Broadcasting in Online Social Networks: An Empirical Study of Music Sales and Artists' Activities

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Abstract

This paper examines artists' broadcasting behaviors on social networking sites and the relationship between broadcasting behaviors and music sales. We employ a panel vector autoregressions (PVAR) model to analyze a dataset containing the activity stream data from MySpace and music sales data from Amazon. This model allows us to study the interactions between artists' promotional activities and music sales and to estimate the effect of a shock to one variable on another variable. We find empirical evidence that intense broadcasting behaviors on MySpace could lead to an increase in music sales and that artists tend to broadcast more when they have higher music sales in previous periods. Between the two types of broadcasting activities on MySpace, we find that friend updates are more effective in promoting sales than bulletins. The number of friends for artists also largely affects the effectiveness of promotions as the impact of friend updates on music sales is much larger and more significant for artists with more friends.

1. Introduction

According to a recent post in The Economist (Feb 26, 2009), members of online social networks are now “broadcasting their lives to an outer tier of acquaintances who aren’t necessarily inside the Dunbar circle”. The Dunbar’s number, rounded to 150, was proposed by Dunbar and is considered to be the limit to the number of people with whom one can maintain stable social relationships (Dunbar 1993). However, in online social networks the number of friends for one person can easily go beyond this number. For example, Lady Gaga has 653,845 friends and Linkin Park has 1,329,248 friends on MySpace as of September 9, 2009. This suggests that people may exploit the benefits of social networking sites by “broadcasting their lives” to a large audience. In other words, there is an emerging trend that online social networks can be used as an effective advertising tool.

MySpace is the world’s largest social networking site and one of the top ten most popular websites on the planet. Over eight million artists and bands (Owyang 2008) have set up their profiles on MySpace. Artists and bands can upload songs, show music videos, communicate with fans, and even sell MP3 downloads through MySpace. There is anecdotal evidence (Calvin 2008; Vincent 2006) that shows MySpace has been hugely successful in helping artists promote their music, as it offers many great free tools (such as bulletins, activity streams, blogs, etc.) and focuses on building a community of artists and music fans.

Though having a presence on MySpace is a standard practice for any bands and artists, there is a lack of in-depth academic research that examines the broadcasting behavior on social networking sites and its effectiveness. How do artists attract eyeballs on MySpace? What is the impact of artists' broadcasting activities on their popularity among music fans? More importantly, can these promotions increase the music sales? Will the impact be the same for artists with different number of friends (or, different network sizes)? Using the activity stream data from MySpace, this study employs a panel vector autoregressions (PVAR) model to study the relationship between artists' music sales and their broadcasting activities and simulate the response of one variable to a shock (or innovation) to another. The activity stream data analyzed in this paper is quite unique -- it is the time series of artists' intentional promotional activities broadcasted within their networks. The results of this research will thus provide implications on how the online social network channel can be integrated into the marketing campaigns for record companies.

2. Literature Review

Vector autoregressions (VAR) is a framework that uses dynamic systems of equations to model multivariate relationships. After the seminal work by Sims (1980), VAR models have become one of the most popular tools to analyze time series and been widely applied in economics, finance, and other fields (See, for example, Bessler 1984, Sims 1992, etc.). VAR models typically make minimal assumptions about the underlying structure of the model and treat all variables as endogenous (control variables can enter as exogenous). Overall, VAR models aim to provide good statistical representations of interactions between variables. In this study, we apply VAR models to a panel data (Holtzeakin et al. 1988).

There are a few recent studies that examine the relationship between consumer activities and music sales. Chen and Chellappa (2009) employs fixed effects models to study the patterns of user activities at social networking sites and their impact on music sales. Dewan and Ramaprasad (2008) uses simultaneous equation models to investigate the inter-relationship between music blogs, consumer sampling behavior and music sales. Dewan and Ramaprasad (2009) uses Granger Causality and two-stage least squares to study the causal relationship between blog buzz and music sales. This study is different from those as we use a more advanced economic model and focus on the relationship between artists' promotional behavior and music sales.

