How Superbowl Commercials Affect My Social Network:
An Empirical Study on the Evolution of Social Ties through Revealed Preferences

Research-in-Progress

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Abstract

Marketers use online social networks for target and promotion. Identifying influentials that disproportionately affect others is challenging due to network dynamics and social interactions. In this paper, we focus on the former by conducting a quasi-natural experiment on American Superbowl to investigate shifting tie strengths through revealed preferences and exploring the interplay between popularity and homophily on dynamic networks. We hypothesize that sociometrics such as centrality and transitivity need not change, but network evolves through strengthening or weakening social ties. Our findings highlight the importance of shared preferences or homophily in retaining social ties in dynamic networks, and show that popular users' networks are not necessarily more robust to external events such as marketing campaigns. The unfavourable endorsement may decay the popular user's relationship with her followers. Our study contributes to dynamic social network research by specifically targeting at shifting tie strength and provides novel insights on social media marketing.

Keywords: Dynamic social network, Tie strength, Homophily, Influentials, Revealed preferences


Introduction

Marketers leverage social networks for targeting and promotions. The notion that some users may pose more “influence” than others because of their network position or personal characteristics has been the battle hymn of marketers. However, researchers note that it’s difficult to identify influentials due to the reflection problem (Manski, 1993) whereby peers have correlated outcomes due to homophily as well as influence. That is, it is difficult to separate between how friendships form and how friends influence each other. In this paper, we investigate the prior – as an antecedent of influence, what are some of the mechanisms that affect friendship formation? By understanding this question, it will help marketers and researchers place context into the environment and factors which may bring rise to some users become influential and not others.

Online social network is not static. Researchers find it is evolving due to various mechanisms such as homophily or revealed preferences (Brown & Reingen, 1987; Kossinets & Watts, 2006). Past studies have only investigated the network evolution through forming and severing links (e.g. Bala & Goyal, 2000; Jackson & Watts, 2002; Watts, 2003). Therefore, in our study, we use a quasi-experiment to identify this network change by homophily and show how the tie strengths shift under an exogenous shock.

External events can affect social ties through revealing preferences. Often, a major social event such as a Presidential Election and World Cup, generates new topics of interest to be shared. This leads friends with common interests to move closer (Lewis, et al., 2012). This effect of homophily in forming relationships has been largely investigated (Lazarsfeld & Merton, 1954; McPherson, et al., 2001; Jackson, et al., 2009). However, little is known about how homophily or shared preferences affect evolving social ties. Having this understanding, marketers can effectively target key individuals in the present, as well as predict who will be influential in the future.

Identifying forces which influence friendship formation is critical because it helps to identify future contagion and influence which flows across social ties (Iyengar, et al., 2011). Marketers can then leverage word-of-mouth on social networks to help spread brand awareness and drive sales. It is believed that some individuals, such as “influentials”, are key to increasing the marketing return-on-investment (Valente & Pumpuang, 2007; Chakravarthy & Bhavani, 2011) while other studies suggest the opposite (Watts & Dodds, 2007; Aral & Walker, 2012). However, social networks can be unstable because of temporal interests at the volition of individuals (Kossinets & Watts, 2006). Influentials are those who can influence and persuade others (Aral & Walker, 2012). Marketers usually target influentials as popular peers with many followers. Given dynamic nature of social networks, we question the prior assumption that influential or popular peers have social status to influence the general public while they themselves act independently from the rest based on the two-segment setting (Van den Bulte, et al., 2007) in online context. In other words, it is questionable to assume that influential or popular peers have network structures more robust to the external event, such as the marketing campaign.

