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"Paying for Content or Paying for Community?" The Effect of Social Involvement on Subscribing to Media Web Sites

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"PAYING FOR CONTENT OR PAYING FOR COMMUNITY?"

THE EFFECT OF SOCIAL INVOLVEMENT ON SUBSCRIBING TO MEDIA WEB SITES

Completed Research Paper

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Abstract

Many sites have recently begun to encourage user participation and provide consumers with a virtual community wherein the user can create an on-site identity, make friends, and interact with other consumers.

We study the interplay between users' functional and social behavior on media sites and their willingness to pay for premium services. We use data from Last.fm, a site offering both music consumption and social networking features. The basic use of Last.fm is free and premium services are provided for a fixed subscription fee. While the premium services mainly improve the content consumption experience, we find that willingness to pay for premium services is strongly associated with the level of social activity of the user, and specifically, the community activity of the user. Our results represent new evidence of the importance of introducing community and social activities as drivers for consumers' willingness to pay for online services.

Keywords: economics of IS; electronic commerce; premium services; social media; social networks

Background and Overview

According to a survey conducted by the Online Publishing Association, more than 40% of time spent online involves content consumption[1]. Some sites that offer online content, such as Flickr.com or YouTube.com, provide mostly user-generated content; other sites, such as MTV.com and NYTimes.com, present professionally generated content that is traditionally accessed through other media. However, sites in the latter group have recently begun to encourage user participation, for example, by allowing users to post comments to news stories (talkbacks). Many sites that enable users to contribute content also provide consumers with a virtual community, wherein the user can create an on-site identity (often by having a personal page), make online friends, attend virtual social events, build a reputation, and interact with other consumers. These 'extras' render the user's consumption experience increasingly interactive and social.

This interactive and social model of online content consumption brings with it new challenges for site owners and users. By encouraging users to contribute, site owners lose some of their control over the content that consumers experience, particularly in cases where owners cannot eliminate negative reviews or delete uninteresting or offensive posts. Correspondingly, the consumers themselves have greater influence on their fellow consumers' consumption experience. Despite this, many site owners encourage user participation because it can add interesting content that other consumers find valuable.

In this paper, we conjecture that there is a less obvious yet important effect of virtual socialization that is facilitated by offering user-generated content and developing a community on one's site. It is likely that in addition to benefiting other consumers, the act of participation positively affects the experience of the contributing consumer. By contributing content and becoming active in the site's social community, the consumer is likely to feel more involved with the site. This involvement might lead to increased brand loyalty, deceased churn, lower defection to competing sites, and more willingness to pay for (additional) premium services.

We investigate the interplay between users' functional behavior (content consumption) and their social behavior on media sites, as well their willingness to pay for premium services. We focus on websites that combine structured content (in this case, music tracks owned by commercial labels) with an open social arena in which users can add content such as comments, reviews, and 'tags'.

We divide consumers' use of such sites into three groups of activities:

- Functional use, which includes content consumption as well as all activities entailed in content organization.

- Local social network activities, which include on-site interaction with one's friends.

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[1] Compared to 5% spent on search and 15% spent on commerce. http://www.online-publishers.org/.

- • Community (or global social network) activities, which include publishing user-generated content that can be consumed by the entire site audience, memberships to discussion groups, or comment posting.

Our research questions are as follows:

1. Are consumers who use social networking features in media websites more likely to pay for premium services?

2. If so, what is the marginal effect of local social network activities versus global (community wide) activities on the propensity to pay for those services?

We use data from Last.fm, a media site that serves both as an online radio and as a social networking site. Similar to other media websites, Last.fm allows users to access a set of basic services for free, and provides additional premium services in exchange for a fixed monthly subscription fee. Even though the premium services mainly improve the content consumption experience (for example, by increasing bandwidth), we find that willingness to pay for premium services is strongly associated with the level of social activity of the user. Specifically, consumers who use global social network features (i.e., features that enable the user to publish content and to engage with the entire network) show a higher propensity to pay for premium services compared with users who do not use these features. Our results represent new evidence of the importance of introducing community and social activities as a means of driving consumers' willingness to pay for online services. To the best of our knowledge, this study is the first to examine the influence of social involvement on consumers' decisions to purchase premium services.

Our work adds to two branches of literature: that on willingness to pay for online services, and that on the economic effects of a brand community on online businesses.

