewer listings with no reduction in revenues earned after community participation. In other words, community participation leads customers to be more efficient at selling on eBay. Although it is outside the scope of the current study to examine the precise underlying psychological processes to account for this result, we note that this finding is the first instance of a potentially negative impact of the customer's community participation on his or her behaviors that determine revenue and profit of the firm. Virtually all previously published research on customer communities (to our knowledge) has found positive effects on customer behaviors (e.g., Algesheimer et al. 2005, McAlexander et al. 2002).

Regarding the decrease in the amount spent by the community participants (while the number of bids remains unchanged), one possible explanation could be that customers become more conservative in their bidding behavior, perhaps because of exposure to stories of overspending on items by others in the community.

We want to underscore that customer communities serve several purposes for the firm, such as for obtaining feedback about its existing products and services and information on developing additional offerings. The increased selling efficiency of community participants that we find could have several consequences that we do not study here.<sup>12</sup>

To summarize, an examination of the results regarding the impacts of community participation on buying

<sup>12</sup> For example, the increased selling efficiency might make these customers more favorably disposed towards eBay. Consequently, these customers could help eBay acquire new customers as well as have more customers join its community as a result of the positive word of mouth. Given the limitations of our study, we cannot say with certainty whether the change in behavior of the customers after participation in the community would have a net positive or negative effect on eBay.

and selling behaviors reveals that the impact of community participation on these behaviors was mixed (Table 4(a)). Participation in the community corresponds to a lower extent of listing items for auction on eBay (whereas the revenue earned remains unchanged) and it also corresponds to a lower amount of money spent on eBay (whereas the number of bids remains unchanged). Both these changes in customer behavior as a result of community participation have a significant impact for the firm. These effects point to an educational value of the community for customers.

As for the impact of other covariates, it can be seen from the estimated coefficients in Table 4(a) that females tend to engage less in outcome behavior (two of the four dimensions of  $\beta_7$ , the coefficient of *Gender*, are negative). Approximately, females tend to place 1.7 fewer bids per month and also tend to spend about 18.9 euros per month less compared with males.

Positive and negative feedback (parameters  $\beta_8$  and  $\beta_9$ , respectively) tend to impact the “selling” behavior (the number of listings and the revenue earned); however, they do not have an impact on the “buying” behavior (the number of bids placed and the amount spent). Each additional positive feedback per year corresponds to an increased listing of 0.6 per month and an increase of 5.7 euros per month in the revenues earned. On the other hand, each additional negative feedback corresponds to a decrease in listings by 26.4 per month and a drop in revenue earned by 102.1 euros. The negative impact of negative feedback tends to be much greater than the positive impact of positive feedback.

The time dummies ( $T_2$ ,  $T_3$ , and  $T_4$ ) control for the impact of time periods  $T_2$ ,  $T_3$ , and  $T_4$  with respect to the first time period ( $T_1$ ). From the estimated coefficients ( $\beta_2$ ,  $\beta_3$ , and  $\beta_4$ ), it appears that there is a dip in the outcome behaviors (number of listings, amount spent, and revenue earned) in the second time period (the estimated signs of the dimensions of  $\beta_2$  when statistically significant are negative). However, as per the summary statistics provided in Tables 1 and 2, no such dip is observed. A closer examination of the outcome behavior in time period  $T_2$  reveals that the Tobit model picks up this dip because the *probability* of a nonzero outcome in this time period is significantly lower than that in time period  $T_1$ , despite the magnitude of the outcome (conditional on it being nonzero) being greater than that in  $T_1$ . Table 5 provides these probabilities for the four time periods. As seen from Table 5, time period  $T_2$  has a dip in the probability of nonzero outcomes compared with other time periods, and this is a feature of our data set.