In this paper, we conduct a quasi-experiment of an exogenous shock from the American Superbowl to empirically test how the mention of the commercials and brands reveal a user’s preferences, and can affect future ties with her peers. We hypothesize that online messages act to reveal preferences and the interactions indicate social ties. The data is collected from college students through collaboration with a popular social network site. The objective is to explore evolving social ties with the impact of newly revealed preferences, and the interplay between homophily and popularity effects on dynamic network structure. Our results show that revealed preferences do have significant impact on strengthening ties. The peer who does not reveal common preferences will suffer from losing superiority over online interactions to the extent that even popularity cannot offset this negative effect. Specifically, the strength of the social tie for the one who does not reveal the common preference is negatively related to her number of friends.

Our findings provide the following implications. Firstly, we extend the existing literature on dynamic networks by investigating the network evolution at the tie strength level. We quantify the evolving social ties under an exogenous marketing shock. Rather than focusing on dyads, our analysis uses triadic comparisons to look at the shifting tie strengths. Our results imply that big social events or an offline campaign could change the network strength dynamics. However, the network sociometrics such as degree centrality and transitivity need not get changed. Marketers running network-leveraging campaigns should pay attention to the potential shifting tie strength because their expected marketing effectiveness
will be affected by the evolving ties between the target and her peers. Secondly, we study the effect of homophily on retaining social tie strengths. Because the social network is unstable at tie strength level, marketers should make use of user homophily to conduct social network campaigns. Otherwise, when target users endorse unfavourable products, the change in homophily pattern will weaken their social ties with followers. Thirdly, we also investigate the impact of popularity and preferences on evolving social ties. We look at the case of popular users and show that not revealing the common preference decays popular user’s social tie with her peers. Therefore, popular peers do not necessarily have more stable social networks. The unfavourable endorsement may decay the popular user’s relationship with her followers. Finally, our findings suggest that influence is a dynamic and complex process.

**Literature Review**

The impact of social structures, particularly in the form of social networks, on economic outcomes has been widely studied. Social networks can affect recruitment, productivity, political alliance, and academic collaboration through qualified information flow, rewards and punishments, and trust (Granovetter, 2005). The value of network structure, namely the way individuals are connected with each other, has been studied in various domains, such as employment (Calvo-Armengol & Jackson, 2004) and purchasing (Ellison & Fudenberg, 1995). Recently, dynamic social networks have also attracted great attention in many contexts like scientific collaboration (Barabási, et al., 2002), organizational productivity (Wu, 2013) and individual creativity (Perry-Smith & Shalley, 2003). Given its importance, the network formation has been explained by many studies such as the random graph theory (Erdos & Renyi, 1960). Watts and Strogatz (1998) have generated “small world” networks with short global separation and high local clustering, by randomly rewiring some links in completely regular networks to increase amounts of disorder. However, a social network is not completely randomly constructed. Rather, at a dyadic level, the link formation can be explained in several ways including assortivity, homophily and preferential attachment. Assortivity is a selective linking special to social networks (Newman, 2003). Assortivity can lead to the homophily effect when people tend to be associated with similar others, or it can result in preferential attachment in the case of people mixing according to vertex degree (Newman, 2003). Homophily, primarily generated from biases in preferences, is the tendency of similar people to form friendship (Lazarsfeld & Merton, 1954; McPherson, et al., 2001). The individuals’ preferences and matchings can determine the emerging patterns of homophily in social ties (Jackson, et al., 2009), so people sharing common preferences tend to befriend with each other. This process changes network structure and friends become similar on salient individual behaviors and attitudes. As a result, homogeneity is observed in social networks (Fararo & Morris, 1964; Lewis, et al., 2012). The behavioral or attitudinal homogeneity hence enhances the interpersonal influence and strengthens social ties.