Academic scholars and practitioners have noted that digital media companies find it difficult to charge their users for access to content services[2;3] (Clemons et al. 2003, Srinivasan et al. 2002, *inter alia*). Therefore, many media sites operate under a two-tiered business model, wherein basic services are provided for free, and premium services are offered for a fee (Picard 2000; Riggins 2003). This business model has received wide attention from the press ― including the coining of the term "freemium business model" by Fred Wilson [4]― yet has drawn surprisingly little academic attention. The two-tiered business model has achieved success in social media sites in and multi-player role-playing sites[5]. Convincing users to switch to a for-pay service is the main challenge of the two-tiered business model. Naturally, providing better content or service encourages users to subscribe to premium services (Ye et al.

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[2] A similar business model is Pay Per Use, in which the user pays for use of the site's services. This payment constitutes the company's main income source. Although this model has seen some documented successes, one of them the *Wall Street Journal* online (Lopes and Galletta 2006), most attempts to apply it have ended in failure.

[3] Naturally, advertising is an additional potential source of income for sites. However, it is beyond the scope of this paper.

[4] http://www.avc.com/a_vc/2006/03/the_freemium_bu.html

[5] The NING social networking site, which enables the user to create a personal social network, has publicized that out of 500,000 social networks in NING, 3% pay premium services subscriptions ($19.95 per month). Multi-player role-playing sites have published a higher rate of between 15% and 25% success in turning players into paying customers (http://news.cnet.com/8301-13953_3-10049806-80.html?part=rss&subj=news&tag=2547-1001_3-0-5).

2004). However, a user's choice might be influenced by his or her level of engagement in the site's virtual community.

Brand communities are defined as online communities built around commercialized products or shared services. Studies have shown that a user's participation in a community that is linked to a brand can increase strong and lasting bonds with that brand and promote brand loyalty, both in the offline and online context (Mael & Ashforth 1992 in the context of offline communities; McAlexander et al. 2002 and Jang et al. 2008 in the context of online communities).

One of the dimensions of brand loyalty is the consumer's willingness to repurchase (Aaker 1991). Loyal customers have lower price elasticities than do nonloyal customers, and they are willing to pay a premium to continue doing business with their preferred retailers (Reichheld and Sasser 1990). In the e-commerce context, Srinivasan et al. (2002) surveyed 1,211 online customers and identified the existence of an online community as one of eight factors significantly influencing brand loyalty and willingness to purchase in online stores. Our work adds to this literature by providing empirical evidence of the effect of social activity on consumers' willingness to pay for online services in media and content websites.

More broadly, our work also adds to the growing literature surveying the effects of social networks on consumption patterns. Marketing literature has long acknowledged the importance of social networks on the diffusion and adoption of new products and services (see Nair et al. 2006 for a detailed survey of the literature on social effects in marketing). Researchers have also attempted to separate social effects from marketing effects, thus requiring the identification of differing social effects (Trusov et al. 2007; Goh et al. 2008). Recently, researchers have focused on separating between local and global network effects when examining the influence of social factors on the adoption decision (for example, see Tucker 2004 on the adoption of a video messaging system in an organization). However, those works study the diffusion of products for which network effects are an inherent characteristic, such as communication technologies. Our work adds to this literature by emphasizing the importance of introducing local and global social networking features even to websites that offer traditional (professionally generated) content.

The rest of this paper is organized as follows: Section 2 provides an overview of the data and methodology. Section 3 presents the results and discussion; and section 4 concludes.

Overview of Data

We collected data from Last.fm, a social media site in which users can listen to music online and create personalized 'radio stations', or playlists. Last.fm also offers its users a social community[6]. A user page in the social network is shown in Figure 1. Currently, Last.fm has more than 30 million registered users based in more than 200 countries[7].

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[6] Last.fm was purchased by CBS in May 2007 for $280 million.
[7] See Sinkkonen et al. (2007) for an analysis of Last.fm's music social network topology.

While the site's main goal is to provide music listening capabilities[8], it also enables the user to create a personal user profile page, join groups (mostly based on musical taste), contribute to blogs (journals) by posting comments, or to take a lead role in those groups and journals. Users can also add tags to artists, albums, and tracks by using chosen keywords.

Last.fm offers its users two levels of membership. The first is regular registration (free service), which enables the user to create a personal profile page, listen to online radio, and use other site's functions. The second is the paid subscription, in which subscribers pay a monthly fee of €2.5 for a package of premium services that include the following:

- Improved infrastructure, including removal of ads from the subscriber's page and top-priority quality-of-service on web and radio servers.
- Extended listening options, including the capacity to listen to unlimited personal playlists on shuffle mode, and to create a 'Loved Tracks' radio channel[9].
- Improved social status, including an icon added to a subscriber's account and the ability to see who has visited one's profile page.
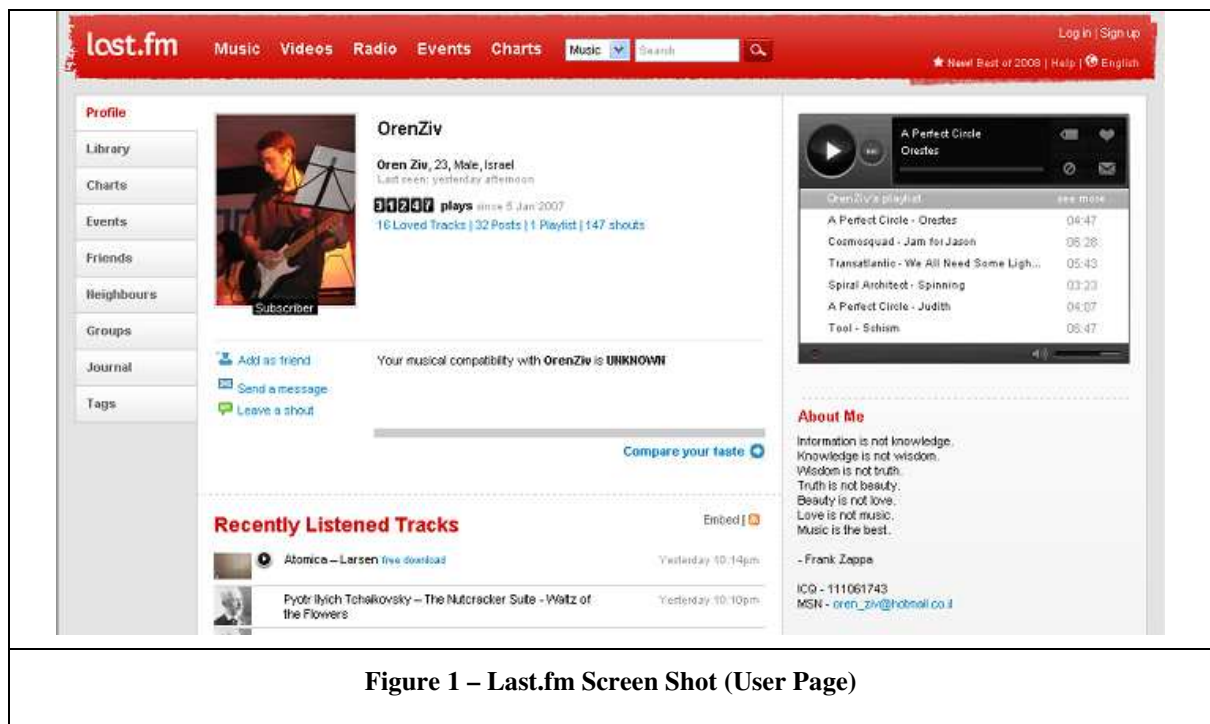
Figure 1 – Last.fm Screen Shot (User Page)

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[8] Last.fm provides a musical profile based on the user's listening habits by connecting to his or her music file software. Last.fm also creates customized radio stations using a collaborative recommendation algorithm in which the user is given the opportunity to add songs that are often played by fellow users with similar musical tastes.

[9] This is a playlist created by the site based on a user's tagging of songs as "Loved".

Data Collection and Preparation

We collected the following data on Last.fm users:

- Demographic information such as age and gender.
- Music consumption information such as number of tracks listened to; number of tracks tagged as 'Loved'; number of user-generated playlists; and time since last visit
- Virtual community activity information such as number of friends; number of blog (journal) posts; number of group memberships; number of groups led; number of user postings to the site's groups

We collected these data using two specially programmed web crawlers. One web crawler gathered information about a random sample of 150,000 Last.fm users (subscribers and non-paying users). For this dataset, we omitted data on subscribers and used only data on non-paying users. A second web crawler collected information about new paying subscribers at the time that they purchased their subscriptions. We were able to access this set of users thanks to a continually updated list of recent subscribers that is featured on Last.fm. By limiting our analysis to new subscribers and omitting members with previously established subscriptions, we control for increased activity that might result from the membership benefits of the premium subscription. Thus far we have collected information on close to 10,000 new subscribers.

Data collection was done over a period spanning 3 months starting in January 2009. In order to omit inactive users from our analysis, we removed data on users who had not visited the site during the 3 months prior to data collection. We also omitted users and subscribers who had in the past used a "Reset" option that reset the logs of their personal site usage. Our final dataset consisted of 39,397 non-paying users and 3,612 new subscribers. Some descriptive statistics about our data are presented in Table 1.