The two covariates (*German<sub>it</sub>* and *Age<sub>it</sub>*) have a mixed impact on the outcome behaviors. Germans, compared with non-Germans, tend to bid less and

**Table 5** Summary Statistics on the *Probability* of Nonzero Outcomes

Time period	$T_1$	$T_2$	$T_3$	$T_4$
Probability of nonzero <i>Bids</i>	0.92	0.79	0.98	0.98
Probability of nonzero <i>Listings</i>	0.48	0.35	0.56	0.53
Probability of nonzero <i>Amount</i>	0.89	0.73	0.94	0.93
Probability of nonzero <i>Revenue</i>	0.47	0.32	0.54	0.52

spend less on eBay, whereas they tend to list more and earn greater revenues compared with non-Germans (the estimated  $\beta_5$  coefficient in Table 4(a)). Older people tend to bid more and spend more on eBay, whereas they tend to earn less revenues (the estimated  $\beta_6$  coefficient). The covariate *Memlength<sub>it</sub>* tends to have a positive impact on the revenues earned on eBay; thus, customers with a longer membership length tend to earn higher revenues.<sup>13</sup>

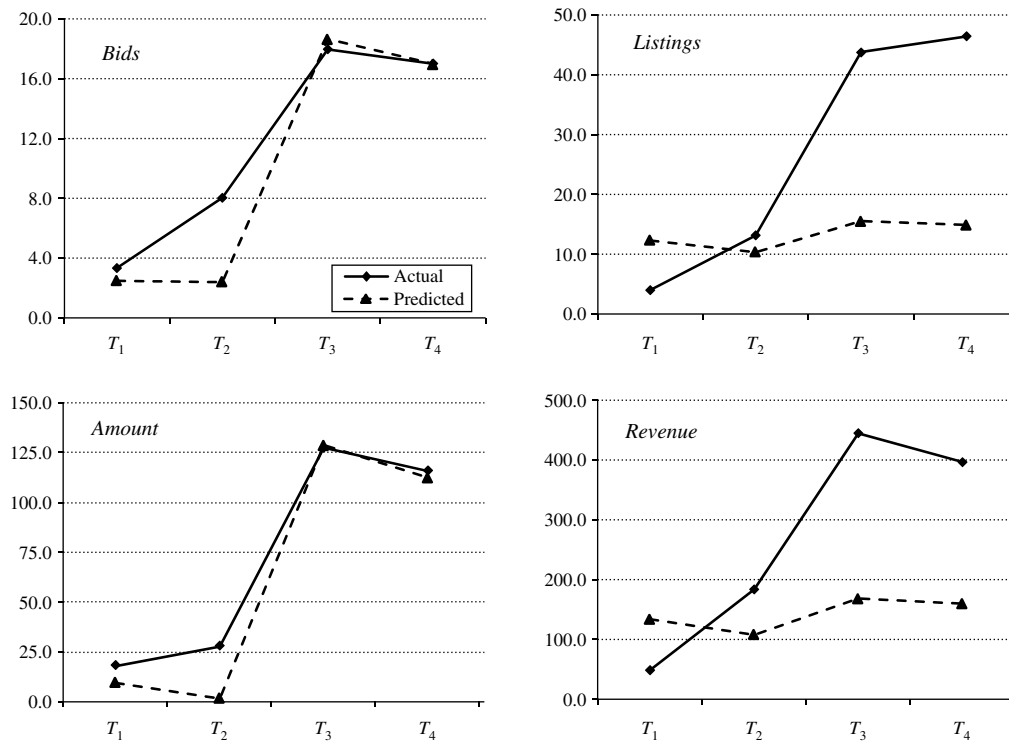
Table 4(b) contains the estimated parameters of the variance and correlation structure specified across the four customer outcomes (Equation (5) in §4.2). Not surprisingly, bidding and spending on eBay purchases are positively correlated (a correlation of 0.345), as are the probabilities of listing and earning revenues from eBay sales (correlation of 0.410). The other correlations are either statistically and/or managerially insignificant.

Finally, in Figure 1 we demonstrate the fit of the model. We held out 20% of the data; i.e., 20% of the customers (2,747 customers) were removed randomly and the model was estimated on the remaining data (the remaining 10,988 customers). Using these estimated parameters we predicted the participation rate as well as outcome data for the held-out customers. The predicted participation rate was 6.5% (compared with the actual participation rate of 6.9%). Furthermore, Figure 1 is a pictorial representation of the actual average outcomes versus the predicted average outcomes across the held-out customers. As seen from the figure, the predictions tend to be much better in the case of predicting the bidding behavior (bids and amounts) compared with the selling behavior (listings and revenue). There is a lot more variance surrounding the selling behaviors; compared to the bidding behaviors, this is also reflected in the estimated variance-correlation structure (see Table 4(b)).