3. How Artists Promote Themselves on MySpace?

As a social networking site, MySpace allows bands and artists to set up profile pages that are different from the ones for normal users. This aims to provide a professional platform for artists to connect with their fans besides building their personal networks. On a typical artist profile page, aside from the basic profile information about the artists, there is usually a music player that allows visitors to play the songs in a playlist specified by the artists. The artists can also list the schedules of their upcoming shows or concert performances. Many artists also leave space for some recent blog entries and upload a few videos to their profile pages. Finally, a top friend list and some recent comments by friends appear at the end of the profile page. For an example of an artist profile page, please visit http://www.myspace.com/onerepublic.

The information provided on the profile page serves as only a starting point of online music promotion. If MySpace users do not visit the profile pages, they might not be aware of the artists' recent activities. MySpace thus provides other tools to exploit the benefits of social networks. One of these tools is the bulletin board. Bulletins are posts that everyone in the friend list can see. They are useful in the sense that artists can reach all their friends (i.e., music fans) without messaging them individually. Artists usually post bulletins on a timely basis to tell their friends what they are doing right now, ask them to listen to their new songs, and invite them to post comments. Once a user becomes an artist's friend, then that user will automatically receive the artist's bulletins and be able to see them until they expire in 10 days.

Another major promotional tool is the friend updates that inform music fans of the artists' recent MySpace activities (MySpace recently renamed "friend updates" to "activity stream"). The benefit of the friend updates lies in the fact that any activities by the artists are automatically updated to their friends if they choose to receive these updates. MySpace, like other social networks, also periodically send emails to users to notify them of the recent friend updates. This feature thus enables artists to spread out a message to their fans very quickly and efficiently in online social networks, especially considering that the number of friends can easily reach hundreds of thousands for popular artists. There are several different types of activities that can show up in an activity stream. Among them, “add new blogs”, “add new photos”, “upload new track”, and “add new friends” are the most common ones. By default, MySpace users can see their friends’ updates in the past month after they login.

To summarize, the fundamental of promoting music for artists is to keep music fans interested in them over time. To achieve this, MySpace provides the bulletin board and activity stream to automatically spread out the artists’ messages across the friend network. Previous research has not studied the marketing impact of these automatic news feeds in virtual social networks. Thus, this research aims to examine the roles of these emerging promotional tools.

4. Data

We use two data sources in this research, namely Amazon sales rank data and MySpace activity stream data. Amazon tracks the sales ranks of all music artists that sell digital albums and songs in the Amazon MP3 store. The rank information are public and can be collected on an hourly basis. The activity stream on MySpace records all the broadcasting activities by artists that are observable to the artists’ friends. To collect this information, we subscribed to a selected sample of artists as their friends and got the daily updates of their MySpace activities. We also collect the number of friends for each artist every day.

One important problem that needs to be dealt with is the selection of sample artists.

Since there are over eight million artist profiles on MySpace Music and the list of all artists is not available to the authors, we selected the sample of artists through the lists of Amazon’s daily Top 450 MP3 Songs for all genres and 22 different individual genres (23 lists per day). We used the top song list instead of the top artist list to avoid selecting only the popular artists (artist sales ranks are based on total sales; so, it is easier for obscure artists to get into the top song list.). We selected three days (August 30, September 10, and September 20) in 2008 and downloaded 23 lists per day. Originally, 5,146 artists appeared in the lists and both major labels and indie (i.e., independent or unsigned) artists are included. A program was written to search these artists’ information on MySpace Music and find their corresponding profile pages automatically. To ensure accuracy, the artist name and the titles of uploaded songs on the profile page were used to match with the information on Amazon (There could be multiple MySpace profiles for the same artist name). Overall 1,604 artists’ profile pages were exactly matched. Next, we tried to subscribe to these 1,604 artists as their friends and until October 18, 2008, we successfully subscribed to 637 artists. The actual data collection started on October 19, 2008 and ended on January 31, 2009 (105 days or 15 weeks in total).

