Content Contribution in Social Media: The Case of YouTube

Qian Tang
The University of Texas at Austin
qian.tang@phd.mccombs.utexas.edu

Bin Gu
The University of Texas at Austin
bin.gu@mccombs.utexas.edu

Andrew Whinston
The University of Texas at Austin
abw@uts.cc.utexas.edu

Abstract

Social media allows individuals and businesses to contribute contents for public viewing. However, little is known about the underlying incentives that why content providers derive utilities 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 video providers on YouTube from Jun 7th, 2010, to Aug 7th, 2011 since top providers are more likely to be encouraged by these incentives. Our results show that video providers value incremental subscribers as much as incremental video views. We also find that top providers’ reputation is influenced more by accumulative subscribers than by accumulative video views.

1. Introduction

Orabrush Inc., a small company that just closed a new funding round of $2.5 million, adopt a major advertising strategy through its YouTube channel. It 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. In the online video market, YouTube has a market share of around 40%, followed by Hulu with only 3%. The total video views for YouTube is over 2 billion a day.

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, including Justin Bieber, Arnel Pineda, Esmee Denters, Terra Naomi, Lisa Lavie, etc. 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 three years, she produced over 100 videos on makeup, style, and skincare, and received more than 300 million video views and 1 million subscribers. Moreover, Lancôme Cosmetics Company offered her the position of official video makeup artist. 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 popular among job seekers. Graeme Anthony innovated video resume by CVIV (interactive video CV), a video resume that consists of several linked videos. This CVIV resulted in great attention and eventually lunched him a job in public relations. Similarly, companies looking for job candidates can 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
providers can receive a portion of advertisement revenue generated by their videos from Google. 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, which 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.

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. 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 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. 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 Magee, 1998).

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.

2. 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 a 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. Uncertainty exists in video production and advertising revenue. As in a typical principal-agency setting, YouTube does not observe providers’ talents and efforts. 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 this paper, we focus on how the revenue sharing and private benefits would influence providers’ behavior.

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.
3. 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. 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. 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. 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. 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. Mortimer (2008) indicates that both upstream and downstream profits can increase by 10 percent under the revenue-sharing contract for popular titles and even more for less popular titles.

Our paper also adds to the growing literature on reputation. Many 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) study 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. Reputation is one of the most important individual motivations for knowledge contribution (Wasko and Faraj, 2005). 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. 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.

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, but access the agent’s past task outputs instead (Dellarocas 2003). 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).

Only a few emerging studies in IS use 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.

4. Model

4.1. Per period utility function

We start with the provider’s discrete choice in every period. Time is discrete with \( t = 1, 2, \ldots, \infty \). There are \( I \) individual providers indexed by \( i = 1, 2, \ldots, I \). 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

\[
a_{it} = \begin{cases} 
1, & \text{post a video on day } t \\
0, & \text{otherwise} 
\end{cases}
\]

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:
\[
U_{it}(\Delta \text{View}_{it}, \Delta \text{Sub}_{it}, a_{it}) = \alpha_1 \Delta \text{View}_{it} + \alpha_2 \Delta \text{Sub}_{it} + \alpha_3 \text{Rep}_{it} - \alpha_4 a_{it} + k_i a_{it} + \varepsilon_i(a_{it}) \tag{2}
\]

where \(\Delta \text{View}_{it}\) is the number of new views provider \(i\) receives on day \(t\), \(\Delta \text{Sub}_{it}\) is the number of new subscribers provider \(i\) receives on day \(t\), so we have

\[
\Delta \text{View}_{it} = \text{View}_{it} - \text{View}_{it-1}
\]

\[
\Delta \text{Sub}_{it} = \text{Sub}_{it} - \text{Sub}_{it-1} \tag{3}
\]

\(\text{Rep}_{it}\) 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. \(\alpha_4\) is the cost of posting a video, and \(\varepsilon_i(a_{it})\) is the action dependent random shock that can take on the value of \(\varepsilon_i(0)\) and \(\varepsilon_i(1)\). \(k_i\) measures the heterogeneity among video providers such as different intrinsic benefits or costs (Wasko and Faraj 2005). We assume that \(\varepsilon_i(0)\) and \(\varepsilon_i(1)\) are type I extreme values that are i.i.d. across \(i\) and \(t\), and \(k_i \sim N(0, \sigma_k^2)\). So \(\sigma_k^2\) 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 \(\varepsilon_i(a_{it})\) are unobservable to researchers.

Since we do not observe the true reputation \(\text{Rep}_{it}\), we assume that reputation is determined by accumulative views and subscriptions:

\[
\text{Rep}_{it} = \delta_1 \text{View}_{it} + \delta_2 \text{Sub}_{it} \tag{4}
\]

where \(\delta_1\) and \(\delta_2\) measure the relative importance of views and subscribers in the reputation component.