We must point out, though, that the focus of our investigation is not to build a predictive model but rather to investigate the impact of participation in communities—specifically, to investigate whether customers who participate in communities tend to be predisposed toward increased behaviors or if

<sup>13</sup> Note that based on the Sargan test for validity of instruments, the variable *Memlength<sub>it</sub>* was used as an instrument only for three of the four outcome variables. It was not used as an instrument for the “revenue” outcome variable.

Figure 1 Model Fit for the Holdout Data



the community participation causes these increased behaviors. Our conclusion is that customers who participate in the community tend to be predisposed toward increased behaviors.

### 5.3. The Importance of Accounting for Self-Selection

To demonstrate the importance of correcting for self-selection, we estimated the outcome model (Equations (4a)–(6)) *without correcting* for self-selection. We directly used the participation dummy variable ( $P_h$ ) as an explanatory variable in the outcome model. The results of this estimation are provided in Tables 6(a) and 6(b).

Interestingly, the impact of participation that would be inferred from these results would be that participation in a community leads to an increase in *all four* outcome behaviors (all four dimensions of the estimated  $\beta_1$  in Table 6(a) are positive). In terms of the magnitude of impact, participation (compared with nonparticipation in a community) leads to 7.9 more bids per month, expenditures of 62.0 euros more per month, an increase in listings of 68.9 per month, and an increase in revenue earned by 1,264.8 euros per month. This is in stark contrast to the impact of participation when we control for self-selection and is evidence that a naïve model not controlling for this effect will lead to erroneous conclusions about the impact of community participation. These results could shed light on

the reason why such communities are commonly considered to increase engagement with the firm.

## 6. General Discussion

### 6.1. The Managerial Importance of Customer Communities

To fully appreciate the significance of our findings to managers, it is useful to briefly situate customer community marketing programs within the current business environment. Recent and evolving technological, social, and business trends have all combined to increase the importance of these programs for managers. First, technology has empowered consumers in significant ways. Not only do consumers have access to detailed quality and price information through manufacturer websites, search engines, enthusiast sites, etc. (e.g., Chen et al. 2002, Iyer and Pazgal 2003), they can also utilize vast amounts of consumer-generated content such as opinions, reviews, and recommendations (e.g., Mayzlin 2006).

Second, the most popular social online activities of consumers involve interacting with other people. For example, a 2007 Forrester Research study revealed that instant messaging, playing games with others, and participating on social networking sites were among the most frequently performed online activities (Golvin et al. 2007). Likewise, a Kaiser Family Foundation survey reported that between 2000 and 2005, the amount of time spent online by consumers

**Table 6(a) Parameter Estimates: Outcome Model Without Correcting for Self-Selection (the Estimated Coefficients for Various Covariates)**