Table 1 – Descriptive Statistics						
Type Of Membership:	Non paying user			Subscribers		
	Mean	Median	Variance	Mean	Median	Variance
Age	23.08	21	39.156	29.43	27	88.415
Gender (1= Male, 2= Female)	1.34	1	0.223	1.29	1	0.204
Tracks listened to	17,616.99	11,265.00	477,622,677.54	21,688.83	11,039.50	998,060,194.11
Playlists created	0.77	1	0.47	1.29	1	7.15
'Loved' tracks tagged	65.97	11	41,872.72	210.34	83	314,062.36
Tags created	9	1	1,400.19	21.27	2	5,298.45
No. of friends	14.56	9	640.923	21.19	10	1,196.87
Posts published	9.12	0	7,596.37	27.31	0	75,401.53
Groups joined	5.27	2	168.69	8.98	3	463.08
Groups led	0.07	0	0.165	0.17	0	0.452
Journal entries published	0.42	0	2.244	0.89	0	5.623

Data Analysis and Results

The descriptive statistics clearly suggest that the usage pattern of subscribers is quite different from that of regular users. Table 2 and Figure 2 summarize the average activity levels of the consumers in our sample, which we divided into (paying) subscribers and (non-paying) users. For each type of activity, the third column of Table 2 shows the ratio between subscriber activity level and user activity level. To test whether the activity levels of the two populations are sufficiently distinct, a *t*-test would normally be in order. However in this case, the populations are not normally distributed and as such do not obey the assumption of the independent samples *t*-test. Therefore we used the Mann-Whitney U-test, where $P < 0.05$ shows that the two populations' medians and means are distinct.

We observe that subscribers consume 23% more music than do their non-paying peers; this difference is not statistically significant, however (Mann-Whitney with $P = 0.427$). Interestingly, subscribers invest significantly more in organizing their pages. On average, subscribers create 67% more playlists on their sites; they choose to tag 218% more tracks as 'Loved'; and create 140% more tags ($P < 0.01$). Since the tags and playlists are available on one's page, it is not clear whether these activities are motivated by the increased level of music consumption, or should be treated as social activities.

Moreover, we observed differences when we compared the social activity levels of subscribers with those of non-paying users. Our measure of local social network activity is the number of friends listed on one's page. In Table 2, one can see that while regular users have an average of 14 friends, subscribers have an average of 21 friends, i.e., subscribers have on average 45% more friends ($P < 0.01$).

Most intriguingly, subscribers are substantially more involved in the site's virtual social community: compared with nonpaying users, paying subscribers post 199% more posts on the site's forums, join 70% more groups, lead on average 142% more groups, and publish 111% more blog entries ($P < 0.01$).

A possible explanation for the evident differences in activity levels might be demographic differences between subscribers and non-paying users. The two demographic variables we obtained were gender and age. We did not observe a significant difference in activity levels or in propensity to subscribe based on gender. We did, however, find that subscribers are on average 6 years older than non-paying users (see Table 1).
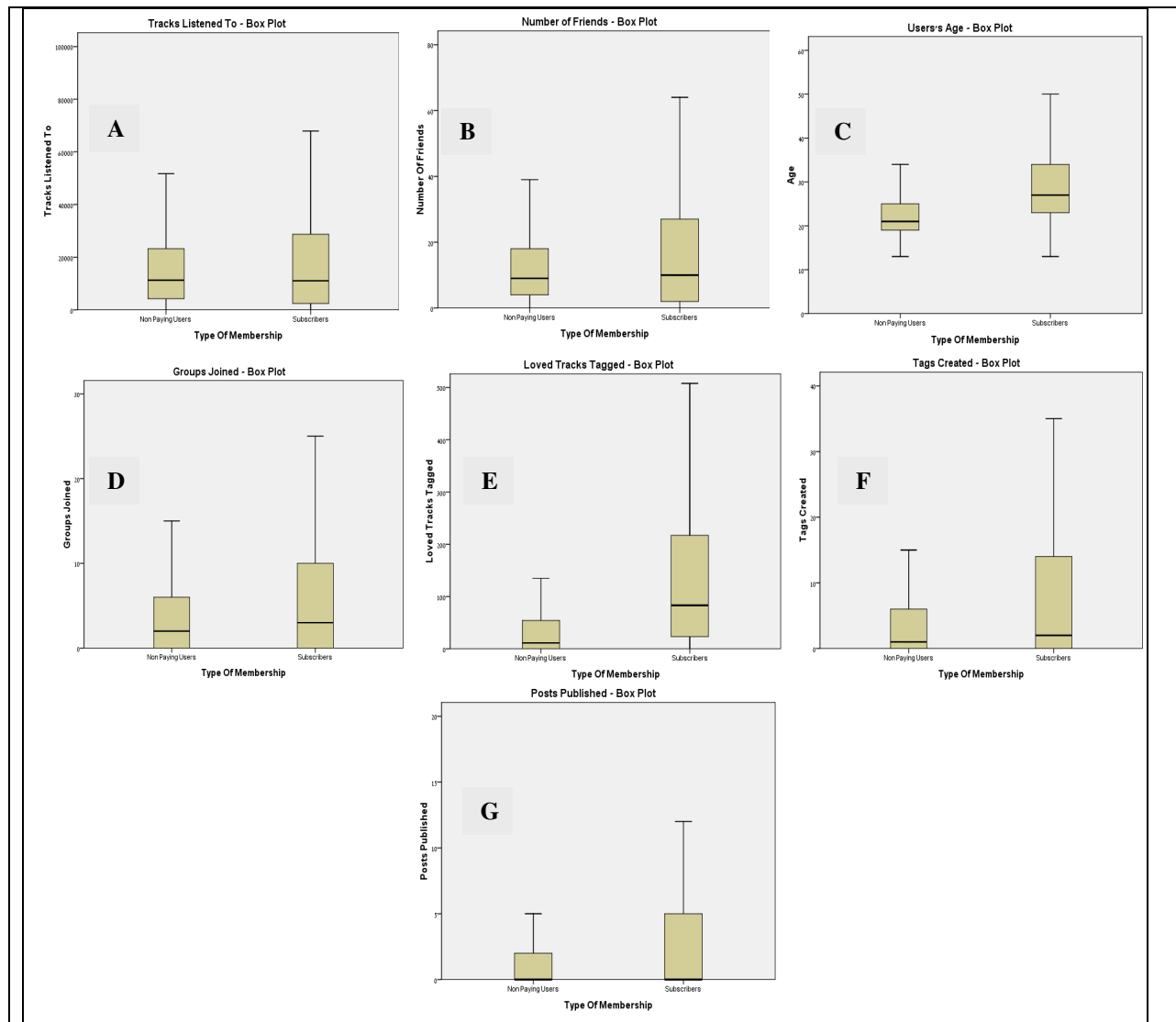
Figure 2 – Box Plot Graphs

