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ONLINE PEER-TO-PEER COMMUNITIES: AN EMPIRICAL INVESTIGATION OF A MUSIC SHARING COMMUNITY AS A DYNAMIC TWO-SIDED NETWORK[1]

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Abstract

Online peer-to-peer communities and online social networks have become increasingly popular. In particular, the recent boost of online peer-to-peer communities leads to exponential growth in sharing of user-contributed content which have brought profound changes to business and economic practices. Understanding the formation and sustainability of such peer-to-peer communities has important implications for businesses. We develop a dynamic two-sided network model that relates growth of communities to interactions between contribution and consumption of resources in online sharing activities. Using online music sharing data collected from a popular IRC music sharing service over five years, we empirically apply the model to identify dynamics in the music sharing community. We find that the music sharing community demonstrates distinctive characteristics of a two-sided network. Contribution in the community leads to more consumption and consumption leads to more contribution, creating positive network effects in the community. Moreover, we find significant negative externalities among consumption activities and among contribution activities. The combination of the positive and negative externalities drives the underlying dynamics and growth of online sharing communities. Using the dynamic model, we quantify equilibrium growth rate of the community. We find that the equilibrium growth rate changes over time, possibly as a result of legal actions taken by the music industry. Our study provides a first glimpse into the mechanism through which peer-to-peer communities sustain and thrive in a constantly changing environment.

Keywords: online communities, two-sided networks, IRC channel, P2P music sharing, evolutionary games, digital piracy

JEL classifications: L14, C73, O34

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1. Introduction and Objectives

The recent explosive growth of popular online peer-to-peer sharing communities (e.g., KaZaa, Gutntella, eDonkey and BitTorrent for file sharing, Wiki for information sharing, FreeNet for storage sharing, PeerCasting for video stream sharing) has generated a renewed interest in the Internet as a new medium for content generation and distribution. This new trend is often considered to be attributable to the Web 2.0 technologies, advances in information technology especially in storage capability and bandwidth, and social computing concepts that make mass user interactions feasible and multi-faceted. Peer-to-peer sharing communities feature large populations of participants and constant change of community memberships. The communities also develop and sustain mainly by themselves without any corporate or commercial sponsorship. Individual users self-organize and construct communities on the Internet through large-scale collaboration and information sharing, which bring significant changes to social life, business practices and organizational computing. As a result, there is an increasing interest in understanding the structure and development of online social communities.

The development and growth of online communities presents a number of challenges to business practitioners and academic researchers. Contribution to online sharing communities is public goods that benefit every member of the community. Since members can benefit from others' contribution without making contribution themselves, resources in peer-to-peer sharing communities is expected to be under-contributed and over-consumed (Krishnan et al. 2004), leading a classic case of the "tragedy of the common" (Hardin 1968). Evidence from peer-to-peer communities indeed reveals rampant free-riding and raises concerns of the sustainability of such communities (Asvanund et al. 2004; Adar and Huberman 2000). However, peer-to-peer sharing communities continue to thrive and grow at an exponential rate despite significant number of free-riders. Moreover, in online peer-to-peer sharing communities, community members interact with thousands of fellow community members with limited knowledge of counterparts. Community participants often have few message exchanges and there are also few pre-existing social ties among them. In addition, most member interactions among very large community populations are short-lived, and the community is dynamic with constant changes. These characteristics indicate that individual community members are myopic in making decisions. However, their decisions influence each other and in aggregate have significant influence over the future direction of the community. The combination of individuals' short horizon and their limited information suggest that peer-to-peer communities are slow to react to changes. It is therefore necessary to consider such communities from a dynamics perspective for a better understanding of the development and sustainability of online sharing communities.

To address the challenges, we model peer-to-peer sharing network as a dynamic two-sided network. Two-sided markets, also called two-sided networks, are economic networks having two *distinct* user groups that provide each other network benefits. In fact, many if not most markets with network externalities are two-sides, such as software, portals and media, payment systems and the Internet (Rochet and Tirole 2003). Our model has two unique characteristics. First, we assume peer-to-peer communities consist of two distinctive groups of members: sharers and downloaders. Sharers obtain utility from sharing files with others. The utility arise due to altruism, warm glow or reputation effects. Downloaders receive utility from downloading files from sharers. The two-sided network model is motivated by the observation that most of the contributions in peer-to-peer communities are provided by a small group of members who rarely consume resource from the community. By explicitly identifying this group of members and model their decision making process, our approach provides a detailed look of the composition of peer-to-peer sharing community and the underlying interactions that shape the community. Second, we provide a dynamic model that links short-term population dynamics to long-term equilibrium in peer-to-peer sharing communities. A key insight obtained in recent virtual community research is that resource and utility obtained from virtual communities influence population dynamics measured by entry and exit of community members (Butler 2001). However, since individuals are myopic, such population dynamics are slow to converge to a long-term equilibrium. This insight provides a foundation to establish an inter-temporal model that relates current utility to population dynamics which in terms influence future utility of the community. The long-term equilibrium of the peer-to-peer sharing community can then be derived from the accumulation of the short-term population dynamics. Our dynamic approach complements traditional economic studies on networks that mainly focus on static equilibrium in networks with full informed and rational economic agents (Economides 1996). Our dynamic approach leverages techniques of population dynamics developed by evolutionary game theory (Samuelson 1997). Evolutionary game theory emphasizes large populations, continuous changes in community memberships, and imperfect information and memory among community members. These models are particularly powerful in interpreting users' behavior in online sharing communities (e.g., Geng et al. 2004). An important element of evolutionary game theory is the establishment of population dynamics and the derivation of long-term equilibrium from intertwining popular dynamics. We adopt the population dynamics approach but revise its dynamic model to explicitly incorporate two-sided network effects. We then derive long-term equilibrium of the peer-to-peer sharing community and identify conditions that lead to its growth and decline.