	$Bids_{ht}$	$Listings_{ht}$	$Amnt_{ht}$	$Revenue_{ht}$
$\beta_0 =$	$\begin{bmatrix} -0.415 \\ (0.0277) \end{bmatrix}$	$\begin{bmatrix} -3.527 \\ (0.3136) \end{bmatrix}$	$\begin{bmatrix} -2.495 \\ (0.1758) \end{bmatrix}$	$\begin{bmatrix} -57.913 \\ (4.6520) \end{bmatrix}$
$P_h$	$\beta_1 = \begin{bmatrix} 0.079 \\ (0.0092) \end{bmatrix}$	$\begin{bmatrix} 0.689 \\ (0.1100) \end{bmatrix}$	$\begin{bmatrix} 0.620 \\ (0.0557) \end{bmatrix}$	$\begin{bmatrix} 12.648 \\ (1.3528) \end{bmatrix}$
$T_{2t}$	$\beta_2 = \begin{bmatrix} -0.004 \\ (0.0054) \end{bmatrix}$	$\begin{bmatrix} -0.986 \\ (0.0683) \end{bmatrix}$	$\begin{bmatrix} -0.332 \\ (0.0328) \end{bmatrix}$	$\begin{bmatrix} -13.872 \\ (0.9191) \end{bmatrix}$
$T_{3t}$	$\beta_3 = \begin{bmatrix} 0.173 \\ (0.0053) \end{bmatrix}$	$\begin{bmatrix} 0.919 \\ (0.0658) \end{bmatrix}$	$\begin{bmatrix} 1.290 \\ (0.0344) \end{bmatrix}$	$\begin{bmatrix} 11.156 \\ (0.8437) \end{bmatrix}$
$T_{4t}$	$\beta_4 = \begin{bmatrix} 0.156 \\ (0.0053) \end{bmatrix}$	$\begin{bmatrix} 0.786 \\ (0.0649) \end{bmatrix}$	$\begin{bmatrix} 1.130 \\ (0.0328) \end{bmatrix}$	$\begin{bmatrix} 8.895 \\ (0.8683) \end{bmatrix}$
$German_h$	$\beta_5 = \begin{bmatrix} -0.047 \\ (0.0052) \end{bmatrix}$	$\begin{bmatrix} 3.003 \\ (0.0797) \end{bmatrix}$	$\begin{bmatrix} -0.254 \\ (0.0307) \end{bmatrix}$	$\begin{bmatrix} 30.779 \\ (1.3093) \end{bmatrix}$
$Age_h$	$\beta_6 = \begin{bmatrix} 0.128 \\ (0.0073) \end{bmatrix}$	$\begin{bmatrix} -0.629 \\ (0.0826) \end{bmatrix}$	$\begin{bmatrix} 0.738 \\ (0.0462) \end{bmatrix}$	$\begin{bmatrix} -10.496 \\ (1.0516) \end{bmatrix}$
$Gender_h$	$\beta_7 = \begin{bmatrix} -0.018 \\ (0.0048) \end{bmatrix}$	$\begin{bmatrix} -0.074 \\ (0.0618) \end{bmatrix}$	$\begin{bmatrix} -0.192 \\ (0.0282) \end{bmatrix}$	$\begin{bmatrix} -0.997 \\ (0.7871) \end{bmatrix}$
$PosFB_h$	$\beta_8 = \begin{bmatrix} -2.0 \times 10^{-6} \\ (7.8 \times 10^{-6}) \end{bmatrix}$	$\begin{bmatrix} 0.005 \\ (0.76 \times 10^{-4}) \end{bmatrix}$	$\begin{bmatrix} -9.2 \times 10^{-5} \\ (4.5 \times 10^{-5}) \end{bmatrix}$	$\begin{bmatrix} 0.058 \\ (0.0010) \end{bmatrix}$
$NegFB_h$	$\beta_9 = \begin{bmatrix} -0.0009 \\ (0.0009) \end{bmatrix}$	$\begin{bmatrix} -0.231 \\ (0.0082) \end{bmatrix}$	$\begin{bmatrix} 0.011 \\ (0.0049) \end{bmatrix}$	$\begin{bmatrix} -1.057 \\ (0.1102) \end{bmatrix}$
$Memlength_h$	$\beta_{10} = \begin{bmatrix} 0.0 \\ (0.0) \end{bmatrix}$	$\begin{bmatrix} 0.0 \\ (0.0) \end{bmatrix}$	$\begin{bmatrix} 0.0 \\ (0.0) \end{bmatrix}$	$\begin{bmatrix} 6.900 \\ (0.8158) \end{bmatrix}$

Note. Shaded cells indicate statistically insignificant estimates.

