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Content Contribution under Revenue Sharing and Reputation Concern in Social Media: The Case of YouTube

Completed Research Paper

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Abstract

A key feature of social media is that it allows individuals and businesses to contribute contents for public viewing. However, little is known about how content providers derive payoffs from such activities. In this study, we build a dynamic structural model to recover the utility function for content providers. Our model distinguishes short-term payoffs based on ad revenue sharing from long-term payoffs driven by content providers' reputation. The model was estimated using a panel data of 914 top 1000 providers and 381 randomly selected providers on YouTube from Jun 7th, 2010, to Aug 7th, 2011. The two different sets of providers allow us to explore the difference between top and ordinary providers. Our results demonstrate that both providers value incremental subscribers as much as incremental video views. We also find that top providers value accumulative subscribers more than accumulative video views, while ordinary providers value accumulative video views more.

Keywords: Social media, YouTube, revenue sharing, reputation, dynamic model

Introduction

“We are going to be the first company to put out a product with a sticker that says, ‘As Seen on YouTube,’” said Davis, Chief Executive of Orabrush Inc. (Timothy Hay, 2011)

Anyone who doubts the power of social media platforms or who disputes their ability to turn traditional industries like advertising on their heads should consider the case of Orabrush Inc., a small company that just closed a new funding round of \$2.5 million. The company’s major advertising strategy is through its YouTube channel, which has pulled in more than \$1 million in revenue over the last year on the strength of 30 or so videos ranging from the informational to the silly. This is only one of the many examples that social media platforms can empower businesses or individuals to build a brand, promote products/services, and obtain consumer feedbacks.

As social media, which combines user-generated contents and social networking features, has become a major source of information dissemination and social sharing, the online video market has attracted enormous attention from content providers, content consumers, and advertisers. According to statistics from comScore, during the 12-month period from December 2009 to December 2010, the average daily viewers of web videos grew from 67.3 million to 88.6 million; the average number of videos watched per viewer grew from 187 to 201; the average time viewers spent watching online videos grew from 12.7 hours to 14.2 hours. During the month of February 2011, 170 million US Internet users engaged in more than 5.0 billion video viewing sessions. Among all the video sharing sites, YouTube by far outweighs all other sites in terms of the total number of videos viewed, the number of viewers, and the number of videos each viewer viewed. In the online video market, YouTube has a market share of around 40%, followed by Hulu with only 3%. 24 hours of videos are uploaded to YouTube every minute. The total video views for YouTube is over 2 billion a day, 70% of which come from outside of the United States.

What YouTube offers is more than just video sharing. Through social broadcasting, YouTube opens up innovative ways of sharing information, exhibiting talent, and building careers. It provides a platform for talents. In fact, many contemporary celebrities came from YouTube videos. Justin Bieber, a popular singer among teenagers, was discovered by his manager through his early YouTube videos. Other examples include Arnel Pineda, Esmee Denters, Terra Naomi, Lisa Lavie, and Mia Rose. Besides offering a new venue for the discovery of stars, YouTube also revolutionizes the traditional labor markets. Since video is a visualization tool, people who are looking for a job can demonstrate to potential employers their abilities, skills, and expertise. We found makeup artists making various makeup tutorial videos on YouTube. Michelle Phan is a well-known successful example for this regard. She started her video channel on YouTube in 2008 when she was still a college student. Within 3 years, she produced over 100 videos on makeup, style, and skincare, and received more than 300 million video views and 1 million subscribers in total. Because of the creative makeup and styling skills she showed in her videos and her popularity among YouTube users, Lancôme Cosmetics Company offered her the position of official video makeup artist. Her popularity on YouTube also allowed her to start her own skincare and makeup brand, iQQU. YouTube is popular not only among artists, designers, and performers that require video demonstrations, but also among professionals that are not traditionally associated with visual demonstrations. For example, we found videos from surgeons on cutting edge surgeries they performed. Video resume is also becoming increasingly popular among job seekers. Graeme Anthony took video resume to a whole new level by creating a CVIV (interactive video CV), a video resume that consists of several linked videos. This CVIV resulted in great attention and eventually landed him a job in public relations. Similarly, companies that are looking for job candidates can also post video announcements on YouTube.

Being a popular video provider on YouTube could mean substantial monetary income. After acquiring YouTube for a price of \$1.65 billion in October 2006, Google has been searching for ways to encourage providers to improve video quality and to monetize video views. In December 2007, YouTube launched YouTube partner program. Qualified video providers can apply to be a YouTube partner, and as a partner, providers can receive a portion of advertisement revenue generated by their videos from Google. According to estimates by myu2b.com, the most popular partner can make over \$3,000 a day. Michelle Phan, the makeup artist we introduced above, can make over \$500 a day. However, YouTube has strict requirements for a provider to become a partner with respect to video views, channel subscribers, video posting frequencies, etc. Therefore, it was difficult for most providers to obtain a share of advertising

revenue. In August 2009, YouTube announced individual video partnership program. While the full partnership has requirements for a provider's entire video production, the individual partnership only focuses on individual videos. It enables providers, including both partners and non-partners, to profit from specific videos. As long as the video itself is popular enough, YouTube would invite the provider to participate in ad revenue sharing for the video even if the provider is not a partner. Besides ad revenue sharing, YouTube has launched other grant programs to further encourage providers' video production.

With the ad revenue, grant, and career opportunities, making videos on YouTube is no longer simply for fun. Providers are strategic in their decision making process. They not only post videos, but also take the initiative to promote their videos and channels, connect with audience, and their feedback. Understanding their behavior can provide important implications for YouTube, other online communities, and advertisers. It is important for YouTube to create for providers incentive mechanisms that are in alignment with YouTube and its advertiser's interests. While providers benefit from YouTube's vast platform and various opportunities, YouTube relies on providers' improved video productions to compete with rivals, among which Hulu is the primary concern. While YouTube focuses on individual created video content, Hulu focuses exclusively on professional videos such as TV series and movies. It is thus easier for advertisers on Hulu to target potential consumers. Although YouTube has far more videos and viewers than Hulu, it is at a significant disadvantage with respect to advertising. According to comScore, in July 2010, Hulu had 783.3 million video ads and on average 27.9 ads were viewed by each viewer, while YouTube only had 219.3 million ads and 4.6 ads were viewed by each YouTube viewer. Under revenue sharing, providers not only care about the popularity of their videos, but also the interest for potential advertisers. Understanding how providers value their short term revenue and long term reputation would help Google improve their incentive mechanism design.