The main variables constructed for the analysis are artists’ weekly average sales rank (in logarithm), the number of bulletins, and the number of friend updates in each week. Table 1a shows the descriptive statistics of these variables for all artists. The number of observations is 9,555 and the panel data set is strongly balanced. The sales rank for artists ranges from 2 to 111,093, indicating that both popular and unpopular artists are included in the sample. The average number of bulletins in each week is only 0.72, but the maximum number could reach 43 (i.e., in the extreme case, artists can post about 6 bulletins per day). Similarly, the average number of friend updates in each week is also small (0.61), but the maximum could reach 11.

Another important variable in our analysis is the network size of different artists. To measure this, we calculate the average daily number of friends across the study period for each artist. Table 1b presents the detail summary of this variable. We can see that the median number of friends is 40,525, which is a fairly large number. The average (107,466) is much larger than the median and the maximum number of friends is more than one million in our sample. Later on, we will use this variable to divide the sample into two groups and study how network size is playing a role in affecting the relationship between artists' promotional activities and music sales.

5. Panel VAR

We use the reduced form of the panel vector autoregressions (PVAR) in which each variable is a linear function of its own past values, the past values of all other variables, and an error term. The error terms will be correlated across the equations. Using the panel-data approach, we assume that the coefficients for the main variables are the same for each cross-sectional unit. To allow for unobserved individual heterogeneity, we introduce fixed effects (f_{si}, f_{bi} and f_{fi}) to the model. Following Love and Zicchino (2006), we employ forward mean-differencing (also called the Helmert procedure, see

Arellano and Bover, 1995) to avoid biased coefficients. As the fixed effects are correlated with the independent variables due to lags of the dependent variables, the commonly used mean-differencing procedure would yield biased coefficients. The forward mean-differencing removes only the mean of all future observations, thus preserving the orthogonality between transformed variables and lagged variables.

$$\begin{aligned}\ln(SalesRank_{it}) = {} & f_{si} + \beta_{ss,1}\ln(SalesRank_{it-1}) + \beta_{ss,2}\ln(SalesRank)_{it-2} + \ldots + \beta_{ss,p}\ln(SalesRank)_{it-p} \\ & + \beta_{sb,p+1}Bulletins_{it-1} + \beta_{sb,p+2}Bulletins_{it-2} + \ldots + \beta_{sb,p+q}Bulletins_{it-q} \\ & + \beta_{sf,p+q+1}FriendUpdates_{it-1} + \beta_{sf,p+q+2}FriendUpdates_{it-2} + \ldots + \beta_{sf,p+q+r}FriendUpdates_{it-r} + \varepsilon_{it}\end{aligned} \tag{1}$$

$$\begin{aligned}Bulletins_{it} = {} & f_{bi} + \beta_{bs,1}\ln(SalesRank_{it-1}) + \beta_{bs,2}\ln(SalesRank)_{it-2} + \ldots + \beta_{bs,p}\ln(SalesRank)_{it-p} \\ & + \beta_{bb,p+1}Bulletins_{it-1} + \beta_{bb,p+2}Bulletins_{it-2} + \ldots + \beta_{bb,p+q}Bulletins_{it-q} \\ & + \beta_{bf,p+q+1}FriendUpdates_{it-1} + \beta_{bf,p+q+2}FriendUpdates_{it-2} + \ldots + \beta_{bf,p+q+r}FriendUpdates_{it-r} + \delta_{it}\end{aligned} \tag{2}$$

$$\begin{aligned}FriendUpdates_{it} = {} & f_{fi} + \beta_{fs,1}\ln(SalesRank_{it-1}) + \beta_{fs,2}\ln(SalesRank)_{it-2} + \ldots + \beta_{fs,p}\ln(SalesRank)_{it-p} \\ & + \beta_{fb,p+1}Bulletins_{it-1} + \beta_{fb,p+2}Bulletins_{it-2} + \ldots + \beta_{fb,p+q}Bulletins_{it-q} \\ & + \beta_{ff,p+q+1}FriendUpdates_{it-1} + \beta_{ff,p+q+2}FriendUpdates_{it-2} + \ldots + \beta_{ff,p+q+r}FriendUpdates_{it-r} + \sigma_{it}\end{aligned} \tag{3}$$