We empirically test our model using data collected from a major online music sharing community. Our results provide a clear demonstration of the dynamic processes of member contribution and consumption of the music sharing community. In particular, we find clear evidence for two dynamics that characterize the mechanism of development of sharers and downloaders respectively. The two dynamics are consistent with the theoretical prediction of a two-sided network. Increase in sharers leads to increase in downloaders, which in turn leads to increase in sharers. This feedback mechanism represents positive indirect network effect that drives the growth of the peer-to-peer sharing communities. However, we also find that increase in sharers leads to exits of existing sharers and increase in downloaders leads to exits of existing downloaders. These negative externalities are significant and limit the growth of the community. The combination of the positive and negative externalities reveals the mechanism through which peer-to-peer communities sustain, thrive and decline in a constant changing environment. Our model also finds that the long term equilibrium of a peer-to-peer sharing network can be described by its ratio of sharers to downloaders and its growth (or decline) rate given the positive and negative externalities among its members. The ratio of sharers is fixed in the long-term equilibrium. When sharer ratio decreases below certain threshold, downloaders exit and new sharers join the communities. This process gradually restores equilibrium to the peer-to-peer network. Similarly, when share ratio increases above certain threshold, sharers start to exit while new downloaders join the community. The growth rate of the peer-to-peer sharing network is determined by a trade-off between positive externalities between downloaders and sharers and negative externalities among themselves. When positive externalities exceed the negative externalities, a condition that would be made precise later, we observe growth in the peer-to-peer sharing community. When negative externalities prevail, we observe decline in the community.

The remainder of this paper is organized as follows. Section 2 summarizes related literature on online communities. Section 3 constructs a dynamic two-sided network model that motivates our empirical analysis. Section 4 tests the model empirically using data from IRC music sharing communities. Section 5 concludes the paper with a discussion of the results and implications as well as identifying future research opportunities.

2. Literature Review

We view online sharing communities, e.g., the peer-to-peer music sharing network, as a special type of online communities. Online communities have long attracted researchers' interest for its ability to bring geographically dispersed people together and communicate with others. Rheingold (1994) defines online communities as "a group of people who may or may not meet one another face-to-face, and who exchange words and ideas through the mediation of computer bulletin boards and networks".

Online communities often emerge with the development of new technologies, that offer users new ways to express their preference and interact with others. Increasingly, the direct exchange of words or ideas is no longer necessary for a community to exist. For example, online users can vote, rate, and tag to express their opinion on a given piece of content contributed by the fellow users. Thus users can get the idea of the aggregate preference of other users without having to communicate with them in the traditional sense. As people engage in a wider variety of activities on the Internet, more implicit communications have been observed online. Since online users' objective is more geared to obtain and share content than to establish social ties, communities are built more centered on content and less on traditionally defined social exchanges. For example, YouTube and Flickr have much fewer messages than the videos and pictures uploaded and shared by members, and the few messages that exist are made about the content, not specifically around a user. Xia et al. (2007) define the new extended communication as *implicit* communication to capture the aggregate and indirect aspect of the interaction. In this paper, we focus on such communities where utilities are mainly derived from contents rather than direct or indirect interactions.

Like any other communities, the long-term sustainability and growth of an online sharing community is determined by its current users' voluntary decision to join, stay, and contribute. Without the voluntary user participation, the community has little value for existing users as well as outsiders who may consider joining. A number of studies have examined voluntary participation in online communities. Butler et al. (2001) noted the important role voluntary participation play even in commercially supported online communities. In all four types of behaviors that are essential for online communities to sustain – infrastructure administration, social management, external promotion, and active participation, the voluntary participation is found to be instrumental.

Given the importance of voluntary participation, especially voluntary content contribution, existing literature on virtual communities has focused on analyzing individual rationales to participate and contribute to online communities. Based on the classical economic theory, researchers suggest that individuals may contribute to maximize their direct payoff through messages exchange, files downloaded, and traffic redistribution (Asvanund et al. 2004; Krishnan et al. 2004), Other research reveals that individuals may join the community because of their own psychological and social characteristics, such as satisfying user needs (Raymond 2000; Lakhani and Wolf 2005), reciprocity (Kollock 1999), and altruism (Hars and Ou 2001).

Individuals' incentive to contribute to virtual communities is not only influenced by their intrinsic motivation but also by the network effect in the communities. Jones et al. (2004) studied the effect of individual messages and information overload in online forums on user interactions (replies) and propensity to stay. The results suggest that too much information in a community has a significant negative impact on individual participation and contribution. Butler (2001) examined the role of communication activity on membership size using data collected from Internet ListServs. He proposed a resource-based model that treats membership size and communication activity as resources and benefits of the community. The model also recognizes that the large number of participants and communication activities in the community may also incur costs to members. He found that as membership size grows, the community experiences a faster "churn" rate, i.e., the percentage of membership loss increases. The results suggested that while more community activities provide more value to members in general, the net benefit does not increase monotonically. He thus cautions researchers and developers of online social structures to be aware of the opposing forces and the endogenous nature of membership size and communication activity, as well as their interplay, and adjust their expectations of the growth of a community accordingly. While both Jones et al. (2004) and Butler (2001) infer the negative externalities from community member behavior, Asvanund et al. (2004) provides a direct measure of the cost of network size. They show that network congestion increases exponentially with network size thus limiting the benefit of a large peer-to-peer network.

These studies reveal that both positive and negative externalities exist in peer-to-peer networks and such network externalities influence member participation and contribution in the community. A natural question to ask is how the presence of such network externalities influences the formation and long-term equilibrium of the peer-to-peer network. The objective of this paper is to take a first step to answer this question.

To address this question, we consider the dynamics of the network. Network dynamics have long been recognized as an important factor that determine resource allocation and outcome of social and economic networks (Jackson and Watts 2002). Prior studies on network dynamics focus on traditional networks where resource in the network resides with individual members. In these networks, individuals develop relationship with each other to gain access to resources. Bala and Goyal (2000) show that the equilibrium network has simple architecture such as the wheel or star or generalization of the two shapes. Different from traditionally networks, content availability of online peer-to-peer communities does not depend on bilateral relationship between community members. Instead, resource provided by one member is available to everyone in the community. This paper offers a model to identify dynamics in these networks and using the model to identify the long-term equilibrium of the network.

We also note that extant studies in IS often treat online communities, especially the online sharing networks (e.g, peer-to-peer music sharing network) as one-side network. For example, Asvanund et al. (2004) examined the network externalities in peer-to-peer networks. They found both positive and negative externalities in the network in regard the overall network size, but did not distinguish the impact of different members in the network. Butler (2001) investigated the membership variation caused by the overall community activities. The study implicitly assumes homogeneity of members in a community who share information with each other. Recent studies (Asvanund et al. 2004; Adar and Huberman 2000) however have shown that a significant number of members in these communities are free-riders while others are dedicated contributors. This suggests members in online peer-to-peer sharing community are heterogeneous. Measuring their integrated impact therefore may not be able to reveal the true dynamics and evolution of the community. To fill this gap, in this study, we draw the inferences of two-sided networks in online sharing communities, which clearly defines two distinguished groups in the community and characterize their interactions and dynamics in the process of network development.