A key contribution of this study is that we distinguish providers' explicit benefits brought by advertising revenue from their implicit reputation. We use a dynamic model to capture the provider's decision on video postings over time. In each period, the provider has the option to post a video or not. When making this decision, the provider is forward looking, considering both current period utility and discounted utilities in all the future periods. Our empirical approach is based on the principle of revealed preference (Samuelson, 1938) - agents maximize expected payoffs and their actions reveal information on the structure of their value functions. This concept allows us to use data on agents' decisions to recover structural parameters for which there is very limited information from other sources (Aguirregabiria and Magesan, 2010). Since only YouTube partners can share advertising revenue with YouTube, the incentive schemes on partners and non-partners should be quite different from each other. To test the difference, we collected data on top providers and random selected providers. While most of the former are YouTube partners, most of the latter are not.

This paper is the first to study voluntary individual video contribution using a dynamic structural model. The goal of this paper is to model the strategic decisions by individual contributors and quantify providers' utility function under the incentives of revenue sharing and reputation concern. The components of reputation and their relative weights are also explored. The analysis allows social network operators to develop an in-depth understanding of content providers' value proposition and behavior. In particular, the dynamic structural model allows social network operators to conduct counterfactual analysis and identify optimal strategies to engage content providers. Our findings also provide a better understanding of contributors' behavior in other online communities such as the open source community, which are analogous to the online video community.

Research Context

The relationship between YouTube and video providers can be viewed as a principal-agency problem. YouTube provides a platform for video providers to post videos. As the principal, YouTube relies on individual providers, which are the agents, to deliver videos that can attract viewers and advertisers. The quantity and quality of videos determine advertisement revenue YouTube can receive from advertisers. There is no enforceable contract between YouTube and each video provider. Video production and posting is up to each provider. So there exists significant uncertainty in video production and thus the ad revenue. As in a typical principal-agency setting, YouTube does not observe providers' talents and efforts. However, the results are perfectly observable to YouTube based on how much advertisers would pay for an advertisement. Atkinson et al. (1988) have shown that revenue sharing is a potentially powerful incentive

scheme in such settings because it encourages an optimal distribution of resources among agents. In the YouTube case, revenue sharing encourages both providers to produce quality videos and YouTube to improve platform service. Although providers produce and post videos on YouTube for free, they depend on YouTube's powerful platform to distribute their contents and generate revenue from advertisement.

On the other hand, although YouTube gets videos from providers and distributes videos to viewers for free, they have little control over video production and quality (except for those with copyright issues). YouTube charges advertisers for ad exposure based on video views, and shares revenue with the providers of those videos. There are private, monetary and nonmonetary costs on both the provider's and YouTube's sides. Analogously, there are private, monetary and nonmonetary benefits for both sides as well. For providers, private benefits include the enjoyment of sharing videos, the prestige of showing off talents or skills, product and brand exposure, and potential jobs offers. For YouTube, popular videos attract more viewers, providers and advertisers. Atkinson et. al (1988) suggest that the effectiveness of revenue sharing mechanism is mitigated by agents who enjoy private, nonmonetary benefits that are not shared. In this paper, we focus on how the revenue sharing and private benefits would influence providers' behavior. Our approach is to model and identify the underlying utility function of providers, which is critical to the establishment of an optimal incentive scheme in a principal-agent problem.

For providers who develop original videos online, building an audience is important since providers get attention and exposure from video views. However, building a loyal audience is more important because loyalty ensures sustainable attention and exposure in the long run. YouTube offers each provider a subscription-based channel. Viewers who are interested in current and future videos from a provider can subscribe to the provider's YouTube channel so that they will be notified immediately every time her new video comes out. Views and subscribers have become the two major measures for a provider's success on YouTube. Besides monetary income from advertising revenue, providers also earn their reputations, which may lead to other benefits from YouTube or other companies such as investments, sponsorships, or job offers.

Related Literature

Our research is inspired by findings in existing literature on revenue sharing. Atkinson et. al (1988) study the use of revenue sharing as an incentive mechanism in a professional sports league to encourage the desired behavior of teams in the league. They find revenue sharing to be a powerful incentive scheme by internalizing externalities that arise across the team owners. Their results based on National Football League also indicate that the effectiveness of revenue sharing is mitigated by agents who enjoy private, nonmonetary benefits that are not shared. Black and Lynch (2004) use a sample of U.S. businesses surveyed in 1993 and 1996 to examine the relationship between workplace innovations and business performance. They also consider the influence of incentive schemes and find that introducing profit sharing is associated with increased productivity. Arthur and Jelf (1999) look at the long-term impact of gainsharing on workplace union-management relations. They find that the introduction of a Scanlon-type gainsharing plan was followed by a gradual and permanent decline in grievance rates and employee absenteeism, which are two key indicators of workplace union-management relations.

Cachon and Lariviere (2005) suggest that revenue-sharing contracts are very effective in a wide range of supply chain settings and especially for the video rental industry. Blockbuster was a well-known example for successfully implementing rental revenue with movie studios. It increased the availability of hit videos, making customers happy and boosting both its own profits and those of suppliers (Cachon and Lariviere 2001). Dana and Spier (2001) study the revenue sharing and vertical control in the video rental industry and show that revenue sharing is valuable in vertically separated industries in which demand is either stochastic or variable. Mortimer (2008) uses a structural econometric model of firms' behavior to describe the nature of firms' contract choices. Estimates from his study indicate that both upstream and downstream profits increase by 10 percent under the revenue-sharing contract for popular titles and even more for less popular titles. Our paper studies a special case of revenue sharing where the suppliers provide videos to the distributor for free and participate in the revenue sharing according to a scheme set by the distributor.

Our paper also adds to the growing literature on reputation. In Electronic Commerce, most studies consider online reputation systems as a technology for building trust in electronic markets (Dellarocas

2003) and examine the impact of reputation on sales and pricing. Ghose et al. (2009) studies how different dimensions of a seller's reputation affect pricing power in electronic markets through the interplay between buyers' trust and seller's pricing power. The reputation profile consists of three dimensions: the number of transactions, the summary of ratings, and the textual feedback. Their results suggest that different dimensions affect pricing power differentially. While most studies examine the reputation effect, only a few look at the reputation building process. However, all believe that reputation is built upon the observable outcomes of past work. Andersson (2002) suggests that a reputation for producing high quality of an old good may be necessary to introduce and maintain the production of a new good. Weigelt and Camerer (1988) believe that a firm's reputation summarizes its past strategic actions, and enables other market participants to assess its strategic type.

Reputation is also one of the most important individual motivations for knowledge contribution (Wasko and Faraj, 2005). According to social exchange theory (Blau 1964), individuals engage in social interactions based on an expectation that it will lead to social rewards such as approval, status, and respect. Many individuals contribute to social media because they expect their active participation leads to enhanced reputation (Jones et al. 1997, Donath 1999, Constant et al. 1996). Stewart (2005) shows that an individual's online reputation also extends to his/her profession life.