Figure A presents the statistical distribution differences between the non paying users (on the right) and subscribers (on the left) for the 'music tracks listened to" variable. Similarly, Figure B presents the distribution of the variable 'User's number of friends'; Figure C the distribution of the user's age; Figure D the distribution of the number of groups joined by the user; Figure E the distribution of the number of tracks that were tagged as "loved"; Figure F the distribution of tags created; and Figure G the distribution of the number of posts published to user groups.

	Subscriber mean	User mean	Ratio	U-test *P* Value
No. of tracks listened to	21,688.83	17,616.99	1.23	0.427
No. of friends	21.19	14.56	1.45	0.00***
No. of playlists	1.29	0.77	1.67	0.00***
No. of Loved tracks	210.34	65.97	3.18	0.00***
No. of tags created	21.27	9	2.40	0.00***
No. of journals / blog entries	0.89	0.42	2.11	0.00***
No. of posts	27.31	9.12	2.99	0.00***
No. of group memberships	8.98	5.27	1.70	0.00***
No. of groups led	0.17	0.07	2.42	0.00***
Users' age	29.43	23.08	1.27	0.00***
Days of use	652.08	720.53	1.10	0.00***

Table 2 – Comparing Subscribers to Non-paying Users

*** - Significant at the 0.01 level

Model Estimation

To better understand the interplay between music consumption, local social activity, social involvement in the site's social community, and willingness to pay for a subscription, we estimate a logistic (binary) choice equation, predicting the probability of paying for a subscription[10]. Formally, we estimated the model:

$$\log \frac{\Pr(Subscribe)}{1 - \Pr(Subscribe)} =$$
$$\alpha_0 + \alpha_1 * Age + \alpha_2 * TracksDivThousand + \alpha_3 * PlayListCnt + \alpha_4 * LovedTracksCnt$$
$$+ \alpha_5 * FriendsCnt + \alpha_6 * GroupCnt + \alpha_7 * GroupLeadCnt + \alpha_8 * JournalCnt$$

Note that by controlling for the music consumption characteristics of the user, we are able to measure and quantify the marginal contribution of the social activity levels to the propensity to pay for premium services.Estimating this model presented us with two econometric challenges:

First, we wanted to control for increased use of the site due to the actual subscription decision. It is possible that after subscribing to premium services, consumers tend to use the site more because of the benefits a subscription provides. For that reason, we limited our analysis to non-paying users and to new subscribers whose data had been collected immediately at the time of subscription, that is, before their usage could be influenced by the subscription

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[10] Since premium services are offered for a fixed monthly fee, we use a logistic regression model with a binary dependant variable.

itself. We therefore merged two sets of data: one consisting of randomly chosen non-paying users, and one consisting of users who had just purchased a subscription.