An alternative mechanism for dynamic networks is preferential attachment where new nodes attach preferentially to the existing nodes that have more connections gain benefits like social capital (Barabasi & Albert, 1999). This leads to scale-free power law distributions followed by vertex connectivities of many large networks (Barabasi & Albert, 1999) such as the network of online stores (Stephen & Toubia, 2009). Therefore, popular individuals with more friends are more likely to gain new friends than individuals with fewer friends. In other words, leveraging one’s popularity can help her establish social ties. In sum, the foregoing link formation processes drive the evolution of network structure at dyadic level. While “rich-club” phenomenon suggests about the preferential interaction (Vaquero & Cebrian, 2013), little evidence has been shown on the effect of preferential attachment on maintaining social connections, which motivates us to bring the popularity angle into the current study. It also remains to be explored that how homophily (i.e. preference) and preferential attachment (i.e. popularity) affect the network structure in an evolutionary manner. In addition, little is known about the interplay effect between preference and popularity on the dynamic social networks.

While marketers use social networks for brand or product promotion, they believe it is better to target popular individuals with as many followers. But this strategy may not perform effectively. Related to the popularity angle, there is a stream of studies on influentials, in certain social circles. Katz and Lazarsfeld (1955) propose a two stage flow process where some individuals receive exogenous information and relay the information to their peers through word-of-mouth (Glock & Nicosia, 1966). It has also spurred managerial interest in that marketers can now run the network-leveraging campaigns hinging on influentials instead of masses - to exert social influence on the rest (Iyengar, et al., 2011). This leads
marketers to identify these key individuals for marketing purpose due to their significant impact on consumer behaviors (Valente & Pumpuang, 2007; Chakravarthy & Bhavani, 2011). On the other hand, there is another stream of studies pointing out that marketing through influencers may not work as effectively as expected (Watts & Dodds, 2007; Aral & Walker, 2012). However, one reason for the inconsistent findings is because prior studies may overlook the effect of evolving homophily in dynamic network structure. When revealed preferences change the pattern of homophily, the strengths of social ties between influencers and their peers will shift. Therefore, this change in the interpersonal relationship affects the expected influence of popular individuals on the rest.

Moreover, since social network is not static, researchers have developed a number of dynamic analytical models to capture the network formation and evolution characteristics (e.g. Bala & Goyal, 2000; Jackson & Watts, 2002; Watts, 2003). These models will provide insights for marketers to use on dynamic networks for targeting and promotion. For example, Bala and Goyal (2000) have developed dynamic network formation model where links are formed unilaterally. Jackson and Watts (2002) have developed a dynamic model by allowing individuals to form and sever links based on the expected improvement to be achieved or occasionally by mistake. Watts (2003) further proposes a model to make self-interested individuals sever links unilaterally but form links upon agreement by both sides. These models show marketers the characteristics of evolving networks under different assumptions. Existing studies mostly focus on adding and severing links. However, in reality, the network evolution is incurred as tie strength shifts, and the interpersonal links are always maintained. While there are few literatures on the evolution of social tie strength in dynamic network, in this study, we specifically aim to investigate the impact of popularity and preference on evolving social ties in a dynamic social network.

Model Development

The homophily in our context is equivalent to the shared preference, such as common topic. The topic is newly revealed means it does not appear in prior communication. Individuals may hide their preference intentionally or unintentionally. For example they may not realize their interest in certain topic until that is finally released after a social event or an accident, or reminded by anyone else. The ideal case is that this topic is also time sensitive, so that the effect is magnified to be well captured even in a limited data set. In our context, we assume the revealed topic is one of the hottest and most popular topics during a limited duration. Based on the revealed topic, we define three types of participating users. Firstly, the ego is the focal user who talks about any things including the revealed topic. Secondly, the prior friend is who reciprocally interacts with the ego on any things except for the revealed topic. Thirdly, the revealed friend is who reciprocally communicates with the ego on the revealed topic after the topic is released. Therefore, by these definitions of users, we can establish the homophily as revealed topics between the ego and revealed friend. Furthermore, we can also bring in the popularity as number of connections of the prior friend. Hence, we construct a triangular model with two focused dyadic relations, namely ego and prior friend, and ego and revealed friend. The interplay between popularity and preference can be investigated through the ego’s interactions with the prior friend and revealed friend.