In Economics, research on reputation studies the impact of reputation consideration on an agent's behavior under the incentive of career concern. Holmstrom (1999) discusses a reputation model with career concern assuming that wages are a function of an employee's innate ability for a task. Employers cannot directly observe an employee's ability. Instead, they can access the agent's past task outputs, which depend on ability and labor (Dellarocas 2003). The agent thus has the incentive to work hard to improve today's performance in order to influence the employers' perception of her ability and thus wage level in the future (Holmstrom 1999). Koch et al. (2009) confirm that career concerns are effective in providing effort incentives. It has long been noticed that there is a widening inequality in social and labor market outcomes by skills (Blau 1998). Oftentimes, skills are difficult to observe or measure directly. YouTube makes it easier with the format of video and the environment of social broadcasting, which result in each provider's reputation for his/her skills. Our study considers different dimensions of reputation and their relative importance for providers.

There are a few emerging studies in IS using dynamic structural model to analyze individual contribution in social media. Huang et al. (2010) use a dynamic structural framework to analyze blog creation and consumption by employees within a company. Ghose and Han (2009) use a dynamic structural model to study user learning in mobile media content. These papers introduced dynamic structural modeling method into IS area and explored its use in the study of social media content. Building on these papers, our paper considers the influence of potential monetary payoffs associated with individual video contribution in social media.

Model

Per Period Utility Function

Per period utility is influenced by incremental views and incremental subscribers. YouTube partners are paid according to page impressions and total page effective cost per mille (eCPM). A page impression is generated every time a user views a page displaying Google ads. Earnings are determined by page impressions multiplied by eCPM/1000. Page impression is generally measured by views, and eCPM is based on advertisers' bids. It seems that for short time benefits, providers as well as YouTube only care about video views. However, building following is the key to sustained engagement in the long run, so subscriber number is also important. Moreover, eCPM is potentially affected by the number of subscribers if the advertisers consider both the current popularity and sustainability in the future. Therefore, subscription length may have an impact on short term advertising revenue by influencing advertisers' bidding on eCPM as well as affect the provider's reputation.

Per period utility is also influenced by the provider's reputation. We have already mentioned that besides, advertising revenue, providers have abundant opportunities such as investments, grants, sponsorship, and job offers. All these benefits are based on the provider's reputation. In social media, reputation has two aspects. One is popularity, which can be measured by accumulative video views. The other is quality,

which can be approximated by accumulative subscribers. Therefore, we use a linear combination of accumulative video views and subscribers to measure reputation. Although the linear combination is a simplification of reputation measure, we can still derive implications on the relative importance of views and subscribers for a provider's reputation.

However, it is almost impossible to get data on providers' shared advertising revenue or explicit reputation. Under such circumstance, reduced form models cannot be used to derive providers' valuation of views, subscribers, current period revenue, and long term reputation based on objective data observed on YouTube. Therefore, we resort to structural modeling to solve the problem. In this paper, we use a dynamic structural model to capture a video provider's video posting decision. A dynamic model is employed because providers' behavior in current period would impact their states in future periods and thus their utility in the future. We start with the provider's discrete choice in every period. Time is discrete with $t = 1, 2, \dots, \infty$. There are I individual providers indexed by $i = 1, 2, \dots, I$. Every period, providers decide whether to post new videos or not, which is a binary choice. Let a_{it} denote provider i 's action at time t . So we have

$$a_{it} = \begin{cases} 1, & \text{post a video on day } t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

A provider receives per period utility, denoted by U_{it} , from incremental views and subscribers on day t , and current reputation reflected in accumulative views and subscribers. She/he also incurs a cost of posting a video if she/he chooses to take action $a_{it} = 1$. We allow for heterogeneity across providers in their costs for video posting and an additive random component in the utility function. Therefore, we make the following parametric assumptions on the per period utility function:

$$U_{it}(\Delta View_{it}, \Delta Sub_{it}, a_{it}) = \alpha_1 \Delta View_{it} + \alpha_2 \Delta Sub_{it} + \alpha_3 Rep_{it} - \alpha_4 a_{it} + k_i a_{it} + \varepsilon_{it}(a_{it}) \quad (2)$$

where $\Delta View_{it}$ is the number of new views provider i receives on day t , ΔSub_{it} is the number of new subscribers provider i receives on day t , so we have

$$\Delta View_{it} = View_{it} - View_{it-1}, \text{ and } \Delta Sub_{it} = Sub_{it} - Sub_{it-1} \quad (3)$$

Rep_{it} is the reputation of provider i at the beginning of day t (i.e. by the end of day $t - 1$), which is latent but determined by both accumulative views and accumulative subscribers. α_4 is the cost of posting a video, and $\varepsilon_{it}(a_{it})$ is the action dependent random shock that can take on the value of $\varepsilon_{it}(0)$ and $\varepsilon_{it}(1)$. k_i measures the heterogeneity among video providers such as different intrinsic benefits or costs (Wasko and Faraj 2005). We assume that $\varepsilon_{it}(0)$ and $\varepsilon_{it}(1)$ are type I extreme values that are *i. i. d.* across i and t , and $k_i \sim N(0, \sigma_k^2)$. So σ_k^2 measures the degree of heterogeneity of posting videos among video providers.

Using this functional form for utility, we assume that the utility the provider receives from videos is linear in incremental video views, incremental subscribers, reputation status, the average cost of posting a new video, the heterogeneous cost, and the choice dependent random shock that is only observable to the provider. Both k_i and $\varepsilon_{it}(a_{it})$ are unobservable to researchers.

Since we do not observe the true reputation Rep_{it} , we assume that reputation is determined by accumulative views and subscriptions:

$$Rep_{it} = \delta_1 View_{it} + \delta_2 Sub_{it} \quad (4)$$

where δ_1 and δ_2 measure the relative importance of views and subscribers in the reputation component.