Substituting (4) into (2), we obtain

\[
U_{it}(\Delta \text{View}_{it}, \Delta \text{Sub}_{it}, \text{Rep}_{it}, \text{View}_{it}, \text{Sub}_{it}, a_{it}, \varepsilon_i) = \alpha_1 \Delta \text{View}_{it} + \alpha_2 \Delta \text{Sub}_{it} + \alpha_3 \delta_1 \text{View}_{it} + \alpha_3 \delta_2 \text{Sub}_{it} - \alpha_4 a_{it} + k_i a_{it} + \varepsilon_i(a_{it}) \tag{5}
\]

Let \(\omega_1 = \alpha_2 \delta_1\) and \(\omega_2 = \alpha_3 \delta_2\), we have

\[
U_{it}(\Delta \text{View}_{it}, \Delta \text{Sub}_{it}, \text{Rep}_{it}, \text{View}_{it}, \text{Sub}_{it}, a_{it}, \varepsilon_i) = \alpha_1 \Delta \text{View}_{it} + \alpha_2 \Delta \text{Sub}_{it} + \omega_1 \text{View}_{it} + \omega_2 \text{Sub}_{it} - \alpha_4 a_{it} + k_i a_{it} + \varepsilon_i(a_{it}) \tag{6}
\]

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

\[
U_{it}(\Delta \text{View}_{it}, \Delta \text{Sub}_{it}, \text{View}_{it}, \text{Sub}_{it}, a_{it}, \varepsilon_i) = u_{it}(\Delta \text{View}_{it}, \Delta \text{Sub}_{it}, \text{View}_{it}, \text{Sub}_{it}, a_{it}) + \xi_{it}(a_{it}) \tag{7}
\]

4.2. State variables

According to Equation (7), the state variable \(S_{it}\) in our problem is a vector including \(\Delta \text{View}_{it}, \Delta \text{Sub}_{it}, \text{View}_{it}, \text{Sub}_{it}, \text{Rep}_{it}\).

\[
S_{it} = (\Delta \text{View}_{it}, \Delta \text{Sub}_{it}, \text{View}_{it}, \text{Sub}_{it}) \tag{8}
\]

The transition process on other state variables is modeled as

\[
\Delta \text{View}_{it+1} = \lambda_0 + \lambda_1 \text{View}_{it} + \lambda_2 \text{Sub}_{it} + \lambda_3 \Delta \text{View}_{it} + \xi_{it} + \delta_{it}
\]

\[
\Delta \text{Sub}_{it+1} = \gamma_0 + \gamma_1 \text{Sub}_{it} + \gamma_2 \text{Sub}_{it} + \gamma_3 \Delta \text{View}_{it+1} + \gamma_4 (\Delta \text{View}_{it+1})^2 + \delta_{it} + \xi_{it}
\]

\[
\text{View}_{it+1} = \Delta \text{View}_{it+1} + \text{View}_{it}
\]

\[
\text{Sub}_{it+1} = \Delta \text{Sub}_{it+1} + \text{Sub}_{it} \tag{9}
\]

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 \(\Delta \text{View}_{it+1}\) 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 \(\text{View}_{it}\) and \(\text{Sub}_{it}\). \(\text{Sub}_{it}\) is used to capture the influence of channel popularity (in terms of subscribers) on viewers’ decision. \(\alpha_{it}\) \(\text{Sub}_{it}\) 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. \(\Delta \text{View}_{it}\) is used to control the serial correlation. Similarly, the evolution of \(\Delta \text{Sub}_{it+1}\) depends on \(\text{Sub}_{it}\) and \(\text{Sub}_{it}\). \(\Delta \text{View}_{it+1}\) and \(\Delta \text{View}_{it+1}\) are used to model the conversion from viewers to subscribers. \(\xi_{it}\) and \(\xi_{it}\) are the error terms. Naturally, \(\text{View}_{it+1}\) and \(\text{Sub}_{it+1}\) update accordingly once we get \(\Delta \text{View}_{it+1}\) and \(\Delta \text{Sub}_{it+1}\).

4.3. 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

$$\max_{a_t} E[\sum_{t=1}^{\infty} \beta^{t-1} U_t(S_{it}, S_t, d_t, a_t)]$$ (10)

where $\beta$ is the common discount factor. The operator $E[.]$ 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

$$V_0(S_{it}, d_{it}) = \max_{d_{it}} u_t(a_{it}, S_{it}) + \beta E[V_0(S_{it+1}, d_{it+1}|a_{it}, S_{it}, d_{it})]$$ (11)

where

$$E[V_0(S_{it+1}, d_{it+1}|a_{it}, S_{it}, d_{it})] = \sum_{S'_{it+1}} \sum_{d'_{it+1}} V_0(S_{it+1}, d_{it+1}|a_{it}, S_{it}, d_{it}) \Pr(d_{it+1}|d_{it}, a_{it}, S_{it}, d_{it})$$ (12)

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

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

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

$$\theta = (a_1, a_2, \omega_1, \omega_2, \alpha, \sigma^2, \lambda)$$ (14)

Using estimates for $\omega_1$ and $\omega_2$, we can derive

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

5. Data

We collected panel data on top 1000 YouTube providers for two months from June 7th to August 7th, 2011. We choose to collect data on top providers because most of these providers are YouTube partners and thus are motivated by the revenue sharing mechanism. For these top providers, video production has become a business, while most other providers are casual about their video postings.