Two-sided markets (networks) have long been studied in economics literature. Two-sided markets, also called two-sided networks, are economic networks having two distinct user groups that provide each other network benefits. In fact, many if not most markets with network externalities are two-sides, such as software, portals and media, payment systems and the Internet (Rochet and Tirole 2003). As a burgeoning extension of network literature, many recent studies has focusing on theoretical development of identifying the optimal competitive strategy in the two-sided market (see Rochet and Tirole (2006) for a comprehensive survey of the literature). In particular, Parker and Alstyne (2005) considered two-sided network effects in information product design, which helps to explain many recent strategies taken by IT firms and the Internet businesses.

Despite the significant amount of study on theoretical model of two-sided network, empirical testing for two-sided networks is still in its fledging stage. Rysman (2004) estimated the importance of network effects for Yellow Page market. It is shown that network effects play an important role for both consumers and advertisers. In this paper, we aim to model and empirically test the online music sharing community as dynamic two-sided networks to advance our understanding of the formation and sustainability of such networks.

3. Peer-to-peer Communities and Network Effects

The continual growth of the Internet and telecommunication networks boosts up the recent development of peer-to-peer online sharing communities. As a relatively new phenomenon, online peer-to-peer sharing communities are characterized by their user-centered, content-based, quickly-expanded, and loosely-connected structure and development. The growth of online communities challenges the traditional economic notion of the individual as a payoff maximization agent interacting with the market with full information and complete rationality. Unlike a traditional marketplace where a few economic agents interact with each other, individuals in online sharing communities interact with thousands or tens of thousands of other members with limited information of counterparts. In addition, in a traditional marketplace, market condition can be summarized by market clearing prices, however little summary information is available in peer-to-peer communities. As such, individual's behavior and community development is influenced by his experience with the community without the benefit of observing the overall provision and consumption activities and the interactions among community members. These unique characteristics of online peer-to-peer sharing communities indicate that community members are reactive to exogenous changes but they are not strategic in foreseeing the future and they have little ability to influence the community. Nonnecke et al. (2006) suggest that individual behavior (in MSN communities) is temporary and usually adapts to exogenous and endogenous factors. In this scenario, the traditional game theory approach that focuses on equilibrium analysis has limited power to characterize the dynamics of individual strategies.

In this paper, we model the interactions between individuals in a peer-to-peer community as interaction between random individuals who can not choose their counterpart. The payoff for an individual in a given time period is determined by her strategy and the strategy of her counterpart, as in the traditional game theory framework. However, different from the traditional game theory with regard to its assumption of individual rationality, we do not assume individuals choose strategies based on perfectly rational expectation of the future. We assume individuals are myopic and their choices of strategy are influenced only by their payoffs in the most recent time period (Taylor and Jonker 1978). This process leads to popular dynamics and exit and entry of community members as individuals could have different experience in the same community. The lower requirement on rationality also suggests that individuals do not reach optimal strategy instantly. Rather, it is a gradual process played out over time.

3.1. Population dynamic and payoffs in online sharing communities

In online sharing communities, we assume an individual makes two separate decisions. First, she decides whether she would like to share music files with other users of the peer-to-peer network. Second, she decides whether she would like to download music files from the network. Individuals who decide to share music files are called sharers, while those who decide to download are called downloaders. We assume the two decisions are considered separately. That is, the sharing decision is only concerned about providing resources to others while the downloading decision is only concerned with obtaining resources from others. Different from Krishnan et al. (2005), our assumption implies that an individual's sharing decision does not influence her download speed and thus does not influence the utility of downloading. Our assumption reflects the nature of large-scale peer-to-peer community where each individual has little impact on the overall community. An individual can decide to both share and download music files, but the two decisions are assumed to be independent from each other. Given the independence assumption, the state of an online peer-to-peer sharing community can summarized by total number of individuals who share music and total number of individuals who download music. We denote sharer's subpopulation at time t as $x_S(t)$ and downloader's subpopulation as $x_F(t)$.

Both sharers and downloaders derive payoffs from the online peer-to-peer network. Sharers take joy in sharing his or her music collection with others. Such joy could come from community status, influence and self-perception. The payoff received by each sharer may vary. Sharers whose music files have been downloaded more frequently may receive a higher payoff than those whose files are downloaded less frequently. Similarly, downloaders receive payoff in obtaining music downloads. Those who have obtained more downloads receive higher payoff than others. To model the behavior of the population that consists of such heterogeneous individuals, we assume that the population is large and the interactions between individuals are random[4]. Given the assumption, the behavior of the population is contingent upon average payoffs of the two types of individuals. We denote sharers' average payoff at time t as $v_S(t)$ and downloaders' average payoff as $v_F(t)$. Sharer's average payoff is influenced by number of average downloads requested from each sharer, which is in turn determined by number of downloaders and sharers in the community. $v_S(t)$ can therefore be considered as a function of number of downloaders $x_F(t)$ and number of sharers $x_S(t)$ at time t Likewise, downloader's average payoff is influenced by number of downloads they obtain from sharers, which is in turn determined by the number of sharers in the community $x_S(t)$ and number of downloaders $x_F(t)$. The above discussion indicates that a peer-to-peer network is uniquely determined by its population state $(x_S(t), x_F(t))$. Given the population state, sharers and downloaders realize their

[4] This assumption fits well with peer-to-peer music sharing networks where downloaders and sharers are anonymous and have no social interaction except for music downloading. It however may not fit with other types of social networks where individuals may develop social ties that lead to repeated interaction with each other.

payoffs $v_S(t)$ and $v_F(t)$, which determine the change of subpopulations in the next period. This process creates a path of evolution.