Second, when we looked at the random set of users on whom we collected information, we noticed that subscribers made up only 0.89% of the site population. If we used this correct ratio in composing our dataset, the occurrence of ones in our dependent variable (*Subscribe*) would be a *rare event*. The biases that rare events create in estimating logit models have been discussed in the literature (Ben-Akiva and Lerman 1985). In a nutshell, this poses a problem when estimating a logit model in that the model would predict that everyone would be a regular, non-subscribing user while still obtaining a 99% level of accuracy. To overcome the problem of misclassification, one should re-estimate the model while deliberately under-sampling the non-paying users, so that a more balanced sample of ones and zeros in the dependent variable is obtained. This sampling technique is called *choice-based sampling* (Ben-Akiva and Lerman 1985). To this end, we used our collected set of 3,612 new subscribers and only 5,000 non-paying users. However, using choice-based sampling leads to inconsistent intercept estimation when traditional maximum likelihood methods are used. Two alternative solutions have been suggested in the literature: Manski and Lerman (1977) developed a weighted endogenous sampling maximum likelihood (WESML) estimator, which accounts for the different weights in the zeros and ones from the population of interest. However, this estimator has the undesirable property of increasing the standard errors of the estimates (Manski and Lerman 1977; Greene 2000). A second approach, which we follow, is to adjust the estimated intercepts for each alternative by subtracting from the exogenous maximum likelihood estimates of the intercept the constant $Ln(S_i/P_i)$, where S_i is the percentage of observations for alternative i in the sample, and P_i is the percentage of observations for alternative i in the population (Manski and Lerman 1977; see Villanueva et al. 2008 for a similar implementation).

The correlation matrix is presented in Table 3 and the estimation results using the choice-based sample are reported in Table 4[11]. The odds of a user subscription decision are positively associated with the number of (thousands) of tracks the user listens to (*Odds Ratio = 1.003*). We also find that content organizing activities, such as creating a playlist and tagging music tracks as 'Loved', are positively correlated with the subscription behavior (*Odds Ratio =1.245* for *PlaylistCnt* and *Odds Ratio = 1.002* for *LovedTracksCnt*). However, this is understandable given that a premium service subscription gives users extra playlist listening capabilities and the possibility to listen to "loved tracks" as if they were a "radio station". It is therefore natural to assume that heavy users of those features will be more inclined to pay for premium services.

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[11] The equation includes only the coefficients in the regression that are statistically significant. The Tags (*TagsCnt*) and Postings (*PostsCnt*) are not found to be significant predictors of a user's subscription decision.

Table 3 – Correlation Matrix											
	Gender	Age	Number Of Friends	Tracks Listened To	Playlist Created	Loved Tracks Tagged	Posts Published	Groups Joined	Groups Led	Journal Entries Written	Tags Created
Gender	1.000	-.181[**]	.053[**]	-.097[**]	.023[**]	.005	-.015[**]	-.025[**]	-.051[**]	.000	-.035[**]
Age	-.181[**]	1.000	-.067[**]	-.057[**]	.101[**]	.097[**]	.004	-.057[**]	-.008	.019[**]	.041[**]
Number Of Friends	.053[**]	-.067[**]	1.000	.289[**]	.094[**]	.194[**]	.111[**]	.310[**]	.184[**]	.219[**]	.126[**]
Tracks Listened To	-.097[**]	-.057[**]	.289[**]	1.000	.042[**]	.130[**]	.127[**]	.216[**]	.164[**]	.212[**]	.119[**]
Playlist Created	.023[**]	.101[**]	.094[**]	.042[**]	1.000	.269[**]	.014[**]	.066[**]	.025[**]	.069[**]	.100[**]
Loved Tracks Tagged	.005	.097[**]	.194[**]	.130[**]	.269[**]	1.000	.070[**]	.183[**]	.064[**]	.123[**]	.209[**]
Posts Published	-.015[**]	.004	.111[**]	.127[**]	.014[**]	.070[**]	1.000	.195[**]	.194[**]	.159[**]	.102[**]
Groups Joined	-.025[**]	-.057[**]	.310[**]	.216[**]	.066[**]	.183[**]	.195[**]	1.000	.370[**]	.233[**]	.219[**]
Groups Led	-.051[**]	-.008	.184[**]	.164[**]	.025[**]	.064[**]	.194[**]	.370[**]	1.000	.223[**]	.166[**]
Journal Entries Written	.000	.019[**]	.219[**]	.212[**]	.069[**]	.123[**]	.159[**]	.233[**]	.223[**]	1.000	.180[**]
Tags Created	-.035[**]	.041[**]	.126[**]	.119[**]	.100[**]	.209[**]	.102[**]	.219[**]	.166[**]	.180[**]	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

Interestingly, we find that after controlling for content consumption and the use of content organization features (the activities that are most enhanced by premium services), the number of friends the user has listed on his or her page (i.e., the user's level of local social network activity) is positively associated with the user's propensity to pay for premium services (*Odds Ratio = 1.002*).