**Table 6(b) Parameter Estimates: “Outcome Model” Without Correcting for Self-Selection (the Estimated Variance-Covariance Structure)**

$\Sigma$  (Equation (5)) in terms of variance and correlation matrix

	Variance	$Bids_{ht}$	$Listings_{ht}$	$Amnt_{ht}$	$Revenue_{ht}$	
$Bids_{ht}$	$\begin{bmatrix} 0.202 \\ (0.0013) \end{bmatrix}$	<b>1.0</b>	$\begin{bmatrix} -0.011 \\ (0.0051) \end{bmatrix}$	$\begin{bmatrix} 0.344 \\ (0.0037) \end{bmatrix}$	$\begin{bmatrix} -0.022 \\ (0.0056) \end{bmatrix}$	$Bids_{ht}$
$Listings_{ht}$	$\begin{bmatrix} 21.559 \\ (0.2026) \end{bmatrix}$	$\begin{bmatrix} -0.011 \\ (0.0051) \end{bmatrix}$	<b>1.0</b>	$\begin{bmatrix} -0.005 \\ (0.0055) \end{bmatrix}$	$\begin{bmatrix} 0.410 \\ (0.0045) \end{bmatrix}$	$Listings_{ht}$
$Amnt_{ht}$	$\begin{bmatrix} 7.344 \\ (0.0466) \end{bmatrix}$	$\begin{bmatrix} 0.344 \\ (0.0037) \end{bmatrix}$	$\begin{bmatrix} -0.005 \\ (0.0055) \end{bmatrix}$	<b>1.0</b>	$\begin{bmatrix} 0.007 \\ (0.0052) \end{bmatrix}$	$Amnt_{ht}$
$Revenue_{ht}$	$\begin{bmatrix} 3,683.0 \\ (35.468) \end{bmatrix}$	$\begin{bmatrix} -0.022 \\ (0.0056) \end{bmatrix}$	$\begin{bmatrix} 0.410 \\ (0.0045) \end{bmatrix}$	$\begin{bmatrix} 0.007 \\ (0.0052) \end{bmatrix}$	<b>1.0</b>	$Revenue_{ht}$

in social activities increased threefold on average, to 1 hour and 22 minutes a day (Rideout et al. 2005).

Third, businesses, and particularly their advertising and direct marketing programs, are viewed in an increasingly negative light by many consumers. For example, a much-publicized large-scale survey reported that between September 2002 and June 2004, 40% fewer consumers agreed that ads are a good way to learn about new products, 59% fewer consumers

said that they bought products because of their ads, and 49% fewer consumers found ads to be entertaining (Kim 2006, Nail 2005). Similarly, according to a Direct Marketing Association (DMA) study, 53% of consumers desire to receive less direct mail (DMA 2005), and telemarketing faces the obstacles of “do not call” lists and telephone caller ID use (Schmitt 2006).

In this changing, increasingly hostile environment, customer community programs offer a potential alternative means of marketing to one’s customer base. By offering online and/or offline venues for consumers to meet and interact with one another, and by orchestrating, moderating, or facilitating consumer-to-consumer social interactions, these programs can bypass many of the hurdles created by the social and business trends and take advantage of the available technological affordances. In the customer community, the interactions and relationships among customers occur with a close association to the firm and its brands. The positive experience from these interactions can strengthen the consumer’s relationship with the brand (McAlexander et al. 2002).

Indeed, recent research has revealed that customer communities can be used by firm for various marketing purposes such as providing credible, low-cost customized service (from expert to novice customers), rapidly disseminating new information, providing high-quality feedback from customers, signaling early warnings from the marketplace, and giving the firm access to its loyal and engaged customers (Johnson 2004, Bagozzi and Dholakia 2006, Nail 2005). Therefore, there are sufficient reasons to be optimistic about the potential of customer community marketing programs.

## 6.2. Discussion of the Study Results

Against the backdrop of the managerial significance of these programs, a number of findings from our study deserve further discussion. The first set of results from the analysis link customers’ participation in the community to the firm’s e-mail-based invitations and their own demographic characteristics. An important finding in this regard is that a simple e-mail invitation (along with two reminders) by the firm significantly increased customer participation in the firm’s community. In fact, after controlling for the demographic factors, invitations led to a 22.7% higher probability of participation in the community by customers.