We begin with a conceptual model to show the preference revealing process and explain the change of tie strength with respect to one’s utility function. Matrix or vector is denoted by notation in bold, while scalar or simple coefficient is not. Let i, j, k denote an ego and alter users, respectively, in a period of time t, t ∈ {0,1,2,3}. We define topics of interest α as the focal topic to be revealed at t′ = 1, and α′ as any topics other than α. So τat is the set of topics user a has at time t, and τat = μatθaα′ + μatθaα, where μ is an indicator if a topic is revealed and θ is the utility parameter. We also define three types of users: the ego, prior friend and revealed friend. Specifically, user i is the ego or focal user with α to be revealed. The prior friend, j, interacts with i on other topics, not including α, such as μ′iτiα′ ∩ μ′jτjα′ during t < t′, and μ′jt = 0 for all t such that τjt = μ′jτjα′. Finally, the revealed friend, k, interacts with the ego, i, on α when t ≥ t′. Then we define ego’s utility function as Uit = ∑N Uiat over N friends, and Uiat = θF(τit, τat) + δ, where F(τiat, τibt) is the utility that a user a gets from sharing similar interest with her peer b. We operationalize the function using cosine distance F(τiat, τibt) = cos(τiat, τibt) = τiat ‖ / ‖ τibt ‖ / ‖, and δ captures any other factors related to ego’s utility such that Uiat ≈ F(τit, τat).

H1: Revealing common topic strengthens future online interactions.
Intuitively, more shared topics, more interactions expected. As shown by utility function, revealing topics decreases cosine distance, and thus increases perceived utility. Technically, the link formation process can be driven by homophily – the notion that bird of a feather flock together (Lazarsfeld & Merton, 1954; Currarini, et al., 2010). Individuals tend to become closer with people sharing same topics, thus the dyadic tie becomes stronger in the next period.

\( H2: \) Compared with revealed friends, popular prior friends will have less future online interactions with the ego.

To test this, we operationalize two constructs - one is the two-way interaction frequency, and the other is popularity as measured by number of connections. We can infer that number of connections is positively related to \( \| \mu_i^t \alpha^t \| \approx \| r_i \| \), so that \( U_{ij} \) is negatively related to popularity of \( j \). In other words, the more popular the prior friend is, the less likely for ego to contact her after the focal topic that the prior friend is not interested in is revealed. However, based on existing literature, the competing result of popularity and preference is inconclusive. Both of the two mechanisms help form links, but preferential attachment is more at graph level (Barabasi & Albert, 1999). If we focus at dyadic level, preferential attachment does not help strengthen the social ties while homophily also plays a vital role in maintaining relationship (Kossinets & Watts, 2006; Jackson, et al., 2009). Therefore, preference is more important in strengthening relations than popularity.

\( H3: \) If the revealed friend has online interaction with ego before the event, the ego will continue to interact with this friend after the event, but to a significantly higher extent as compared to her other prior friends.

It assumes that if \( \mu_{i(t',c)}^t \alpha^t, \mu_{k(t',c)}^t \alpha^t \neq \emptyset \) just like \( \mu_{i(t',c)}^t \alpha^t, \mu_{j(t',c)}^t \alpha^t \neq \emptyset \) by definition of \( j \), and \( i \) and \( k \) share a representative topic \( \alpha \) from \( t = t' \). Finally, \( U_{ij(t,\alpha)} < U_{ij(t',\alpha)} \) is expected. In other words, it is equivalent to compare the ego’s relationships with two friends from the beginning to the end. After the topic is revealed, only one friend is interested in and will communicate with the ego on this revealed topic. Therefore, we expect a stronger homophily between this friend and the ego, leading to a stronger tie strength and higher extent of continuing interaction.