3.2. *Population Dynamics*

Sharer and downloader subpopulations change through gaining new users and losing existing users (also called birth rate and death rate in popular dynamic literatures). Recent studies on virtual communities suggest user gain and user loss are determined by their payoffs (Butler 2001). This view is also consistent with findings from evolutionary game theory that, in large communities, payoff has a gradual impact on community popularity through gain and attrition of community members (Samuelson 1997). When payoff increases, the community gains more new users and loses less existing users. For tractability, we assume change is a linear function of the payoff. For example, when $x_S(t)$ sharers have $v_S(t)$ payoff in period t, we assume the change to sharer population $\frac{dx_S(t)}{dt}$ equals to $a_S x_S(t) + b_S x_F(t)$, where $a_S < 0$ represents the degree to which the change is influenced by number of sharers in the community. Increase in sharer population leads to more competition between sharers for the attention of downloaders, thus decreasing the payoff to sharers. a_S captures this negative externality among sharers. $b_S > 0$ represents the degree to which the change to sharer population is affected by number of downloaders in the community. Increase in number of downloaders leads to higher payoff to sharers and b_S captures the positive externality. We can further decompose the change in sharer population $dx_S(t)$ into gain of new sharers $dx_S^g(t)$ and loss of existing sharers $dx_S^l(t)$ where $dx_S(t) = dx_S^g(t) - dx_S^l(t)$. The decomposition provides more details of the dynamics how the sharer population in a peer-to-peer network evolves. We therefore propose

$$\frac{dx_S(t)}{dt} = a_S x_S(t) + b_S x_F(t) \tag{1}$$

$$\frac{dx_S^g(t)}{dt} = a_S^g x_S(t) + b_S^g x_F(t) \tag{1a}$$

$$\frac{dx_S^l(t)}{dt} = a_S^l x_S(t) + b_S^l x_F(t) \tag{1b}$$

Equations (1a) and (1b) indicate net change in sharer subpopulation is determined by gain in new sharers $a_S^g x_S(t) + b_S^g x_F(t)$ and the loss of existing sharers $a_S^l x_S(t) + b_S^l x_F(t)$. When the network offers higher payoff to sharers, the peer-to-peer network obtains a net gain of sharers. Otherwise, the network incurs a net loss of sharers.

We apply the same analysis to downloaders. We model the net change of downloaders $\frac{dx_F(t)}{dt}$ as a linear function of number of downloaders and number of sharers in the community: $b_F x_S(t) + a_F x_F(t)$ where $a_F < 0$ represents the negative externality due to competition among downloaders for the same resource in the sharing community and $b_F > 0$ captures the positive externality that more sharers lead to higher payoff for downloaders. Again, we have

$$\frac{dx_F(t)}{dt} = a_F x_F(t) + b_F x_S(t) \tag{2}$$

$$\frac{dx_F^g(t)}{dt} = a_F^g x_F(t) + b_F^g x_S(t) \tag{2a}$$

$$\frac{dx_F^l(t)}{dt} = a_F^l x_F(t) + b_F^l x_S(t) \tag{2b}$$

Differential equations in Equations (1) and (2) capture the complete dynamics for the growth or the decline of the peer-to-peer networks. The objective of this study is to derive the long-term equilibrium for the sharing community given the population dynamics and to empirically validate the dynamics using data collected from real life of peer-to-peer networks.

3.3. Long-term Equilibrium

Based on Equations (1) and (2), Sharer and downloader subpopulations change according to different payoffs they receive from the community. Because the numbers of sharers and downloaders are interdependent, the population dynamics lead to a unique equilibrium of the sharing community. The long-term equilibrium has two characteristics. We first show that the community has a constant sharer-to-downloader ratio in equilibrium:

Proposition 1 (equilibrium sharer ratio). $\frac{x_S(t)}{x_F(t)} = k^* = \frac{(a_S - a_F) + \sqrt{(a_S - a_F)^2 + 4b_S b_F}}{2b_F}$**.**

The ratio of downloaders and sharers will be fixed at k^* regardless of the size of the community.

When the population reaches the equilibrium ratio, downloaders and sharers have the same net growth rates and therefore the community maintains the same population ratio. Proposition 1 suggests that the ratio of sharers to downloaders is inherent determined by the dynamics of the community. Any exogenous addition or remove of community members has little long-term impact on the community. Rather, it is the negative and positive externalities between downloaders and sharers that determine the equilibrium population ratio. Figure 1 presents equilibrium sharer ratio as a function of various externality measures. Figure 1a shows that equilibrium sharer ratio decreases with the negative externality among sharers. This is because high negative externality among sharers suggests that sharers are sensitive to competition from other sharers, making it difficult for the community to keep sharers. Figure 1b shows that equilibrium sharer ratio increases with negative externality among downloaders, as the negative externality reduces number of downloaders in the community. Figure 1c and 1d consider the relationship between sharer ratio and positive externalities between sharers and downloaders. The figures reveal that sharer ratio increases with downloaders' positive externality to sharers as the positive externality increases incentive for sharers to join the community. At the same time, the sharer ratio decreases with sharers' positive externality to downloaders as the positive externality increases incentive for downloaders to join the community. The figures also reveal that despite the underlying linear model, the relationship between sharers and various externalities are not linear in nature.

The second important characteristic of the long-term equilibrium is the growth (decline) rate of the peer-to-peer sharing community. The growth rate can be derived from the population dynamics and the result of Proposition 1.

Proposition 2 (growth rate in equilibrium).

$\frac{dx_S(t)}{dt} = \frac{dx_F(t)}{dt} = \frac{(a_S + a_F) + \sqrt{(a_S - a_F)^2 + 4b_S b_F}}{2}$**. The peer-to-peer sharing community experiences positive growth if and only if** $b_S b_F > a_S a_F$ **, i.e., the positive externalities in the community overweighs the negative externalities in the community.**

This proposition clarifies how the positive externalities and negative externalities interact in influencing the growth and sustainability of the sharing community. It is well-known that network effect in a two-sided network requires positive externalities on both directions. However, little studies have been conducted with regard to how the presence of negative externalities influences network effect. This proposition provides two insights. First, it shows the exact trade-off between negative externalities and network effects. Second, the results reveal that negative externality limited to one side of the network has no impact on the growth of the network.

4. Empirical Analysis

4.1. Data Description

Music sharing is one of the first large-scale applications of online sharing. The wide availability of music files from music CDs and improvements in compression and digitization technologies, such as MP3, are now available to everyone, it is easy to produce digital copies and share with others. Each user makes individual decisions on when to join or leave a music sharing community and whether to contribute his resources to others. Therefore such a community acts as a network with a dynamic population. In this paper, we study music sharing communities in Internet Relay Chat (IRC) networks to test the two-sided dynamic network model.

IRC is originally designed for instant communication through a collection of topic-oriented chat rooms (called IRC channels). To participate in a channel, a user must first log in with a username – one can use any username as long as it does not conflict with the existing ones. Users often install scripts such as SDFind and OmenServe, which can turn individual personal computers into small file servers and share users' file collections through special channels (called serving channels). Each user can send to the central channel file search and download requests, which are then broadcast to all sharing users, and the script servers will automatically respond to the requester if they have matching files in their local collections.