Prior research has been unclear regarding the question: Which type of customers are community marketing programs suitable for? Conventional wisdom as well as the customer samples utilized in many of the published studies seem to imply that communities will be effective mainly for customers who are already fans—that is, already engaged and interested

in the firm and its brand(s) to begin with (Bagozzi and Dholakia 2006). However, an alternative possibility, and one that we find support for in the current research, is that firm-sponsored communities are appealing to a broader, more-diverse set of a firm's customers than just its fans. In the present case, inviting a randomly chosen sample of customers led to a significant increase in likelihood of participation in the community by them afterward.

Additionally, we found that older customers and customers with high positive feedback are more likely to participate in eBay Germany's customer community. On the other hand, longer-tenure customers and those receiving more negative feedback have lower likelihood of participation. The results do not show the effect of gender and nationality to be significant. We believe these results to be idiosyncratic to the firm. It is likely to be the case that of other firms, demographics may influence community participation differently. For example, men may be more interested in a community concerning fishing equipment. However, from the firm's perspective, it is important to do the sort of analysis we reported here to determine the target customers for one's community or to design the community to appeal to target customer profiles.

The increased likelihood of community participation within a randomly chosen sample of the firm's customers is only meaningful to the extent that it has significant effects on customers' relational behaviors. Our findings revealed interesting nuances in how customers behave after participating in the community. Community participation had mixed effects on customers' likelihoods of initiating buying and selling behaviors. Whereas there was no effect of participation on bidding and the amount of revenues earned, both the number of listings and the amount bid per month declined after participation in the community.

As noted earlier, the eBay platform is quite complex for sellers, involving the consideration and setting of a number of decision variables, the crafting of a compelling product description, and so on. These characteristics make selling an item on eBay to be a much more involved and complex process than bidding for an item on the site. Our results suggest that participation in the eBay community may have educational value for customers. Consistent with this possibility, we see customers willing to list fewer items and still making the same money from the sales; i.e., they become more selective and efficient in their selling behavior.

Our results reveal that although the number of bids remains unchanged after participation, the amount spent by customers is lower postparticipation, suggesting that customers become more conservative in

the amount they bid. This could again be attributed to the educational aspect of the community, where community participants might realize the possibility of overspending on items in eBay auctions. Based on these findings, psychological studies are needed to better explain exactly why these changes happen.

Interestingly, when we use a simple method that ignores customer self-selection into communities to study the effect of community participation on the subsequent behaviors, we find that participation increases all the behaviors. This might help explain the common belief that customer-firm engagements are enhanced as a result of community participation. Our results show that this is not the case in our data, and the effects of community participation are complex. Overall, our findings indicate that customer community marketing programs may not have the potential of increasing relational behaviors of participants and might even decrease these behaviors postparticipation. We find that the value of such communities is educational, and their effects are complex. Our results do, however, show that such communities can be targeted to a broader set of the firm's customers than just its fans.

## 7. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at <http://mktsci.pubs.informs.org/>.

### Acknowledgments

All the authors contributed equally. The names appear in alphabetical order.

### Appendix A. E-mail Invitation Sent to Randomly Chosen eBay Customers in May 2005<sup>14</sup>

Hello [eBay user name]:

We would like to recommend our eBay community warmly to you!

eBay discussion boards and chat rooms are online communities founded by members for members. You will meet other individuals there who share your own interests. And you can follow your interests and hobbies there as well.

Within a few months after introducing the eBay community at eBay.de, a diverse and active community life emerged. For example, if you are interested in topics like collecting something, you'll find several community venues that are open to you. You'll find a collection of these venues below along with direct links to them.

Discussions, notifications to other members, a shared agenda, picture albums and much more...there are many good reasons to visit the eBay community. You'll find most of the community venues within our central page on <http://groups.eBay.de>.

<sup>14</sup> This e-mail message was sent to eBay Germany's customers. This is a translation of the original text sent in German language.

We would be very happy if you visit one of these venues or even start one of your own.

Don't miss the opportunities within the eBay community.  
Your eBay Community Team

#### LOTTERY

By participating in this eBay invitation, you may win one of several Apple iPods that will be raffled off to those who post at least once in an eBay community over the next three months.