**Data and Empirical Model**

The natural event involved is American Superbowl XLIV on Sunday, February 7, 2010, the highest level of professional American football in the United States. The Superbowl sporting event is the most watched TV show that attracts 100 million audiences on average. It provides a sought-after opportunity for business to raise their advertisements, and it may also produce the most expensive and influential commercials for the year. In addition, in 2010, many advertisers encouraged participation on social networks sites, as part of their marketing campaigns. Since the commercials are kept a secret before the event, we will use those TV commercials as an exogenous shock on social network sites. Thus we address the identification issue by leveraging this exogenous shock in the quasi-natural experiment setting. We obtained backend data from a major social networking site (SNS) through collaboration with the company. It consists of three components: first, user profile information of over 1.4 million undergraduate students, who are in class of 2008-2011 from 144 U.S. universities; second, above users’ action data recording their online activities on the SNS during 72 days around the event, including postings and messages from January 1st, 2010 to March 13th, 2010; thirdly, friendship information of above users, specifying who initializes the relationship and the time of friendship establishment. Therefore, we identify the topic of interest in Superbowl commercials as revealed preference (\( \alpha \)), including main brands like Coca-Cola, Dr. Pepper, Hyundai, VW, Honda, Audi, Toyota, Budweiser, Budlight, Snickers, Doritos, Intel, FLO TV, Boost Mobile, Metro PCS, Vizio and Tru TV. We use text mining of keywords to identify the topics.

To identify the ego, prior friend and revealed friend, we take the following steps. First, we select any pairs who reciprocally communicate on \( \alpha^t \) at \( t = 0 \), and randomly choose one side to be the ego (i), and the other side as candidates of prior friends. To identify the prior friend, we remove the candidates who communicate on \( \alpha \) (i.e. \( \mu_i = 1 \)). There are a few egos have more than one prior friends (\( \sum j_o \)). So we take average to evaluate the attributes of prior friend (\( j = \sum j_o / N \)). Second, we identify those users with whom...
the ego reciprocally communicates on α only when \( t \geq 1 \), as revealed friends (\( k \)). Then we mark those revealed friends with \( \mu_{i}^{\alpha} = a^{\alpha} \cap \mu_{i}^{\alpha} \neq \emptyset \) to test for the third hypothesis.

In addition, to measure the tie strength in online social network, ‘frequency’ is one of most significant components (Petroczi, et al., 2006) and it can be quantified. We then calculate tie strength between two friends based on the frequency of two-way interaction. According to Kossinets & Watts (2009), we employ sliding window filter to analyse behaviours in social networks over time. The tie strength for dyad (\( a, b \)) during time period \( t \), is derived as \( M_{a,b,t} = \frac{1}{\|r\|} \sqrt{M_{a,b,t} \times M_{b,a,t}} \) with \( \|r\| = 7 \) days as number of days in period \( t \). \( M_{a,b,t} \) or \( M_{b,a,t} \) is the number of content actions sent from user \( i \) to user \( j \), or user \( j \) to user \( i \) respectively, during period \( t \). Our dependent variable, \( \log \left( \frac{W_{i,j,t}^{a} + 1}{W_{k,k,t}^{a} + 1} \right) \), is the logarithm of fraction value of ego’s tie strength with prior friend over ego’s tie strength with revealed friend during period \( t \). Thus the dependent variable is to compare the interactions of two dyads of the three-person structure.