Substituting (4) into (2), we obtain

$$\begin{aligned} U_{it}(\Delta View_{it}, \Delta Sub_{it}, View_{it}, Sub_{it}, a_{it}, \varepsilon_{it}) \\ = \alpha_1 \Delta View_{it} + \alpha_2 \Delta Sub_{it} + \alpha_3 \delta_1 View_{it} + \alpha_3 \delta_2 Sub_{it} - \alpha_4 a_{it} + k_i a_{it} + \varepsilon_{it}(a_{it}) \end{aligned} \quad (5)$$

Let $\omega_1 = \alpha_3 \delta_1$ and $\omega_2 = \alpha_3 \delta_2$, we have

$$\begin{aligned} U_{it}(\Delta View_{it}, \Delta Sub_{it}, View_{it}, Sub_{it}, a_{it}, \varepsilon_{it}) \\ = \alpha_1 \Delta View_{it} + \alpha_2 \Delta Sub_{it} + \omega_1 View_{it} + \omega_2 Sub_{it} - \alpha_4 a_{it} + k_i a_{it} + \varepsilon_{it}(a_{it}) \end{aligned} \quad (6)$$

We can distinguish the deterministic part from the stochastic part and write U_{it} as

$$U_{it}(\Delta View_{it}, \Delta Sub_{it}, View_{it}, Sub_{it}, a_{it}, \varepsilon_{it}) = u_{it}(\Delta View_{it}, \Delta Sub_{it}, View_{it}, Sub_{it}, a_{it}) + \varepsilon_{it}(a_{it}) \quad (7)$$

State Variables

According to Equation (7), the state variable S_{it} in our problem is a vector including $\Delta View_{it}$, ΔSub_{it} , $View_{it}$, and Sub_{it} .

$$S_{it} = (\Delta View_{it}, \Delta Sub_{it}, View_{it}, Sub_{it}) \quad (8)$$

The transition process on other state variables is modeled as

$$\begin{aligned} \Delta View_{it+1} &= \lambda_0 + \lambda_1 View_{it} + \lambda_2 View_{it}^2 + \lambda_3 Sub_{it} + \lambda_4 a_{it} Sub_{it} + \lambda_5 \Delta View_{it} + \xi_{it} \\ \Delta Sub_{it+1} &= \gamma_0 + \gamma_1 Sub_{it} + \gamma_2 Sub_{it}^2 + \gamma_3 \Delta View_{it+1} + \gamma_4 (\Delta View_{it+1})^2 + \zeta_{it} \\ View_{it+1} &= \Delta View_{it+1} + View_{it} \\ Sub_{it+1} &= \Delta Sub_{it+1} + Sub_{it} \end{aligned} \quad (9)$$

In order to focus on pure strategy Markov perfect equilibrium, where each provider's behavior depends only on the current state and current private shock, we model the updates for daily video views and subscribers based on diffusion model (Bass 1969). The diffusion processes of views and subscribers are interrelated in that new views are brought in by existing subscribers or the herding effect based on subscription length, and new subscribers are converted from new viewers. Therefore, newly increased views in next period $\Delta View_{it+1}$ is assumed to be determined by accumulative views and subscribers, the interaction between video posting behavior and subscribers, and newly increased views in current period. According to the Bass diffusion model, we incorporate both $View_{it}$ and $View_{it}^2$. Sub_{it} is used to capture the influence of channel popularity (in terms of subscribers) on viewers' decision. $a_{it} Sub_{it}$ is used to model the jump in video views caused by new video posting among current subscribers since subscribers would be immediately notified of the new video and are likely to watch it due to their specific interest in the provider. $\Delta View_{it}$ is used to control the serial correlation. Similarly, the evolution of ΔSub_{it+1} depends on Sub_{it} and Sub_{it}^2 . $\Delta View_{it+1}$ and $(\Delta View_{it+1})^2$ are used to model the conversion from viewers to subscribers. ξ_{it} and ζ_{it} are the error terms. Naturally, $View_{it+1}$ and Sub_{it+1} update accordingly once we get $\Delta View_{it+1}$ and ΔSub_{it+1} .

Long Term Utility Function

We model the provider's video posting decisions as a dynamic optimization problem. When making the decisions, providers not only consider current period utility but also take into account of the discounted expected future utility over the infinite horizon. Therefore, when making decisions at time t , the provider's objective is to

$$\max_{a_{it}} \mathbf{E}[\sum_{\tau=t}^{\infty} \beta^{\tau-t} U_{it}(a_{it}, S_{it}, \varepsilon_{it}(a_{it})) | a_{it}, S_{it}, \varepsilon_{it}(a_{it})] \quad (10)$$

where β is the common discount factor. The operator $\mathbf{E}[\cdot]$ denotes the conditional expectation operator given the provider's states at time t . Equation (10) dynamically models the provider's maximization problem. The action and state in the current period not only affect the current period utility but also influence the long term utility by determining the states in future periods. Essentially, the provider is forward looking rather than myopic.

We can use standard dynamic programming methodology to solve our problem in Equation (10). The Bellman Equation can be written as

$$V_{\theta}(S_{it}, \varepsilon_{it}) = \max_{a_{it} \in \{0,1\}} u_{it}(a_{it}, S_{it}) + \varepsilon_{it}(a_{it}) + \beta \mathbf{E}[V_{\theta}(S_{it+1}, \varepsilon_{it+1}) | a_{it}, S_{it}, \varepsilon_{it}(a_{it})] \quad (11)$$

where

$$\mathbf{E}[V_{\theta}(S_{it+1}, \varepsilon_{it+1}) | a_{it}, S_{it}, \varepsilon_{it}(a_{it})] = \int_{S_{it+1}} \int_{\varepsilon_{it+1}} V_{\theta}(S_{it+1}, \varepsilon_{it+1}) \mathbf{Pr}(dS_{it+1}, d\varepsilon_{it+1} | a_{it}, S_{it}, \varepsilon_{it}(a_{it})) \quad (12)$$

To simplify estimation, a conditional independence assumption is adopted from existing dynamic programming (Rust 1987; Hotz and Miller 1993) such that

$$\Pr(S_{it+1}, \varepsilon_{it+1} | a_{it}, S_{it}, \varepsilon_{it}(a_{it})) = \Pr(S_{it+1} | a_{it}, S_{it}) \Pr(\varepsilon_{it+1} | S_{it+1}) \quad (13)$$

This conditional independence assumption allows us to simulate the state evolution and random shock generation separately in our estimation. θ is the set of parameters we need to estimate.

$$\theta = (\alpha_1, \alpha_2, \omega_1, \omega_2, \alpha_4, \sigma_k^2, \lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4) \quad (14)$$

Using estimates for ω_1 and ω_2 , we can derive

$$\frac{\delta_1}{\delta_2} = \frac{\omega_1}{\omega_2} \quad (15)$$

Hypotheses

To examine the provider's relative valuation of incremental video views and incremental subscribers in terms of advertising revenue, and the relative valuation of accumulative video views and accumulative subscribers in terms of reputation measure, we impose several hypotheses on the parameters in the utility function. Although incremental subscribers may have potential impact on eCPM, the per period advertising revenue is mainly based on incremental video views. Therefore, we have the following hypothesis:

H1: *Incremental video views are more important than incremental subscribers in terms of current period utility from advertising revenue. ($\alpha_1 > \alpha_2$)*

Reputation is measured by accumulative views and subscribers. Google and other companies select providers generally based on these two measures. However, no guideline exists on which factor is more important. Therefore, we only impose that these two factors have different impacts as follows:

H2: *Cumulative video views and cumulative subscribers have different impacts on the provider's reputation. ($\delta_1 \neq \delta_2$)*

We also consider the heterogeneity in video posting costs across providers in the model. To test whether it is necessary to do so, we propose another hypothesis on the variance of video posting costs across providers.