Within the community-wide activities, writing a blog (journal) entry is positively associated with the subscription decision. Similarly, joining a group or leading a group are associated with significant increases in the odds of subscribing to premium services (*Odds Ratio = 1.047* for *JournalCnt*; *Odds Ratio = 1.004* for *GroupCnt* and *Odds Ratio = 1.432* for *GroupLeadspCnt*). These results are especially interesting, given that the premium services provided to subscribers generally relate to music consumption and not to other forms of interaction on the site.

	B	S.E.	Wald	df	Sig.	Exp(B)
Table 4 – Binary Logistic Regression Model for Subscribing Decision						
Age	0.112	0.004	877.053	1	0.000***	1.118
TracksDiv1000	0.003	0.001	7.824	1	0.005***	1.003
PlaylistCnt	0.219	0.029	56.185	1	0.000***	1.245
LovedTracksCnt	0.002	0.000	177.530	1	0.000***	1.002
TagsCnt	0.000	0.001	0.177	1	0.674	1.000
FriendsCnt	0.002	0.001	5.897	1	0.015**	1.002
PostsCnt	0.000	0.000	2.017	1	0.156***	1.000
GroupCnt	0.004	0.002	5.048	1	0.025**	1.004
GroupLeadsCnt	0.359	0.067	28.682	1	0.000***	1.432
JournalCnt	0.046	0.015	9.524	1	0.002***	1.047
Constant	-3.820	0.106	1,301.040	1	0.000***	0.022
Revised Constant	-8.20	After estimated intercept adjustment				
N (non-paying users) = 5,000, N (subscribers) = 3,612						
Overall Model Estimation: chi-square = 2,108.086. *df* = 10, *p* = 0.00						
-2 Log likelihood = 9,605.997, Cox & Snell R Square = 0.217, Nagelkerke R Square = 0.292						
- significant at the 0.05 level ; * - significant at the 0.01 level						

Our findings seem to indicate that social activity has an important role in subscription behavior. This can also be seen from Table 5: the model correctly predicts 67.4% of the non-paying users and 75.9% of the subscribers.

Table 5 – Predicted Values of Logit Model				
		Predicted by Membership Type		
Observed		Non-paying	Subscribers	% correct
Membership type	Non-paying	3,370	1,630	67.4
	Subscribers	872	2,740	75.9
	Overall %			70.9

Propensity Score Matching

Although the preceding econometric analysis provides support for a positive and statistically significant association between social online activity and propensity to purchase a premium services subscription, the nature of observational data raises concerns about the causal interpretation of our findings. As mentioned above, through our sampling technique, we control for possible post-subscription increases in site usage. However, we do not control for the bias caused by self-selection. That is, since we did not randomly assign users to treatment groups (for example, increased community activity), we are unable to control for observed and unobserved variables that drive users to self-select themselves into a particular treatment group. It is easy to think of variables that might influence users' social activity level and simultaneously increase their propensity to pay for premium services, hence creating a self-selection bias.

A statistical solution to the self-selection bias is to use a proportional outcome approach. Selection bias due to correlation between the observed characteristics of a user and the user's level of social activity (her "treatment" level) can be addressed by using a matching technique based on propensity scores (Rosenbaum and Rubin 1983; for a recent use of propensity score in the IS literature, see Mithas and Krishnan 2008). In a nutshell, propensity matching techniques enable us to investigate heterogeneous treatment effects in non-experimental data, based on observed variables[12]. The fundamental problem in identifying treatment effects is one of incomplete information. Though we observe whether the treatment occurs and whether the outcome is conditional on the treatment assignment, the counterfactual is not observed.

Let y_{i1} denote the outcome of observation i, if the treatment occurs (given by $T_i=1$), and $y_{i,o}$ denote the outcome if the treatment does not occur ($T_i=0$). If both states of the world were observed, the average treatment effect, τ, would equal y_1-y_0, where the former (latter) average represents the mean outcome for the treatment (control) group. However, given that only y_1 or y_0 is observed for each observation, unless assignment into the treatment group is random, generally, $\tau \neq y_1$-y_0.

Propensity score matching attempts to overcome this problem by finding a vector of covariance, Z, such that $y_1, y_0 \perp T|Z, \; pr(T=1|Z) \in (0,1),$ Where $\perp$ denotes independence. Yet, if one is interested in estimating the average treatment effect, only the weaker condition $E[y_0|T=1,Z] = E[y_0|T=0,Z] = EE[y_0|Z],$ $pr(T=1|Z) \in (0,1),$ is required.