For each set of \( \{ i, j, k \} \), our independent variables could be divided into user characteristics variables, tie variables, and binary variables. Firstly, user characteristics include number of content actions for user \( a \) during period \( t \) (\( NAction_{a,t} \)), and number of friends for user \( a \) right before the first day of period \( t \) (\( NFriend_{a,t-1} \)). Secondly, the tie characteristics include the difference in \( NFriend_{a,t-1} \) between two users \( a \) and \( b \) (\( NFriendGap_{a,b,t-1} \)), age of online friendship between two users \( a \) and \( b \) (\( AgeFriend_{a,b} \)) which is the number of days since user \( a \) and \( b \) established friendship until 00:00:00 Feb 28, 2010 (right after the last day of \( t = 3 \)). Lastly, the binary variables include the variable to show if revealed friend also communicates with ego in \( t = 0 \) (\( RFisPF_{k} \)) where it is true if ego has two-way interaction with revealed friend in \( t = 0 \), and a variable to indicate whether a period \( t \) is after Superbowl event (\( afterSB_{t} \)) and it is true if the period \( t \geq 1 \). In addition, we adopt the lexicon-based sentiment mining approach (Li & Wu, 2010) to get the binary variable (\( SentDiff_{i,k,t} \)) indicating whether the ego and revealed friend share different attitudes on revealed topics in period \( t \). We control for SNS age (\( SNAge_{a} \)) as the days count since user \( a \) joined the social network until \( t \) th day of period \( t = 0 \), and real age of user \( a \) in year 2010 (\( Age_{a} \)). We also have a binary variable to indicate user a’s gender (\( Gender_{a} \)). We also include location dummies to indicate whether the user \( a \) is in the hosting city – Miami, and two cities of teams – New Orleans and Indianapolis respectively (\( \sum_{city} Location \)).

The binary variable \( afterSB_{t} \) is interacted with \( NFriend_{j,t-1} \) and \( RFisIF_{k} \), respectively, to capture the event effect when testing those two variables. The regression function in fixed effect form of panel linear model is as below:

\[
y_{i,t} = \log \left( \frac{W_{i,j,t}^{a} + 1}{W_{k,k,t}^{a} + 1} \right) \\
y_{i,t} = \delta_{i} + \beta x_{i,t} + \varepsilon_{i,t} \\
x_{i,t} = [NAction_{i,t}, NAction_{j,t}, NAction_{k,t}, NFriend_{j,t-1}, NFriend_{k,t-1}, NFriend_{j,t-1}, NFriend_{k,t-1}, NFriendGap_{i,j,t-1}, NFriendGap_{i,k,t-1}, NFriendGap_{j,k,t-1}, AgeFriend_{i,j}, AgeFriend_{i,k}, AgeFriend_{j,k}, RFisPF_{j}, RFisPF_{k} \times afterSB_{t}, afterSB_{t}, NFriend_{j,t-1} \times afterSB_{t}, SentDiff_{i,k,t}, SNAge_{i}, SNAge_{j}, SNAge_{k}, Age_{i}, Age_{j}, Age_{k}, Gender_{i}, Gender_{j}, Gender_{k}, \sum_{city} Location] \]

Preliminary Results

We show the data description in Table 1. The number of directed content actions that user \( a \) sends to user \( b \) during period \( t \) (denoted as \( NActionD_{a,b,t} \)) is used to compute the dependent variable. The user \( a \)’s average sentiment score for content with revealed topic (\( Sent_{a,t} \)) in period \( t \) is used to compute \( SentDiff_{i,k,t} \). The statistics for prior friend (\( j \)) may be in decimal, because we take the average to group together all the prior friends of an ego (\( i \)). Our sample consists of young and experienced SNS users. About 45% of revealed friends (\( k \)) have interaction with the egos before Superbowl event. The average
The Evolution of Social Ties through Revealed Preferences

The frequency of directed interactions between the ego and revealed friend has doubled compared to her interaction frequency with prior friend.