H3: *Different providers have different video posting costs. ($\sigma_k^2 \neq 0$)*

Data

We collected panel data on two different sets of YouTube providers for two months from June 7th to August 7th, 2011. Sample set 1 includes the top 1000 providers of the most viewed YouTube channels, while sample set 2 consists of 1000 providers randomly selected on YouTube. We choose to collect data on these two different sample sets because so far the providers who can share advertising revenue with YouTube as YouTube partners only account for a small portion of all YouTube providers. Only popular providers have the opportunity to become a partner. Therefore, most providers in Sample set 1 are YouTube partners, while most in Sample set 2 are non-partners. For these top providers, video production has become a business, while most other providers are casual about their video postings. Data on both top providers and random providers would allow us to explore and compare their different utility functions.

On a daily basis, we collected data on subscribers, total number of video views, and the number of videos. For both sample sets, we deleted the samples with incomplete observations, missing values, or no video production at all during the two-month period. The data cleaning process reduces the sample size to 914 for Set 1 of top 1000 providers and 381 for Set 2 of randomly selected providers. Table 1 provides a summary statistics for the two sample sets separately. We can see that the two sets vary greatly from each other in terms of number of views, number of subscribers, video posting frequency, and number of videos. Sample set 1, which consists of most viewed providers, has far more video views, channel subscribers, videos, and post far more frequently than randomly selected Sample set 2. Figure 1 and Figure 3 plot the distribution of views and its log transformation for both sample sets, while Figure 2 and Figure 4 plot the

distribution of subscribers and its log transformation. The distribution of views and subscribers shows an obvious long tail phenomenon, with data on Sample set 2 is more skewed than that on Sample set 1. Our test also indicates that the log transformations of views and subscribers fit normal distributions. Therefore, we use the log-transformed number of views and subscribers to control the skewness in data (Susarla et al. 2010).

Table 1. Descriptive Analysis						
	Sample set 1			Sample set 2		
Variable	Mean	Median	SD	Mean	Median	SD
$View_{it}$	139,555,760	59,878,807	298,854,203	960,038	31,081	4,808,266
Sub_{it}	259,952	148,261	372,772	4,765	217	25,951
a_{it}	0.2143	0	0.4103	0.0449	0	0.20704
$Videos_{it}$	1,169	162	6,228	64	35	111