The serving channels act as automatic peer-to-peer networks like Gnutella and OpenNap. As proposed by Asvanund et al. (2004), P2P network structures can be categorized along two axes: the degree of decentralization of content and that of the catalog. Both of the IRC file sharing channels' content and catalog are decentralized as files are indexed and stored by individual computers. The IRC servers only provide centralized message communication that broadcast requests to all users.

Compared to specialized file-sharing applications, such as Napster, Gnutella, and Kazaa, two unique characteristics make IRC a good representative of sharing communities. First, IRC channels have been very popular for keeping touch with friends and persons with similar interests for many years. Therefore IRC user names are relatively stable and represent real users behind. Second, unlike other P2P file sharing networks, users can also look at others' file collections and check file servers' status. These activities strengthen the community feel and make it possible for users to observe the overall status of the community.

We monitored the Mp3passion channel – a music sharing community in the IRC Undernet from March 2001 to May 2006 and recorded all user activities in the community. Figure 2 plots the biweekly (every two weeks) number of downloads during the data collection period. At its peak during the year 2003, more than 56,000 files were downloaded per day in this community, equivalent to 0.05% of the global music sharing volume (Wall Street Journal, 19 November 2003). Based on the IRC broadcasting messages, once a logged-in user turns on the sharing function, we can observe his file server status through automatic reports such as the total number of files provided, workload, and the bandwidth he allocated for sharing. We define a user as a sharer if we observed his server status at least once during a certain time period; and we define a user as a downloader if he required files from others during the time period. During the entire data collection period, the user size of the sharing channel was stable with around 3540 unique users per day. However, the number of sharers grew from 154 to more than 1,440 on a biweekly basis. More than 55,000 unique sharers were observed in total.

Our data provide detailed information on sharers and downloaders at different time periods. In addition, our data also capture changes in user types, sharing and downloading activities. The wealth of the dataset enables us to examine the evolution and dynamics of the community.

Our log data of user activities are aggregated on the daily basis. Tables 1 and 2 show the descriptions and the descriptive statistics for the key variables used in this paper. The summary statistics suggest that on average 3539 downloaders using the peer-to-peer network daily. The downloader population is overall stable as about the same number of downloaders exit from the network daily. We observe similar phenomenon for sharers with an average of 526 sharers use the peer-to-peer network daily. The overall sharer population is also stable with about equal number of sharers joining and exiting the network daily. Table 2 also shows that sharers account for about 13% of the total population with a standard deviation of 4%.

Based on the download requests and associated user IDs in the raw data, we can build a downloader list and count the number of unique individuals who download files in day t as *Downloader(t)*. Downloader gain (loss) was calculated by comparing each day's list to the previous day's to determine the net changes in number of downloaders. Similarly because each file server should announce its status regularly, we can compose a list of sharers and calculate *Sharer(t), SharerGain(t),* and *SharerLoss(t).*

4.2. Empirical Model

To test the two-sided dynamic network model, we convert Equations (1) and (2) to discrete time periods and incorporate noise terms that may influence population dynamics.

$$x_S(t+1) - x_S(t) = a_S x_S(t) + b_S x_F(t) + \varepsilon_t \quad (3a)$$

$$x_F(t+1) - x_F(t) = a_F x_F(t) + b_F x_S(t) + \varepsilon_t \quad (3b)$$

$$x_S^g(t+1) - x_S^g(t) = a_S^g x_S(t) + b_S^g x_F(t) + \varepsilon_t \quad (4a)$$

$$x_S^l(t+1) - x_S^l(t) = a_S^l x_S(t) + b_S^l x_F(t) + \varepsilon_t \quad (4b)$$

$$x_F^g(t+1) - x_F^g(t) = a_F^g x_F(t) + b_F^g x_S(t) + \varepsilon_t \quad (4c)$$

$$x_F^l(t+1) - x_F^l(t) = a_F^l x_F(t) + b_F^l x_S(t) + \varepsilon_t \quad (4d)$$

Equation (3) describes the dynamics with regard to net changes in the two sub-populations, while Equation (4) separate the dynamics for gain and loss of sharers and downloaders.

To test the model, it is necessary to introduce control variables that may influence gain and loss of network users. We consider the following two sets of control variables. First, IRC users have been decreasing over time due to the advent of new peer-to-peer sharing technologies. To control for the time trend, we include time variable in the regression model. Second, the gain and loss of users in the music sharing network are heavily influenced by the legal environment. To control for changes in the legal environments, we include four dummy variables to represent four key legal events in the music industry's pursue of piracy users (Bhattacharjee et al. 2006). The first event corresponds to RIAA's announcement of intention to pursue legal actions (June 26, 2003). The second event captures RIAA's lawsuits against alleged music file sharers (September 8, 2003). The third event marks court ruling against revealing identities of sharers (December 19, 2003). The forth event represents RIAA's use of John Doe lawsuits against piracy users (January 21, 2004). We also note that variance of population changes increases with population size. To control for the heteroscedicity, we normalize the models by population size. Our final estimation models are as follows:

$$\begin{cases} \dfrac{x_S(t+1)-x_S(t)}{x_S(t)} = \left(a_S + b_S \dfrac{x_F(t)}{x_S(t)}\right) + \beta_S t + \sum_{i=1}^{4} \gamma_{Si} Event_i + \varepsilon_t \\ \dfrac{x_F(t+1)-x_F(t)}{x_F(t)} = \left(a_F + b_F \dfrac{x_S(t)}{x_F(t)}\right) + \beta_F t + \sum_{i=1}^{4} \gamma_{Fi} Event_i + \varepsilon_t \end{cases} \tag{5}$$

and

$$\begin{cases} \dfrac{x_S^g(t+1)-x_S^g(t)}{x_S(t)} = \left(a_S^g + b_S^g \dfrac{x_F(t)}{x_S(t)}\right) + \beta_S^g t + \sum_{i=1}^{4} \gamma_{Si}^g Event_i + \varepsilon_t \\ \dfrac{x_S^l(t+1)-x_S^l(t)}{x_S(t)} = \left(a_S^l + b_S^l \dfrac{x_F(t)}{x_S(t)}\right) + \beta_S^l t + \sum_{i=1}^{4} \gamma_{Si}^l Event_i + \varepsilon_t \\ \dfrac{x_F^g(t+1)-x_F^g(t)}{x_F(t)} = \left(a_F^g + b_F^g \dfrac{x_S(t)}{x_F(t)}\right) + \beta_F^g t + \sum_{i=1}^{4} \gamma_{Fi}^g Event_i + \varepsilon_t \\ \dfrac{x_F^l(t+1)-x_F^l(t)}{x_F(t)} = \left(a_F^l + b_F^l \dfrac{x_S(t)}{x_F(t)}\right) + \beta_F^l t + \sum_{i=1}^{4} \gamma_{Fi}^l Event_i + \varepsilon_t \end{cases} \tag{6}$$