#### DETAILED INFORMATION ON HOW TO USE EBAY COMMUNITIES

##### 1. Find the right community venue

Go to the central page on <http://groups.eBay.de>, where you'll find all eBay community venues sorted by their topic into several subcategories. You can also search for venues by keywords or postal codes.

##### 2. Enter a community venue

After you find a community venue you are interested in, click on the venue's link. You will reach the venue's home page.

##### 3. Activities in the community venue

Within the different community venues, you'll find lots of interesting functionalities such as

- discussion boards
- chat rooms
- calendar for general important dates and shared events
- a personal profile that allows you to introduce yourself to other community members
- e-mail functionality to contact other community members
- a picture album that can be shared by all members
- messages from the community venue's organizer or moderator(s)

##### 4. A collection of exemplary eBay community venues\*\*

[Here, a list of actual eBay community venues along with direct links to their Web pages were provided in the e-mail message.]

[Here, some disclosures involving company information were given regarding receiving e-mails on eBay offers like this one, privacy and security issues, and company issues.]

### Appendix B. The Set of Prior Distributions Used in the MCMC Sampling Scheme

In this appendix we provide the set of prior distributions used to estimate the participation model (see §4.1) and the outcome model (see §4.2).<sup>15</sup>

The participation model is specified by Equations (1)–(3). In this set of equations we need to set our priors over the parameters  $\rho_0$  through  $\rho_7$ . We specify a prior distribution of Normal(0, 100) over all these parameters. The prior is chosen to reflect our limited prior information on the magnitude and sign of these parameters.

The outcome model is specified by Equations (4a)–(6a), and we need to set priors over the parameters  $\beta_0$  through

$\beta_{10}$  and the  $4 \times 4$  variance-covariance matrix  $\Sigma$ ; we specify a prior distribution of Normal(0, 100I) over the  $\beta$  parameters and a Inv-Wishart(1, 10I, 10) over the variance-covariance matrix  $\Sigma$ . Again, the priors chosen reflect our limited prior information on the magnitude and sign of these parameters.

### Appendix C. The Linear Probability Model

The linear probability model is a regression model with the dummy participation variable as the dependent variable. We observe a dummy variable  $P_h$  that equals 1 if the customer participated in the community anytime during June 2005 through August 2005 (i.e., time period  $T_2$ ); else it equals 0.

Furthermore, we assume that this  $P_h$  is distributed per a Normal distribution,

$$P_h \sim \text{Normal}[\text{Propen}_h, \xi^2], \quad (\text{C1})$$

where  $[\text{Propen}_h, \xi^2]$  are the mean and variance of the distribution. We interpret  $\text{Propen}_h$  as the propensity to participate in a community for customer  $h$ .

We further specify  $\text{Propen}_h$  in Equation (C1) as follows:

$$\begin{aligned} \text{Propen}_h = & \eta_0 + \eta_1 \text{German}_h + \eta_2 \text{Age}_h + \eta_3 \text{Gender}_h \\ & + \eta_4 \text{Memlength}_h + \eta_5 \text{PosFB}_h \\ & + \eta_6 \text{NegFB}_h + \eta_7 \text{Invite}_h. \end{aligned} \quad (\text{C2})$$

**Table C.1** Parameter Estimates

Intercept	$\eta_0$	0.011 (0.0358)	Mem-length <sub>h</sub>	$\eta_4$	−0.045 (0.0055)	
	German <sub>h</sub>	$\eta_1$		0.008 (0.0080)	PosFB <sub>h</sub>	$\eta_5$
	Age <sub>h</sub>	$\eta_2$	0.058 (0.0078)	NegFB <sub>h</sub>	$\eta_6$	−0.006 (0.0008)
	Gender <sub>h</sub>	$\eta_3$	0.001 (0.0052)		Invite <sub>h</sub>	$\eta_7$

$\xi^2$	0.060 (0.0007)
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Note. Shaded cells indicate statistically insignificant estimates.

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<sup>15</sup> The MCMC sampling scheme consisting of the set of full conditional distributions is provided in the electronic companion.

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