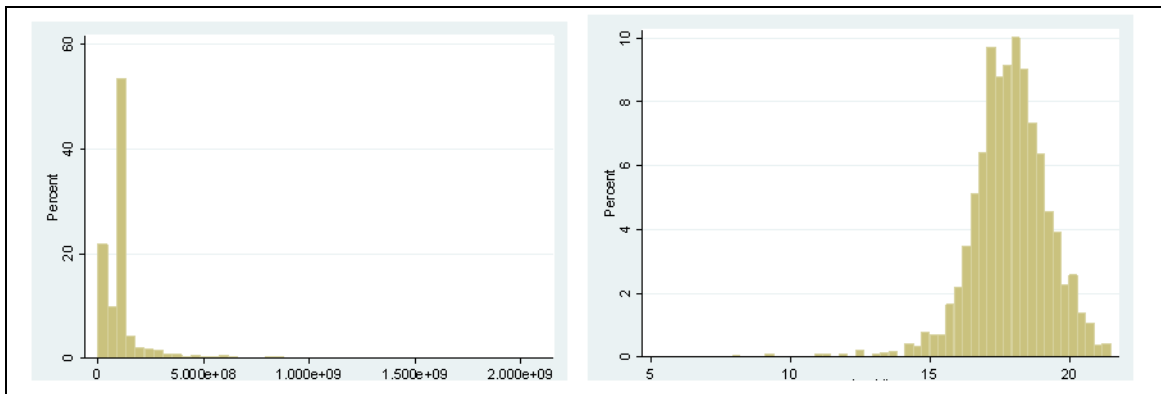


Figure 1. Distribution of views (left) and ln(views) for Sample set 1

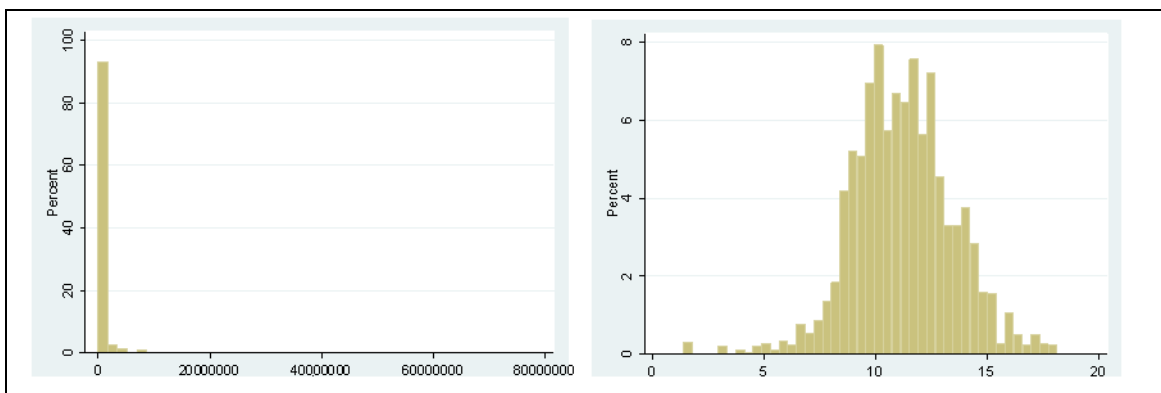
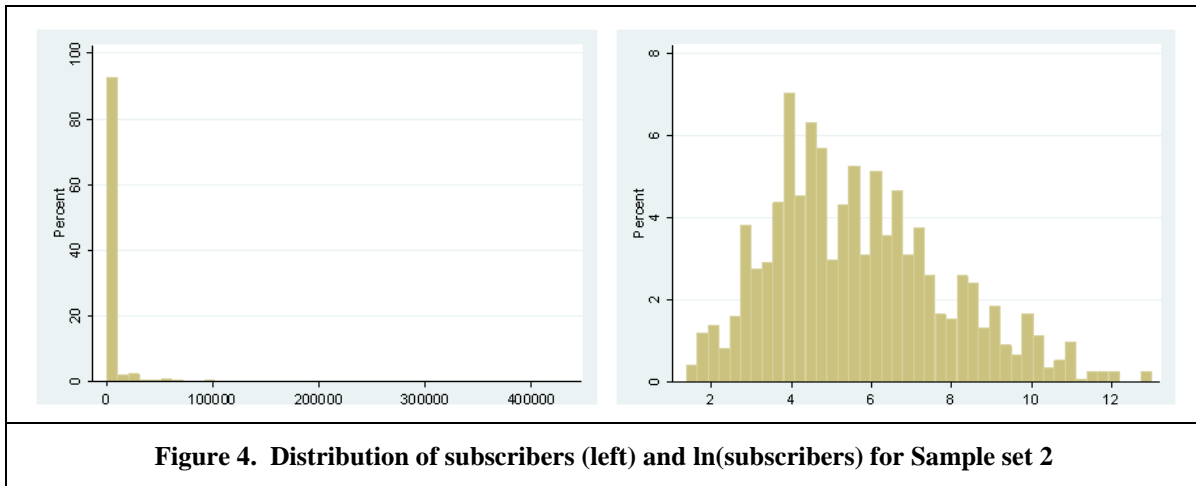
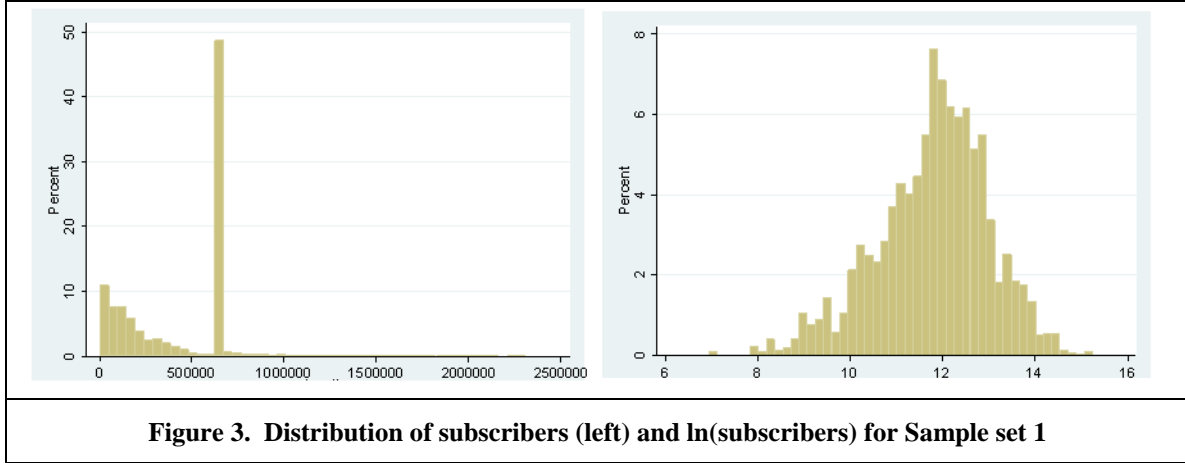


Figure 2. Distribution of views (left) and ln(views) for Sample set 2



Estimation

Estimation Procedure and Identification

We follow the two-stage estimation procedure suggested by Bajari et al. (2007) to estimate the model parameters in θ . Let $V_\theta(S_{it}, a_{it})$ denote the choice-specific value function excluding the private shock $\varepsilon_{it}(a_{it})$, which is the expected utility of choosing a_{it} today and resorting to optimal choice in every period afterwards.

$$V_\theta(S_{it}, a_{it}) = u_{it}(a_{it}, S_{it}) + \beta \mathbf{E}[V_\theta(S_{it+1}, \varepsilon_{it+1}) | a_{it}, S_{it}, \varepsilon_{it}(a_{it})] \quad (16)$$

We assume that a provider's decision is only influenced by her own state variables not by other providers'. With these notations, provider i would optimally choose $a_{it} = 1$ if

$$V_\theta(S_{it}, 1) + \varepsilon_{it}(1) > V_\theta(S_{it}, 0) + \varepsilon_{it}(0) \quad (17)$$

We define the policy function (the decision rule for providers) $\sigma(S, \varepsilon)$ as a mapping from state variables and private shocks to a binary choice. Since $\varepsilon_{it}(1)$ and $\varepsilon_{it}(0)$ are type I extreme values, which gives us a logic choice model, we can recover the choice-specific value functions by inverting the observed conditional choice probabilities at each state (Hotz and Miller, 1993). Then we have

$$V_\theta(S_{it}, 1) - V_\theta(S_{it}, 0) = \ln(\mathbf{Pr}(1|S_{it})) - \ln(\mathbf{Pr}(0|S_{it})) \quad (18)$$

Equation (17) will be used in the first stage of estimation to derive the optimal decision rule.

Recall that our state variables include the number of views and the number of subscribers, which gives us a relatively large state space. In this case, a state-by-state inversion approach is likely to generate very noisy estimates of the policy functions. Bajari et al. (2007) suggests that for continuous states, we can model the choice-specific value functions $V_\theta(S_{it}, a_{it})$ as flexibly parameterized functions of the actions and states.

The two-stage estimation method can be summarized as follows. In the first stage, we recover the video providers' policy functions and the parameters determining the evolution of the relevant state variables. Because the state variables in our model are continuous variables, we model $V_\theta(S_{it}, a_{it})$ as linear function of observed actions and state variables. We use Equation (9) to estimate the parameters for state updates. This step is consistent with the concept of equilibrium that providers have correct beliefs about the evolution of states in equilibrium. Because of the reduced form regression we use for the first step, the results from the first step have great prediction power at the expense of the explanation power. An alternative for the reduced form regression is to develop another structural model on demand from the content viewers' side. The focus of this study, however, is on the structural parameters of the providers' utility function.

The second stage is used to estimate the structural parameters that rationalize the providers' behaviors. We use simulation to derive the minimum distance estimator that minimizes violations of the optimality conditions (Bajari et al., 2007). A single simulated path of play can be obtained as follows:

- 1) Starting at state $S_0 = S$, draw private shocks $\varepsilon_{it}(a_{it})$ for each provider.
- 2) Given the policy function $\sigma(S, \varepsilon)$, identifying the optimal action a_{it}^* and the resulting current period utility U_{it} conditional on state variables and private shock.
- 3) Calculate individual state for next time period according to the updating rule derived in the first stage.
- 4) Repeat 1)-3) for each period.