4.3. Results

Table 3 presents the estimation results. Column (1) and (2) shows the dynamics of net changes in sharers and downloader population. The corresponding equations are as follows[5].

$$\begin{cases} \dfrac{x_S(t+1)-x_S(t)}{x_S(t)} = \left(-0.073 + 0.004 \dfrac{x_F(t)}{x_S(t)}\right) + (4.80E-5)t \\ \dfrac{x_F(t+1)-x_F(t)}{x_F(t)} = \left(-0.068 + 1.211 \dfrac{x_S(t)}{x_F(t)}\right) + (-1.11E-4)t - 0.026 Event_1 \end{cases} \tag{7}$$

Results from Table 3 and Equation (7) verify the validity of the dynamic two-sided network model. They show that sharers' payoff increases with number of downloaders in the community but decrease with number of sharers. Likewise, downloaders' payoff increases with

[5] Insignificant coefficients are not reported

number of sharers but decreases with number of downloaders in the community. All the externalities between downloaders and sharers are of the correc\t sign. To find the equilibrium point for the peer-to-peer network, we use Proposition 1 and the coefficients from Table 3 to calculate the equilibrium share ratio. We find that in the beginning of the study period, the peer-to-peer network reaches an equilibrium sharer ratio at 9% at which point both downloader and sharer populations grow steadily at the same rate. We also find that the equilibrium is self-enforcing. When sharer's ratio falls below 9%, the growth rate of downloaders will fall below 9% while the growth rate of sharers will surpass 9%, which brings back the equilibrium. When sharer's ratio reaches above 9%, the growth rate of downloaders will go beyond 9% while the growth rate of sharers will fall below 9%, again bringing back the equilibrium. Figure 3 provides an illustration of the dynamic equilibrium of the sharing community. The solid straight line represents the equilibrium sharer ratio at 9%. The two dotted straight lines on the two sides represent the growth region bounded by sharer ratio at 7% and 11% respectively. When the network lies within Region III, the paths of population changes are featured by simultaneous increase in number of sharers and downloaders. However, when the network lie outside of Region III (Regions I and II), their paths of population changes are characterized by first a decrease in one of the subpopulations and then simultaneous increases in number of sharers and downloaders. In either case, the population is stable because any sharer ratio will converge to the equilibrium ratio eventually.

Our Results also reveal the mechanism that the peer-to-peer community evolves. We show that the growth of the network is driven by the complementary between downloaders and sharers but limited by negative externalities among downloaders and sharers respectively. Proposition 2 provides a way to calculate the growth rate of the community from the population dynamics. The calculation reveals that the equilibrium growth at the beginning of the study period is about 0.6%.

We also find that out of the four legal events identified by Bhattacharjee (2006), only the first event – "announcement of intention to pursue legal actions" has a significant impact on downloaders. After the announcement, we observe a significant drop in net changes in number of downloaders, but no significant impact on sharers. To measure the impact of the announcement on the long-term equilibrium of the network, we recalculate the equilibrium share ratio and growth rate. The calculation reveals that the announcement increase sharer ratio from 9% to 11%, due to difficulty in attracting downloaders. More importantly, the growth rate has turned from a positive 0.6% to a negative -0.6%. The dramatic change in the community growth rate arises because the announcement amplified the network externalities in the sharing community and the accumulation of the network externalities surpassed the positive externalities in the network. This leads the decline of the peer-to-peer sharing community as we witness in Figure 2.

5. Concluding Remarks

The blossom of online communities has intrigued both academic researchers and popular press. Understanding the dynamics and the sustainability of such communities has important implications in investigating their influences on e-commerce as well as contributing to the current online communities and online social network literature. In this paper, we model online sharing communities as a two-sided network from a dynamic perspective. More importantly, we take the first step to use a structural model to identify dynamics of the online sharing community and derive its equilibrium state of the community using data collected from the IRC music sharing network. Our model also suggests that the two major members (downloaders and sharers) in the community both play an essential role in the community. In contrast to the traditional view that downloaders only consume resources in the community, we propose that sharers derive utility from the presence of downloaders. Our results verify the proposition and suggest that a two-sided network model fits well with the dynamics of online peer-to-peer sharing community. An important contribution of the dynamic model is to separate population dynamics which we directly observe from the data from the long-term equilibrium which is implied but not observable from the data. We show that the growth of an online sharing community depends on the trade-off between positive network externalities and negative externalities rather than absolute number of sharers or downloaders or the ratio between the two population. When positive network externalities overweigh negative externalities, the community grows at a constant pace. Otherwise, the community declines at a constant rate. It is therefore important to understand how external events influence externalities within a peer-to-peer sharing community. Our results also reveal that downloaders are much more sensitive to changes than sharers. As a result, downloaders act as a resistance or stabilizer of a community. Our model and empirical results show strong support for the dynamic process of the community. In addition, our results indicate that users in the music sharing community take a long time to converge to market equilibrium and the market equilibrium is dynamic with constant growth or decline.

This paper takes a new perspective and makes unique contributions in characterizing the dynamic evolvement of online peer-to-peer sharing network. First, we make the first attempts, to our knowledge, to characterize online music peer-to-peer sharing networks as two-sided markets. We identify two distinctive groups, namely, sharers and downloaders, in the community, and model and empirically test the interactions and impacts of those two groups in the process of community evolvement. We find network externalities on both sides, validating our construction of the two-sided markets. Second, we take a dynamic approach in modeling and empirically testing the evolution of the community, which has not been adequately considered in extant research. Facilitated by the long-term and large-scale data collection, the dynamic features of our test offer a comprehensive demonstration and characterization of the community development. More important, we show that a long-term equilibrium can be derived from short-term dynamics of a network. Through the model and the empirical analysis, we provide a better understanding of the dynamics and sustainability of online sharing community.

Our results also add new insights for practitioners of designing, understanding, and managing online communities and sharing networks. Conventional measurement of online communities hinges on calculating the total member sizes. Our results, however, suggest that the sizes of different member groups may have different impact at various time periods of community evolvement. In contrast to the traditional negative view of freeriders for merely consuming resources and generating network congestion, our results demonstrate that pure downloaders in the community could help the community expand in the early stage and help stabilize the community in the long run.