5.1 Coefficient Estimates

We use lagged variables as instruments and estimate the model by Generalized Method of Moments (GMM). The results for three lags are presented in Table 2. In Section 6, we test different numbers of lags for robustness check and show that the results are very similar. The coefficient for friend updates at lag 1 in equation (1) is negative and statistically significant, indicating that sales rank will decrease (i.e., sales goes up) when the number of friend updates in the previous week increases. From the economic perspective, if an artist posts one additional friend update in the previous week, the sales rank will be decreased by 2.3%. The coefficients for bulletins at all lags in equation (1) are negative but insignificant, thus we can infer that friend updates are more effective than bulletins in boosting sales. In addition, the coefficients for sales rank (in logarithm) at lag 1 and 2 in equation (3) are negative and significant at 5%, suggesting that the number of friend updates will decrease when sales rank increases (i.e., sales decreases). This indicates that fewer friend updates are made by artists when their music has lower sales in earlier periods.

5.2 Impulse Response

Impulse response functions are used to describe the effect of one unit increase in one variable (i.e., its error term) on the future values of all variables in the systems. The assumption here is that this error returns to zero in subsequent periods and all other errors are equal to zero (Stock and Watson 2001). By this setting we can learn whether a shock to one variable will have a permanent or transitory effect on any of the three variables, and if the effect is transitory, how long it will take to dissipate. Figure 1 presents the impulse response functions along with asymptotic standard errors. We are particularly interested in how sales rank responses to a shock to the broadcasting activities (Figure 1a and 1b) and how the broadcasting activities response to a shock to the sales rank (Figure 1c and 1d). Figure 1a and 1b illustrate that an unexpected one-unit increase in the number of bulletins (or friend updates) is associated with a persistent decrease (between 1% and 2%) in the sales rank (i.e., increase in sales), implying that artists' broadcasting behavior does yield a favorable impact on sales. Figure 1c and 1d show that there is a persistent decrease in both bulletins and friend updates when there is an unexpected increase in the sales rank. This indicates that bad performance in sales could discourage artists. Finally, Figure 1e demonstrates how a shock to the sales rank fades away over time.

5.3 Network Size

Now we consider how different network sizes could affect the relationship between artists' promotional activities and music sales. The underlying reasoning is that the effect of promotions depends on not only how hard artists promote themselves on social networking sites but also their network size, which determines the target size of their promotional activities. With a small network, artists' promoting messages can be received by only a few people, thus limiting the potential benefits of these broadcasting efforts. However, with a large network, a fair amount of effort in broadcasting may attract a lot of attention from music fans and lead to conversion of music purchasing.

To study this network effect, we divide the sample into two groups by the daily average number of friends and conduct the same analysis for each group. We report the coefficient estimates for artists with network size larger than or equal to median in Table 3 and artists with network size smaller than median in Table 4. Comparing these two tables with Table 2, we find that insignificant coefficients in Table 2 remain to be insignificant in Table 3 and 4 (for instance, the impact of bulletins on music sales is insignificant for either group), but some significant coefficients become insignificant in these two tables and they display interesting patterns. First, for artists with network size larger than or equal to median, the coefficient for friend updates at lag 1 in equation (1) is still negative and statistically significant at 1% level. The coefficient is actually more negative than that of the whole sample (-0.030 vs. -0.023). However, for artists with network size smaller than median, this coefficient is still negative (-0.015) but no longer significant. This implies that friend updates on social networking sites are more effective for artists with large network size in promoting music sales. Second, for artists with network size larger than or equal to median, the coefficients for friend updates at lag 1 and 2 in equation (3) become insignificant and less negative, but for artists with network size smaller than median, these coefficients become more negative and remain to be statistically significant at 5% level. This indicates that bad sales performance in previous periods is more likely to discourage artists' promotional effort when they have a small network size, and for artists with a large network size, their promotional activities may be more consistent over time and less likely to be affected by the sales performance. We also computed the impulse response functions for both groups, the results were very similar to Figure 1 and thus omitted here.