To implement the matching technique, we define the treatment group as the set of people who participated in community activity. Since most propensity score matching techniques use a binary treatment, we grouped user

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[12] In contrast, selection bias stemming from correlation between unobserved variables and the user's social activity level is a more difficult problem. Previous literature has often used the strong ignitability assumption (Rosenbaum and Rubin 1983).

participation in community activities into three distinct binary treatments and repeated the following exercise for each treatment separately:

- *GroupLead_binary*, which is equal to one if the user has ever led a group

- *JournalPost_binary,* which is equal to one if the user has ever posted an entry to a blog

- *GroupMember_binary*, which is equal to one if the user has ever joined a group

Consequently**,** one should observe identical values for all covariates in *Z*. Since this is often untenable, Rosenbaum and Rubin (1983) prove that conditioning on *p(Z)* is equivalent to conditioning on *Z*, where *p(Z)=pr(T=1|Z)* is the propensity score. *p(Z)* is estimated using a logit model. One of the advantages of propensity score methods is that they easily accommodate a large number of control variables. In our context, we are able to identify a number of observed variables that might influence a consumer's propensity to engage in social activity. We therefore estimate the propensity to participate in a community (global) social activity based on demographic information (including gender and age), music consumption patterns (including the number of tracks listened to, and the number of days in the Last.fm site), and the local social activity (including the number of friends listed on the user's page).

Upon estimation of the propensity score, a matching algorithm is defined in order to match the treated and untreated cases. We used the kernel matching estimator matching technique (Heckman 1997). We divide the treated and untreated cases into four equally sized bins according to their propensity scores. Due to space limitations, we only present the estimated mean differences for group-leadership between treatment and control groups (see Table 5). The estimations of the other treatment groups are available upon request.

Our results clearly indicate that after controlling for self-selection bias based on demographics, music consumption as well as local social activities, we observe a significant difference between the treated and untreated conditions in the mean percentage of users who subscribe to premium services. That is, we show that users who use the global community features, such as group leading, group membership and journal writing, have a higher propensity to subscribe to premium services[13]. Moreover, one could consider leading a group to be a variable that represents a higher level of engagement with the site's community (compared to group membership or journal postings), and indeed, both in our logistic regression estimation and in our propensity score analysis we see a strong correlation between group leading and subscription behavior.

Note, that these results were obtained using choice-based sampling. As explained above, because the treatment was a rare event, it was not possible to compute the propensity score using the full sample, and choice-based sampling was required. Since choice-based sampling creates a bias in the intercept alone, it does not change the relative propensity and therefore does not bias our grouping of the cases into bins. However, this sampling technique clearly

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[13] We observe significant differences for all strata but the first one.

Table 5 – Propensity Score Stratification for Group Leading				
Stratum	Non group leaders	Group leaders	%Subscribers of non group leaders	%Subscribers of group leaders
1	2125	28	49.9%	53.5%
2	2098	55	39.9%	47.2%
3	2028	125	28.8%	46.4%
4	1740	413	43.6%	65.6%

provides us with unrealistic percentages of treated users. For example, looking at Table 5, it seems that nearly half the population are group leaders, whereas in reality, about 5% of non-paying users and 10% of the subscribers are group leaders. Therefore, the results in Tables 5–7 should not be read as representing the occurrence of the treatment in the population. Those results simply provide us with evidence that after controlling for the treatment assignment, the effect of each examined social activity on subscription behavior is significant, and the mean subscription rates in the treatment and control groups are significantly different[14].

Concluding Remarks

Our paper emphasizes an important and yet somewhat overlooked role of social activity on websites that provide traditional content. We show an association between community activity and the propensity to pay for premium services. We show that after accounting for content consumption and demographics, both the use of local social network activity features and the use of global network (community wide) activity features are associated with a substantial increase in the probability of paying for premium services.

We extend those results by using propensity score matching, which has been shown to estimate treatment effects from non-experimental data. Through these matching techniques, we provide additional support to our findings. Although we do not control for unobserved heterogeneity in treatment assignment, propensity score matching allows us to control for self-selection bias based on consumption patterns, demographics, and social activity levels and to show that the use of global network features increases users' willingness to pay for premium services.

This study makes an important contribution to the literature of virtual communities and social networks and their influence on electronic commerce. It also provides researchers as well as practitioners with insights into the importance of adding social activities and building virtual communities as part of the media website

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[14] Repeating these estimations with the full dataset and without choice-based sampling produced similar results and those are available upon request.

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