This paper has a number of limitations. First, we use a relatively simple dynamic model to characterize the relationship between downloaders and sharers due to technical difficulties in solving higher-order differential equations. Our model assumes that the network externalities are linear functions of the size of subpopulations. In reality, the relationship could be curved as positive externality may diminish with network size while negative externality may increase with network size. An advanced dynamic model that captures the curvature would be helpful in providing more insights into the dynamic relationship between sharers and downloaders.

Second, our model is of reduced form that relates population changes at the aggregate level with population status in the network. An alternative approach is to aggregate population changes from individual decisions, which provides a better estimation of the dynamics. This approach, however, requires more information about individual needs and their environment that our data are able to provide. A more detailed data collection and analysis at the individual level will shed more lights into the dynamic interaction with the sharing network. Finally, while our paper shows the presence of negative and positive externalities within the sharing networks, we do not have information to explain the cause of such externalities. For example, we do not know whether sharers obtain higher utility from more downloaders due to altruism, reputation or other factors. Further research could help quantify the cause of externalities and their magnitude.

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Appendix

Proof of Proposition 1

Equations (1) and (2) is a system of first order, linear differential equation:

$$\frac{dx_S(t)}{dt} = a_S x_S(t) + b_S x_F(t) \tag{A1}$$

$$\frac{dx_F(t)}{dt} = a_F x_F(t) + b_F x_S(t) \tag{A2}$$

Let

$$x_S(t) = c_S e^{rt} \text{ and } x_F(t) = c_F e^{rt} \tag{A3}$$

So

$$rc_S e^{rt} = a_S c_S e^{rt} + b_S c_F e^{rt} \tag{A4}$$

$$rc_F e^{rt} = b_F c_S e^{rt} + a_F c_F e^{rt} \tag{A5}$$

The solution to the above equation corresponds to the positive eigenvector:

$$\frac{x_S(t)}{x_F(t)} = k^* = \frac{(a_S - a_F) + \sqrt{(a_S - a_F)^2 + 4b_S b_F}}{2b_F} \tag{A6}$$

Proof of Proposition 2

Given A6 and the population dynamics (A1 and A2), we have

$$\begin{aligned} &x_S(t) = k^* e^{(b_F k^* + a_F)t} \\ &and \\ &x_F(t) = e^{(b_F k^* + a_F)t} \end{aligned} \tag{A7}$$

The growth rate is therefore

$$\frac{d(x_S(t))}{dt} = b_F k^* + a_F = \frac{(a_S + a_F) + \sqrt{(a_S - a_F)^2 + 4b_S b_F}}{2}. \tag{A8}$$

Note that the direction of the growth is determined by the sign of $(a_S + a_F) + \sqrt{(a_S - a_F)^2 + 4b_S b_F}$. Since a_F and a_S are negative externalities among sharers and downloaders respectively, they are negative. To identify the condition for positive growth, we must have:

$$\sqrt{(a_S - a_F)^2 + 4b_S b_F} > -(a_S + a_F) \tag{A9}$$

Simple algebra reveals that A9 is true if and only if

$$b_S b_F > a_S a_F \tag{A10}$$

Table 1. Variable Description

Variable	**Description**
Downloader(t)	The number of users who only download music at day t
DownloaderGain(t)	The number of new downloaders observed at day t
DownloaderLoss(t)	The number of downloaders disappeared at day t
Sharer(t)	The number of users who share music at day t
SharerGain(t)	The number of new sharers observed at day t
Sharer Loss(t)	The number of sharers disappeared at day t
SharerRatio(t)	Proportion of sharers in the population at day *t*

Table 2. Summary Statistics of Daily Data

Variable	*N*	*Mean*	*Median*	*SD*	*Min*	*Max*
Downloader(t)	1001	3539.64	3580	355.92	1386	5164
DownloaderGain(t)	1001	2399.93	2410	266.90	835	3841
DownloaderLoss(t)	1001	2402.47	2422	261.27	959	3866
Sharer(t)	1001	526.30	548	174.10	154	1440
SharerGain(t)	1001	203.79	197	110.94	41	1025
Sharer Loss(t)	1001	203.87	195	112.44	35	1047
SharerRatio(t)	1001	0.13	0.14	0.04	0.04	0.31

Table 3. Direct Estimation Results

Variable	Equation (7)		Equation (8)			
	Downloader Change	Sharer Change	Downloader Gain Rate	Downloader Loss Rate	Sharer Gain Rate	Sharer Loss Rate
Constant	-0.07*** (0.01)	-0.07*** (0.02)	14.09*** (0.15)	14.59*** (0.12)	0.32*** (0.02)	0.43*** (0.01)
Sharer/ Downloader	1.21*** (0.06)		-66.02** (2.11)	-74.32*** (1.61)		
Downloader/ Sharer		0.005*** (0.06)			0.002** (0.00)	-0.004*** (0.01)
News1	-0.03** (0.01)	0.00 (0.01)	0.71*** (0.15)	0.87*** (0.12)	0.03*** (0.01)	0.02*** (0.01)
News2	-0.02 (0.01)	0.01 (0.01)	1.26*** (0.15)	1.39*** (0.12)	0.06*** (0.01)	0.06*** (0.01)
News3	-0.03 (0.02)	-0.00 (0.02)	1.67*** (0.22)	1.86*** (0.17)	0.04*** (0.01)	0.04*** (0.01)
News4	0.00 (0.01)	-0.02 (0.01)	1.03*** (0.16)	1.00*** (0.12)	0.02** (0.00)	0.04*** (0.01)
Time	-1.1E-4*** (0.2E-4)	4.8E-5*** (1.8E-5)	-2E-5*** (0.00)	7.0E-4** (0.00)	-2.3E-6*** (0.00)	-7.0E-5*** (0.00)