6. Robustness Check

In this section, we consider different specifications to check the robustness of our model. First, we incorporate the network size into the main model for the whole sample and see if our main results remain the same. Second, we carry out the estimates using different numbers of lags for each variable and test how lag selection could affect the results.

6.1 An Alternative Way of Considering Network Size

To consider the effect of network size for the whole sample, we create two new variables by multiplying the weekly average number of friends with the number of bulletins and friend updates in each week, respectively. These two new variables could be used to measure the number of broadcasting messages sent to each artist's friends in each week. Then we can estimate the following model:

$$\begin{aligned}\ln(SalesRank_{it}) = {} & f_{si} + \beta_{ss,1}\ln(SalesRank_{it-1}) + \beta_{ss,2}\ln(SalesRank)_{it-2} + ... + \beta_{ss,p}\ln(SalesRank)_{it-p} \\ & + \beta_{sb,p+1}Bulletins \times Friends_{it-1} + \beta_{sb,p+2}Bulletins \times Friends_{it-2} \\ & + ... + \beta_{sb,p+q}Bulletins \times Friends_{it-q} \\ & + \beta_{sf,p+q+1}FriendUpdates \times Friends_{it-1} + \beta_{sf,p+q+2}FriendUpdates \times Friends_{it-2} \\ & + ... + \beta_{sf,p+q+r}FriendUpdates \times Friends_{it-r} + \varepsilon_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}Bulletins \times Friends_{it} = {} & f_{bi} + \beta_{bs,1}\ln(SalesRank_{it-1}) + \beta_{bs,2}\ln(SalesRank)_{it-2} + ... + \beta_{bs,p}\ln(SalesRank)_{it-p} \\ & + \beta_{bb,p+1}Bulletins \times Friends_{it-1} + \beta_{bb,p+2}Bulletins \times Friends_{it-2} \\ & + ... + \beta_{bb,p+q}Bulletins \times Friends_{it-q} \\ & + \beta_{bf,p+q+1}FriendUpdates \times Friends_{it-1} + \beta_{bf,p+q+2}FriendUpdates \times Friends_{it-2} \\ & + ... + \beta_{bf,p+q+r}FriendUpdates \times Friends_{it-r} + \delta_{it}\end{aligned} \tag{5}$$

$$\begin{aligned}FriendUpdates \times Friends_{it} = {} & f_{fi} + \beta_{fs,1}\ln(SalesRank_{it-1}) + \beta_{fs,2}\ln(SalesRank)_{it-2} + ... + \beta_{fs,p}\ln(SalesRank)_{it-p} \\ & + \beta_{fb,p+1}Bulletins \times Friends_{it-1} + \beta_{fb,p+2}Bulletins \times Friends_{it-2} \\ & + ... + \beta_{fb,p+q}Bulletins \times Friends_{it-q} \\ & + \beta_{ff,p+q+1}FriendUpdates \times Friends_{it-1} + \beta_{ff,p+q+2}FriendUpdates \times Friends_{it-2} \\ & + ... + \beta_{ff,p+q+r}FriendUpdates \times Friends_{it-r} + \sigma_{it}\end{aligned} \tag{6}$$

Table 5 reports the coefficient estimates for this model. Our main interest is in the coefficients for lagged $Bulletins \times Friends$ and $FriendUpdates \times Friends$ in Equation (4). We can see that the coefficients for all lagged $Bulletins \times Friends$ remain insignificant, while the coefficient for $FriendUpdates \times Friends$ at lag 1 is negative and significant at 5% level. This is consistent with the previous result that friend updates is more effective than bulletins in boosting music sales and sales rank will decrease when the total number of friend updates sent to friends in the previous week increases. In addition, we also consider transforming these two new variables by taking the logarithm (e.g., transforming $Bulletins \times Friends$ into $\ln(1+Bulletins \times Friends)$), the results are very similar and available upon request.