Table 1: Data Description

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>-0.11</td>
<td>-2.57</td>
<td>0.89</td>
<td>( N_{\text{Action}}_{i,t} )</td>
<td>1.13</td>
<td>0</td>
<td>10</td>
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<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>77.32</td>
<td>0</td>
<td>577</td>
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<td>0.23</td>
<td>0</td>
<td>5.50</td>
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<tr>
<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>95.20</td>
<td>0</td>
<td>967.83</td>
<td>( N_{\text{Action}}_{i,t} )</td>
<td>0.27</td>
<td>0</td>
<td>25</td>
</tr>
<tr>
<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>64.53</td>
<td>0</td>
<td>1073</td>
<td>( N_{\text{Action}}_{i,t} )</td>
<td>3.04</td>
<td>0</td>
<td>88</td>
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<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>298.40</td>
<td>25</td>
<td>1065</td>
<td>( N_{\text{Action}}_{i,t} )</td>
<td>3.35</td>
<td>0</td>
<td>98</td>
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<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>300.20</td>
<td>34</td>
<td>1044</td>
<td>( \text{SNAge}_{i,t} )</td>
<td>1247</td>
<td>275</td>
<td>1673</td>
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<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>226.2</td>
<td>9</td>
<td>1248</td>
<td>( \text{SNAge}_{i,t} )</td>
<td>1244</td>
<td>530</td>
<td>1839</td>
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<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>170.61</td>
<td>9</td>
<td>623</td>
<td>( \text{SNAge}_{k,t} )</td>
<td>1285</td>
<td>525</td>
<td>1978</td>
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<tr>
<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>184</td>
<td>2</td>
<td>973</td>
<td>( \text{Age}_{i,t} )</td>
<td>20.79</td>
<td>19</td>
<td>23</td>
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<tr>
<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>162.31</td>
<td>1</td>
<td>731</td>
<td>( \text{Age}_{i,t} )</td>
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<td>19</td>
<td>2350</td>
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<td>448.30</td>
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<td>3207.70</td>
<td>( \text{Age}_{k,t} )</td>
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<td>19</td>
<td>24</td>
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<td>543.48</td>
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<td>( \text{Sent}_{i,t} )</td>
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<td>185.36</td>
<td>0</td>
<td>1363.44</td>
<td>( \text{Sent}_{k,t} )</td>
<td>0.30</td>
<td>-5</td>
<td>7</td>
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<tr>
<td>( \log \left( \frac{W_{i,j,t} + 1}{W_{i,k,t} + 1} \right) )</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
<td>( \text{SentDiff}_{i,k,t} )</td>
<td>0.90</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

We compare several statistical models: Pooled Ordinary Least Squares, Fixed Effects and Random Effects. They are all statistically significant and the adjusted R-squares are 0.42134, 0.27309 and 0.34734 respectively. By Hausman test, we identify the Fixed Effects model to be the best fit and most consistent. Note that all the location dummies are insignificant. The sentiment dummy (\( \text{SentDiff}_{i,k,t} \)) is significantly positive, which is consistent with hypotheses, namely when the ego and revealed friend have different attitudes towards newly revealed topic, the ego will prefer to interact with prior friend more often than with revealed friend. The results are partially shown in Table 2 as below:

Table 2: Statistical Results

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Pooled OLS</th>
<th>FE</th>
<th>RE</th>
</tr>
</thead>
<tbody>
<tr>
<td>( RFisPF_{k} )</td>
<td>-4.7891e-01(***))</td>
<td>(omitted)</td>
<td>-4.9401e-01(***))</td>
</tr>
<tr>
<td>( afterSB_{t} )</td>
<td>-2.3138e-01(***))</td>
<td>-2.5240e-01(***))</td>
<td>-2.2764e-01(***))</td>
</tr>
<tr>
<td>( NFriend_{i,t-1} \times afterSB_{t} )</td>
<td>-1.3310e-04</td>
<td>-4.5136e-04</td>
<td>-1.3256e-04</td>
</tr>
<tr>
<td>( RFisPF_{k} \times afterSB_{t} )</td>
<td>2.3236e-01(***))</td>
<td>2.5234e-01(***))</td>
<td>2.4149e-01(***))</td>
</tr>
<tr>
<td>Other Controls</td>
<td>(included)</td>
<td>(included)</td>
<td>(included)</td>
</tr>
</tbody>
</table>

Balanced Panel: n=95, T=4, N=380

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Result for H1: \( afterSB_{t} < 0 \).