Averaging provider i 's discounted sum of utilities over all simulated paths as above yields an estimate of $V_i(S; \theta)$ for any policy function $\sigma(S, \varepsilon)$ including $\sigma^*(S, \varepsilon)$, which is the optimal decision rule that results from first-stage estimation. Because the policy function from first stage is the equilibrium policy, the following inequality should be satisfied at the true values of parameters θ_0 :

$$g_{\theta_0}(S_i; \sigma_i^*) = V_{\theta_0}(S_i; \sigma_i^*) - V_{\theta_0}(S_i; \sigma_i) \geq 0 \quad (19)$$

The estimator $\hat{\theta}$ minimizes the objective function below (Bajari et al. 2007):

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \frac{1}{T} \sum_{i=1}^T (\min(g_{\theta_0}(S_i; \sigma_i^*), 0))^2 \quad (20)$$

The common discount factor β is set to be 0.97. Using data on providers' actions, we are able to recover the utility function of providers. However, the limitation is that we can only identify the parameters up to scale. Therefore, we normalize α_1 to be 1 and estimate $\alpha_2, \omega_1, \omega_2, \alpha_4$ and σ_k^2 in proportion to α_1 . The variations in state variables and observed actions allow us to identify the coefficients on views and subscribers $\alpha_2, \omega_1, \omega_2$ and the average cost α_4 . The simulation for heterogeneity helps to identify σ_k^2 . Observed state evolutions are used to identify $\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4$. δ_1 and δ_2 cannot be identified separately based on $\alpha_1, \alpha_2, \omega_1$, and ω_2 , but we can identify the ratio of δ_1/δ_2 using Equation (15). Therefore, for the component of reputation, we can get the relative coefficient of views and subscribers.

Results

The first step in the two-stage estimation procedure is simply reduced form regression to derive the parameters for state updates. Results for both sample sets are presented in Table 2. All the parameters of the two sample sets except for λ_3 for sample set 2 are significant. For the update of $\Delta \ln View_{it+1}$, parameter λ_5 on $\Delta \ln View_{it}$ is more than 100 times of other parameters, indicating that there is significant serial correlation among $\Delta \ln View$ across different periods. The serial correlation is stronger for random Sample set 2 than Sample set 1 of top providers. This is due to the fact that top providers post videos more frequently so that the set of a top provider' videos changes frequently while the set of an ordinary provider's videos remains the same for a long time. Estimate for $\ln Sub_{it}$ is 0.00026 for Sample set 1 and

0.00009 for Sample set 2, suggesting that existing subscribers are more important in determining the incoming views for top providers. However, estimate for $a_{it}LnSub_{it}$ is much smaller for Sample set 1, suggesting that although top providers have much more subscribers, the probability that their subscribers watch their new videos is smaller than average providers.

$\Delta LnSub_{it+1}$ is determined by $\Delta LnView_{it+1}$ to a great extent, especially for Sample set 1, which suggests that a larger portion of viewers of top providers would become subscribers than those of average providers. This finding that top providers have higher conversion rate from viewers to subscribers implies that top providers' videos usually have higher quality. Estimates on $(\Delta LnView_{it+1})^2$ are negative for both sample sets, indicating that the conversion rate from incoming viewers to subscribers decreases as incoming viewers increases. As a result, it is impossible to get all the viewers to subscribe, even for top providers. Coefficient for $LnSub_{it}$ is positive for Sample set 1 but negative for Sample set 2, suggesting that while popular providers can attract more subscribers as existing subscribers increase, the new subscribers ordinary providers can obtain decrease as existing subscribers increase. The results prove that while popular providers receive general attention from the masses and thus have an expanding market, ordinary providers only have limited market niche.

Table 2. Estimates for State Updating Rules		
(***) p = 0.01; ** p=0.05; * p=0.10		
	Parameter Estimates(Standard Errors)	
	Sample set 1	Sample set 2
Update of $\Delta LnView_{it+1}$		
λ_0 (constant)	-0.00198 (0.000763)***	0.03375 (0.002071)***
λ_1 ($LnView_{it}$)	0.00023 (0.000087)***	-0.00543 (0.000368)***
λ_2 ($(LnView_{it})^2$)	-0.00001 (0.000002)***	0.000213 (0.000017)***
λ_3 ($LnSub_{it}$)	0.00026 (0.000012)***	0.00009 (0.000105)
λ_4 ($a_{it}LnSub_{it}$)	0.00007 (0.000002)***	0.00055 (0.000107)***
λ_5 ($\Delta LnView_{it}$)	0.23465 (0.003088)***	0.40030 (0.005999)***
R ²	0.13	0.18
Update of $\Delta LnSub_{it+1}$		
γ_0 (constant)	-0.00032(0.000153)**	0.00281 (0.000898)***
γ_1 ($LnSub_{it}$)	0.000037(0.000010)***	-0.00075 (0.000299)**
γ_2 ($(LnSub_{it})^2$)	0.00001(0.000001)***	0.00006 (0.000023)**
γ_3 ($\Delta LnView_{it}$)	0.33417(0.004159)***	0.04030 (0.013464)***
γ_4 ($(\Delta LnView_{it})^2$)	-0.56121(0.010763)***	-0.01333 (0.004933)***
R ²	0.11	0.01

For conditional choice probabilities, we use logistic regression of providers' actions on state variables. The results are presented in Table 3. These estimates are used to calculate the empirical probabilities of $\Pr(1|S_{it})$ and $\Pr(0|S_{it})$ at each state, which are further used to derive the optimal decision rules based on Equation (17) and (18).

Table 3. Estimates for Conditional Choice Probabilities		
(***) p = 0.01; ** p= 0.05; * p=0.10)		
	Parameter Estimates(Standard Errors)	
Pr(1 S_{it})	Sample set 1	Sample set 2
$\Delta LnView_{it}$	80.92003 (4.109313)***	8.23673 (2.141700)***
$\Delta LnSub_{it}$	96.95183 (5.975460)***	24.75715 (3.130356)***
$LnView_{it}$	0.31513 (0.010085)***	0.07721 (0.021575)
$LnSub_{it}$	-0.19347 (0.010720)***	0.12482 (0.021102)
Constant	-5.01087 (0.152311)***	-4.77407 (0.179991)***

In the second stage, we estimate the structural parameters involved in utility function. As we mentioned earlier, α_1 is normalized to be 1 while the estimation results are presented in proportion to α_1 (Table 4). α_1 and α_2 measure the relative contribution of daily incremental views and subscribers to current period utility respectively. Our estimates for α_2 for both sample sets are less than α_1 , suggesting that, for current period utility, providers value new views more than new subscribers, since the shared ad revenue is largely determined by daily views. However, a test of H1 ($\alpha_1 > \alpha_2$), which is equivalent to test $\alpha_2 < 1$, shows that the t value of is not statistically significant (Table 5). Therefore, we cannot conclude that daily views are more important than daily subscribers in terms of current period utility.