6.2 Lag Selection

Lag selection is critical in estimating Panel VAR models, as this determines how much information should be used and whether the model can be identified. Too short a lag may not capture the dynamics of the system and yield biased coefficients. Too long a lag leads to a rapid loss of degrees of freedom and generate an excessive large number of coefficients to estimate. Thus, there is a trade-off in selecting the correct lag for estimation and it is important to know whether this affects the sensitivity of the results.

To examine this, we estimate the Panel VAR model using four different lags (one to four). We choose the maximum lag to be four based on the following two considerations. First, four weeks is already a long time period in this context as broadcasting activities on social networking sites are carried out on a timely basis and not likely to have a long-time effect. Second, bulletins on MySpace expire in ten days and users will also not be able to see their friends' updates one month ago. Thus, maximum of four lags is a safe choice in selecting lags.

The results for different specifications in lags are presented in Table 6. Since equation (1) is of most interest in our analysis, we only report the coefficient estimates for this equation. Also, only the coefficients for independent variables at lag 1 are common among four specifications, so we omit the coefficients for other lags. The results turn out to be extremely similar for different lags. All the coefficients have the same sign and close in magnitude across different lags, and coefficients for both sales rank (in logarithm) and friend updates are significant at 1% level for all specifications. Thus, we are confident that our results are not sensitive to the selection of different lags.

7. Conclusion and Future Research

To keep music fans interested in their music, artists regularly update their MySpace profile pages and those activities are automatically broadcasted to their friends by the bulletin board and activity stream features provided by MySpace. Using a panel vector autoregressions model, we find evidence that intense broadcasting behavior could lead to an increase in sales and that artists tend to broadcast more when they have higher music sales in previous periods. Between the two types of broadcasting activities on MySpace, we find that friend updates are more effective in promoting music sales than bulletins. The number of friends for artists also largely affects the effectiveness of promotions as the impact of friend updates on music sales is much larger and more significant for artists with more friends.

One interesting extension is to conduct some other VAR analysis suggested by the literature. We can perform Granger causality tests (Granger 1969) to examine whether the broadcasting activities can help predict the artists’ sales rank. In addition, forecast error variance decomposition (FEVD) can be used to evaluate the proportion of the variance of the error made in forecasting the sales rank at a given horizon due to a specific shock to the broadcasting activities.

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Table 1a. Descriptive Statistics (All Artists)

Variable	Mean	Std. Dev.	Median	Min	Max
SalesRank	4,891.7	8,509.1	1,940	2	111,093
Bulletins	0.72	2.16	0	0	43
FriendUpdates	0.61	1.10	0	0	11

Table 1b. Average Number of Friends (Network Size)

	25%	50%	75%	Min	Mean	Max	Std. Dev.
Avg. # Friends	8,302	40,525	118,896	0	107,466	1,158,050	173,736

Table 2. Panel VAR Coefficient Estimates (All Artists)

Number of Observations Used : 7,007

Independent Variable	Lag	**Dependent Variable** (1) ln(SalesRank)	(2) Bulletins	(3) FriendUpdates
ln(SalesRank)	1	0.690**	-0.132	-0.449*
		(0.092)	(0.283)	(0.223)
	2	0.053*	-0.154	-0.171*
		(0.026)	(0.092)	(0.069)
	3	0.099**	-0.037	-0.149
		(0.033)	(0.113)	(0.085)
Bulletins	1	-0.001	0.424**	0.039*
		(0.004)	(0.057)	(0.016)
	2	-0.001	0.143**	-0.009
		(0.004)	(0.050)	(0.013)
	3	-0.0002	0.169**	0.003
		(0.004)	(0.054)	(0.016)
FriendUpdates	1	-0.023**	-0.026	0.186**
		(0.007)	(0.037)	(0.027)
	2	-0.003	-0.030	0.093**
		(0.005)	(0.035)	(0.022)
	3	0.001	-0.060	0.062**
		(0.005)	(0.031)	(0.022)

Notes: Numbers in parentheses are standard errors; ** and * denote significance at 1% and 5%, respectively.