*Note: *** p<.01 ** p<.05 * p<.10*

Figure 1a: Sharer Ratio as a Function of Negative Externality among Sharers

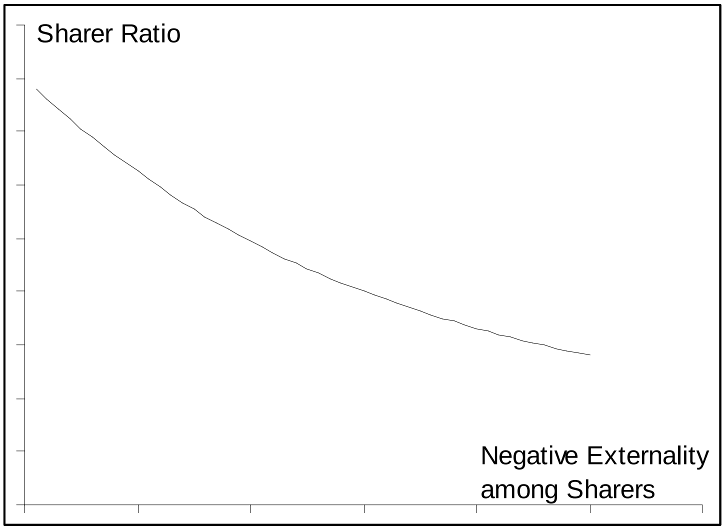

Figure 1b: Sharer Ratio as a Function of Negative Externality among Downloaders

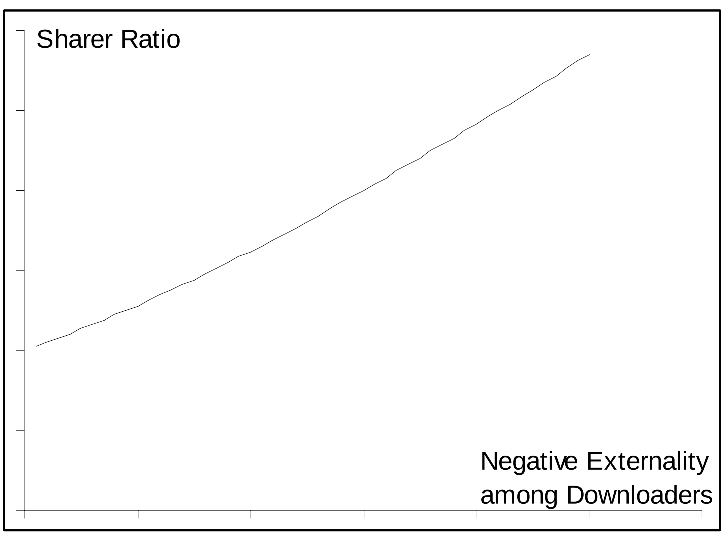

Figure 1c: Sharer Ratio as a Function of Downloaders' Positive Externality on Sharers

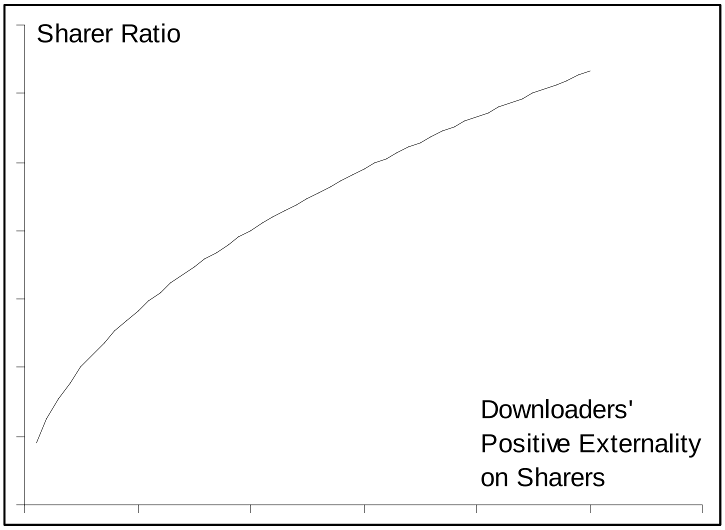

Figure 1d: Sharer Ratio as a Function of Sharers' Positive Externality on Downloaders

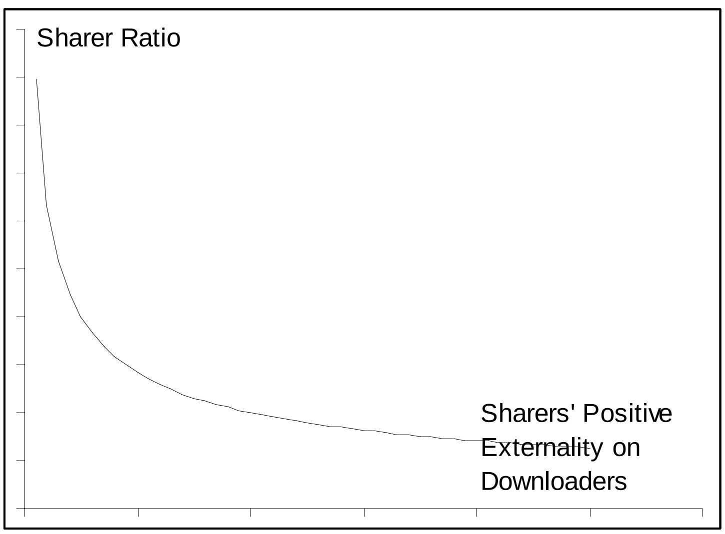

Figure 2: Plot of Number of Downloads (biweekly)

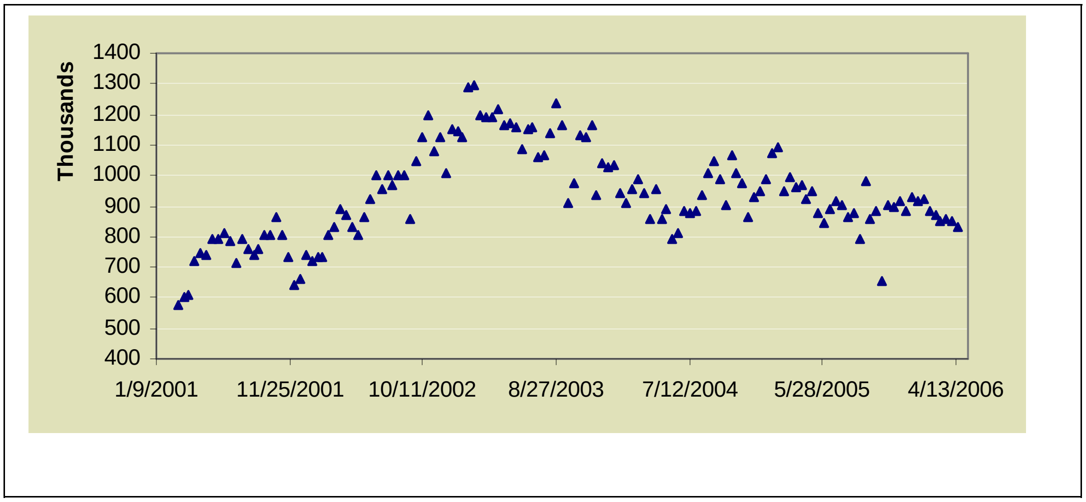

Figure 3. Sharer Ratios and the Paths of Population Changes