Table 4. Estimates for Structure Parameters (in proportion to α_1)		
(***) p = 0.01; ** p= 0.05; * p=0.10)		
	Parameter Estimates(Standard Errors)	
	Sample set 1	Sample set 2
α_2	0.9831(0.1416)***	0.8700(0.1408)***
ω_1	1.0040(0.0875)***	1.4158 (0.1647)***
ω_2	1.0384(0.0747)***	1.1487(0.1080)***
α_4	0.8114(0.2188)***	0.7355(0.1289)***
σ_k^2	1.0217(0.0969)***	0.8912(0.3141)***
$\frac{\delta_1}{\delta_2} = \frac{\omega_1}{\omega_2}$	0.9792	1.2325

δ_1 and δ_2 measure the relative contribution of cumulative views and subscribers to the provider's reputation. δ_1/δ_2 is calculated as ω_1/ω_2 , which is equal to 0.9792(<1) for Sample set 1 and 1.2325(>1) for Sample set 2. The test of H2 is supported for both sample sets. This result indicates that we have $\delta_1 < \delta_2$ for Sample set 1 and $\delta_1 > \delta_2$ for Sample set 2. Both results are statistically significant. This finding suggests that while a top provider's reputation is determined more by subscribers than views, an ordinary provider's reputation is determined more by views than subscribers. It also suggests the shift in a provider's focus as he/she gain popularity. At the beginning, a new provider try to get as much exposure (measured by views) as possible, starting an innovative topic, or posting new videos as response to other

popular videos. Once he/she has attracted sufficient exposure and views, to the provider changes his focus to be more skilled in video making in order to retain viewers' long term attention, that is, to convert viewers into subscribers. Our structural model reveals this general growth path of a video provider on YouTube.

α_4 measures the relative cost of posting a video, which is 0.8114 for Sample set 1 and 0.7355 for Sample set 2. Compared with benefits providers receive from ad revenue and reputation, the cost for posting a video is relative small, which explains why YouTube providers can afford to continue providing videos. The estimates for two sample sets indicate that the cost for top providers is relatively higher than that for average providers, suggesting that top providers are more devoted to video production.

σ_k^2 measures the heterogeneity among the providers in terms of their costs of posting a video. The test of H3 is supported for both sample sets. Our analysis further suggests that top providers are more heterogeneous than ordinary providers.

Hypothesis	Sample set 1		Sample set 2	
	t value	Result	t value	Result
H1: $\alpha_1 > \alpha_2$	0.1194	Not supported	0.9236	Not supported
H2: $\frac{\delta_1}{\delta_2} \neq 1$	9.0395***	Supported	26.4756***	Supported
H3: $\sigma_k^2 \neq 0$	10.5459***	Supported	2.83762***	Supported

Conclusion

In this paper we develop a dynamic structural model to identify video providers' utility function based on their content contribution decisions in social media using the case of YouTube. YouTube provides revenue sharing along with other monetary and nonmonetary payoffs for video providers. These payoffs constitute the incentives for video providers and can change their contribution decisions strategically. When making decisions for video production and posting, providers consider both the potential revenue they may obtain because of revenue sharing mechanism and other benefits such investment, funding, or career opportunities brought by their reputation. They are also forward-looking, taking into account discounted future benefits as well as current period payoffs. Their future benefits are influenced by their current states and decisions.

However, the YouTube partners that can share ad revenue with YouTube only account for a small part of all the YouTube providers. Most providers do not share ad revenue and thus are not necessarily motivated by the revenue sharing incentive. Therefore, top providers and ordinary providers may have different utility functions. We collected data on both top 1000 providers and randomly selected providers. Data on two different sample sets allows us to explore the difference between top providers and ordinary providers. The results indicate that two sample sets have different utility function parameters and state evolution processes. Although top providers have much more subscribers than ordinary providers and their subscribers have more influence on future views, the probability that their subscribers watch their new videos is lower than the probability for ordinary providers. In this respect, top providers have fewer loyal subscribers than ordinary providers. Generally speaking, the more viewers a provider can attract, the more subscribers he/she can get out of these viewers. The conversion rate from viewers to subscribers decreases as incoming viewers increases. Our results also indicate that while top providers have an expanding market for subscribers so more existing subscribers can generate more new subscriptions, ordinary providers only have limited market that more current subscribers mean less future subscribers.

Counterintuitively, our hypothesis that daily viewers are more important than daily subscribers in terms of current period utility was rejected by both datasets. This finding suggests that although ad revenue is largely based on views, providers value subscribers as much as views. The incentive created by ad revenue sharing has not twisted providers' value system. We also find that while the number of subscribers is more important to a top provider's reputation than the number of views, number of views is more important to an ordinary provider's reputation. This finding suggests that while a beginning provider try to get as much exposure as possible, a provider with a large viewer base would focus more on changing a viewer into a subscriber. Our analysis also suggests that the cost of posting video is relative low compared to the benefits. We also find that top providers incur a higher cost for posting a video than ordinary providers. It confirms that top providers are more devoted to their "YouTube career". The cost for video posting varies substantially across providers. The heterogeneity is more substantial among top providers than ordinary providers.

As a typical example of social media websites, the YouTube case demonstrates that as the growth of online social media, these websites not only gain more content from individual users but also create a profession for some users. For these users, content contribution is not only for fun but also a source of ad revenue, investment, funding, and job opportunities. They are strategic and forward-looking in content contribution. As they have reached a certain level of popularity online, they begin to care more about their sustainable viewer base, which is enabled by the function of subscription. There is a certain level of tradeoff between viewership and subscription. Popular providers have a larger base of subscribers but low probability that these subscribers would view their new content, while average providers have few subscribers but high probability that these subscribers would view their new content. This trend implicates that when measuring the reputation of a content provider, subscription base should be discounted more as the size increases.

The analysis carried out in this paper can be extended along a number of dimensions. First, we only consider the aggregate viewership for all of the provider's videos in this paper. However, the distribution of viewers among the videos would also impact the provider's utility. For instance, the utility from a single hit video might be greater than the utility from several less popular videos. Data at the video level is necessary to carry out more detailed analysis. Second, we can incorporate the influence of competition among providers such that a provider's decision is not only influenced by her/his own state but also by her/his competitors' states and decisions. In addition, this paper assumes that each provider has perfect knowledge of state transitions while ignoring the social learning process that the provider may go through. We believe that for providers that have been productive on social media for a long time, their beliefs of state transitions would converge to the true transition process. However, social learning could play an important role in the decision of the users who are relatively new to the economic value of social media that warrants future research.

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