Table 3. Panel VAR Coefficient Estimates (Artists with Network Size ≥ Median)

Number of Observations Used : 1,760

Independent Variable	Lag	**Dependent Variable** (1) ln(SalesRank)	(2) Bulletins	(3) FriendUpdates
ln(SalesRank)	1	0.756**	-0.350	-0.372
		(0.221)	(0.802)	(0.565)
	2	-0.006	-0.223	-0.148
		(0.039)	(0.167)	(0.113)
	3	0.095	-0.101	-0.117
		(0.069)	(0.271)	(0.187)
Bulletins	1	-0.001	0.438**	0.044*
		(0.005)	(0.068)	(0.019)
	2	-0.001	0.147*	-0.010
		(0.005)	(0.063)	(0.015)
	3	-0.0007	0.184**	-0.0007
		(0.005)	(0.066)	(0.020)
FriendUpdates	1	-0.030**	-0.004	0.211**
		(0.011)	(0.055)	(0.037)
	2	0.002	-0.032	0.124**
		(0.007)	(0.051)	(0.028)
	3	0.00003	-0.056	0.081**
		(0.007)	(0.045)	(0.025)

Notes: Numbers in parentheses are standard errors; ** and * denote significance at 1% and 5%, respectively.

Table 4. Panel VAR Coefficient Estimates (Artists with Network Size < Median)

Number of Observations Used : 1,749

Independent Variable	Lag	(1) ln(SalesRank)	(2) Bulletins	(3) FriendUpdates
ln(SalesRank)	1	0.600**	-0.074	-0.500*
		(0.087)	(0.258)	(0.211)
	2	0.116**	-0.092	-0.208*
		(0.036)	(0.113)	(0.093)
	3	0.116**	-0.009	-0.182
		(0.039)	(0.133)	(0.098)
Bulletins	1	-0.00005	0.359**	0.017
		(0.007)	(0.109)	(0.029)
	2	-0.001	0.111	-0.016
		(0.006)	(0.076)	(0.023)
	3	0.002	0.107	0.008
		(0.005)	(0.079)	(0.021)
FriendUpdates	1	-0.015	-0.044	0.141**
		(0.009)	(0.053)	(0.046)
	2	-0.009	-0.026	0.042
		(0.007)	(0.038)	(0.033)
	3	0.0008	-0.072	0.025
		(0.007)	(0.043)	(0.042)

Column header "Dependent Variable" spans columns (1)–(3).

Notes: Numbers in parentheses are standard errors; ** and * denote significance at 1% and 5%, respectively.

Table 5. Panel VAR Coefficient Estimates (All Artists Considering Network Size)

Number of Observations Used : 7,007

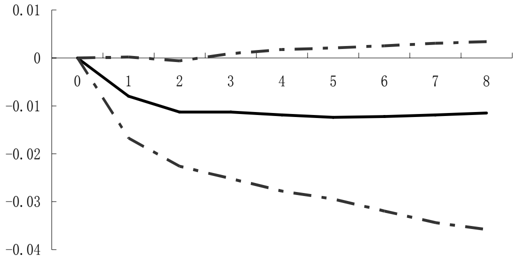
Independent Variable	Lag	(1) ln(SalesRank)	(2) Bulletins × Friends	(3) FriendUpdates × Friends
		Dependent Variable		
ln(SalesRank)	1	0.720**	-17323.678	-8436.558
		(0.087)	(55413.843)	(36765.432)
	2	0.059*	-10825.737	-9349.520
		(0.024)	(22374.425)	(12807.474)
	3	0.108**	-1394.342	5448.633
		(0.031)	(25833.357)	(17074.666)
Bulletins × Friends	1	1.432e-08	0.472**	0.050
		(1.181e-08)	(0.128)	(0.029)
	2	-1.495e-08	0.257*	-0.010
		(1.233e-08)	(0.106)	(0.023)
	3	-5.312e-09	0.190*	-0.009
		(1.671e-08)	(0.080)	(0.019)
FriendUpdates × Friends	1	-8.752e-08*	0.073	0.269**
		(3.591e-08)	(0.113)	(0.049)
	2	1.300e-08	-0.106	0.179*
		(2.434e-08)	(0.117)	(0.088)
	3	1.814e-08	-0.130	0.110*
		(1.804e-08)	(0.085)	(0.052)

Notes: Numbers in parentheses are standard errors; ** and * denote significance at 1% and 5%, respectively.