The ratio \( \frac{W_{i,j,t+1}}{W_{i,k,t+1}} \) decreases as ego interacts more with the one who shares \( \alpha \), and less with the one who does not share, so H1 is proved to be true. Hence, shared preference has a positive impact on tie strength.

Result for H2: \( NFriend_{i,t-1} \times afterSB_{t} < 0 \).

The ratio \( \frac{W_{i,j,t+1}}{W_{i,k,t+1}} \) decreases as prior friend’s online popularity increases, so H2 is proved to be true. Although the estimate’s magnitude value is smaller than that in H1, it is still negative, which means popularity does not offset all the negative effects on peer who does not reveal \( \alpha \). The simple rationale behind could be the average tie strength is generally weak due to so many edges branching out from...
popular prior friend, provided with human’s limited information processing capacity (Dunbar, 1992). Therefore, to some extent, people with more connections may have a lower average influential power (Katona, et al., 2011) for maintaining relationship. Hence, popular users’ networks are not necessarily more robust to external event, and shared preference is more important in retaining tie strength.

Result for H3: RFisPF_k * afterSB_t > 0.

The ratio \( w_{i,t+1}^{\text{before}} / w_{i,t+1}^{\text{after}} \) increases if revealed friend also interacted with ego in \( t = 0 \) (RFisPF \( = 1 \)), so H3 is proved to be false and ego will interact more with her prior friend who is not interested in \( \alpha \). This statement goes against intuitive judgment. Reason may be the interaction between the ego and revealed friend goes offline. So their friendship is still developed in reality, but it is not observed online in a short term. On the other hand, if we think about the cosine function to conceptualize ego’s utility, this can also be explained by the diminishing marginal contribution of \( \alpha \) as \( ||\alpha'|| \) increases. Hence, stronger homophily does not significantly strengthen social ties as much as expected.

Concluding Remarks

In the study, we conduct a quasi natural experiment on American Superbowl XLIV to investigate the impact of popularity and homophily on evolving social tie strength in the dynamic social network. First, out study contributes to social network research by assessing the strength of evolutionary social ties as a result of exogenous marketing efforts. We emphasize the importance of shared preferences (or homophily) in retaining tie strength in dynamic network, and also show the interplay between homophily and popularity on network structure. Also, our results imply that social network is unstable at the tie strength level such that marketers should make use of shared preferences to conduct social network campaigns. Our results shed caution into targeting popular users for promotions. For example, a less well-known public figure but popular Youtube contributor, Michelle Phan, has been said to collect $1 million to produce content and endorse cosmetic products. However, based on the result of H2, we question the effectiveness of such strategies. While popular users can increase the reach of the marketing message and spread awareness, the marketing content reveals a preference and changes homophily pattern in the network. Popular users’ social ties with followers become weaker if followers do not share the revealed preference. Worst, followers may sever links to these popular users when they endorse the unfavourable products. That is, marketer-backed tactics may decay the popular user’s relationship with her followers.

However, our study in its current form has several limitations. Firstly, during the user identification process, we group all identified prior friends of an ego into one group, which may lead to loss of individual-level heterogeneity. Secondly, we set each period as one week to account for a ‘weekly effect’, and the total effective duration is only 28 days due to data limitation. Thirdly, we only have online data, and we assume to exclude other major real-world factors except for Superbowl event. Lastly, the data set only includes undergraduate users in U.S, which may not support for socially (or demographically) heterogeneous group configuration in reality. Therefore, by extending the current study, in the future, we would like to go deeper in the triangle model and develop a more sophisticated analytical framework. We will also try to develop a more rigorous quantitative measure of tie strength, in terms of frequency, sentiment, etc. Another interesting future research is to specifically investigate if popular users are vulnerable to exogenous shocks and how their social networks can be affected by revealed preferences.

References