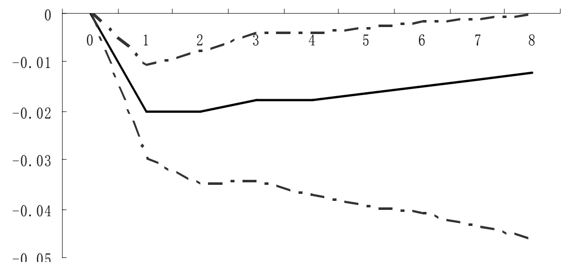
Table 6. Lag Selection - Equation (1)

Lag	**Independent Variable**	**Dependent Variable ln(SalesRank)**
1	$\ln(SalesRank)_{t-1}$	1.086**
		(0.188)
	$Bulletins_{t-1}$	-0.003
		(0.004)
	$FriendUpdates_{t-1}$	-0.023**
		(0.007)
2	$\ln(SalesRank)_{t-1}$	0.776**
		(0.105)
	$Bulletins_{t-1}$	-0.003
		(0.004)
	$FriendUpdates_{t-1}$	-0.025**
		(0.007)
3	$\ln(SalesRank)_{t-1}$	0.690**
		(0.092)
	$Bulletins_{t-1}$	-0.001
		(0.004)
	$FriendUpdates_{t-1}$	-0.023**
		(0.007)
4	$\ln(SalesRank)_{t-1}$	0.612**
		(0.091)
	$Bulletins_{t-1}$	-0.002
		(0.004)
	$FriendUpdates_{t-1}$	-0.018**
		(0.007)

Figure 1. Impulse Responses (All Artists)

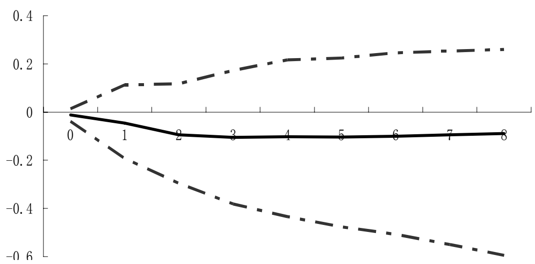


(a) Response in ln(SalesRank) due to a shock to Bulletins

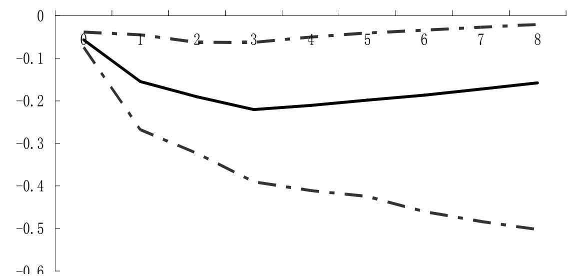


(b) Response in ln(SalesRank) due to a shock to FriendUpdates

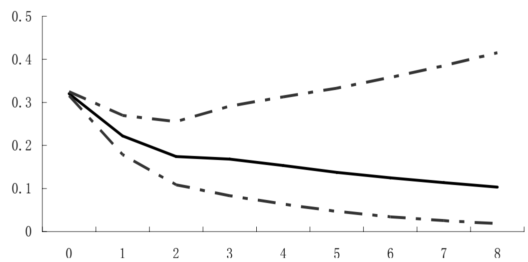
Deviation from Mean



(c) Response in Bulletins due to a shock to ln(SalesRank)



(d) Response in FriendUpdates due to a shock to ln(SalesRank)



(e) Response in ln(SalesRank) due to a shock to ln(SalesRank)

Weeks after Shock

Note: Dotted lines are the 5th and 95th percentiles.