On a daily basis, we collected data on subscribers, total number of video views, and the number of videos. We deleted the samples with incomplete observations or missing values. The data cleaning process reduces the sample size to 914 providers. Table 1 provides a summary. We can see that all the variables vary greatly across different providers. Number of videos is referred to as the total number of videos that have been posted on each provider’s YouTube channel.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>View$_{it}$</td>
<td>139,555,760</td>
<td>59,878,807</td>
<td>298,854,203</td>
</tr>
<tr>
<td>Sub$_{it}$</td>
<td>259,952</td>
<td>148,261</td>
<td>372,772</td>
</tr>
<tr>
<td>$a_{it}$</td>
<td>0.2143</td>
<td>0</td>
<td>0.4103</td>
</tr>
<tr>
<td>Videos$_{it}$</td>
<td>1,169</td>
<td>162</td>
<td>6,228</td>
</tr>
</tbody>
</table>

On a daily basis, we collected data on subscribers, total number of video views, and the number of videos. We deleted the samples with incomplete observations or missing values. The data cleaning process reduces the sample size to 914 providers. Table 1 provides a summary. We can see that all the variables vary greatly across different providers. Number of videos is referred to as the total number of videos that have been posted on each provider’s YouTube channel.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>64</td>
<td>7.00%</td>
</tr>
<tr>
<td>2006</td>
<td>304</td>
<td>33.26%</td>
</tr>
<tr>
<td>2007</td>
<td>192</td>
<td>21.01%</td>
</tr>
<tr>
<td>2008</td>
<td>144</td>
<td>15.75%</td>
</tr>
<tr>
<td>2009</td>
<td>128</td>
<td>14.00%</td>
</tr>
<tr>
<td>2010</td>
<td>78</td>
<td>8.53%</td>
</tr>
<tr>
<td>2011</td>
<td>4</td>
<td>0.44%</td>
</tr>
<tr>
<td>Total</td>
<td>914</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Table 2. Summary on when sample providers joined YouTube

Figure 1 plots the distribution of views and its log transformation for both sample sets, while Figure 2 plot the distribution for subscribers and its log transformation. The distribution of views and subscribers shows an obvious long tail phenomenon. Our test also indicates that the log transformations better 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 2 shows the summary on the join date of our sample providers. Most (33.26%) of our top providers joined YouTube in 2006, as the tenure decreases, the less likely a provider can make it to the top 1000 list.
6. Estimation

6.1. Estimation procedure and identification

We follow the two-stage estimation procedure suggested by Bajari et al. (2007) to estimate the model parameters in $\theta$. Let $V_0(S_{it}, a_{it})$ denote the choice-specific value function excluding the private shock $\epsilon_i(a_{it})$, which is the expected utility of choosing $a_{it}$ today and resorting to optimal choice in every period afterwards.

$$V_0(S_{it}, a_{it}) = u_{it}(a_{it}, S_{it}) + \beta E[V_0(S_{it+1}, \epsilon_{it+1})|a_{it}, S_{it}, \epsilon_{it}(a_{it})]$$

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

$$V_0(S_{it}, 1) + \epsilon_{it}(1) > V_0(S_{it}, 0) + \epsilon_{it}(0)$$

We define the policy function (the decision rule for providers) $\sigma(S, \epsilon)$ as a mapping from state variables and private shocks to a binary choice. Since $\epsilon_{it}(1)$ and $\epsilon_{it}(0)$ 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

$$V_0(S_{it}, 1) - V_0(S_{it}, 0) = \ln(\Pr(1|S_{it})) - \ln(\Pr(0|S_{it}))$$

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 $V_0(S_{it}, a_{it})$ 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 $V_0(S_{it}, a_{it})$ 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 $\varepsilon_t(a_t)$ for each provider.
2) Given the policy function $\sigma(S, \varepsilon)$, identifying the optimal action $a_t^*$ and the resulting current period utility $U_t$ 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 $V_i(S; \sigma; 0)$ 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 $\theta_0$:

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

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

$$\hat{\theta} = \arg\min_{\theta} \sum_{i=1}^I (min (g_{0i}(S_i; \sigma^*_i), 0))^2 \quad (20)$$

The common discount factor $\beta$ 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 $\alpha_4$ to be 1 and estimate $\alpha_2, \omega_1, \omega_2, \alpha_4$ and $\sigma^2_k$ in proportion to $\alpha_4$. 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 $\alpha_4$.

The simulation for heterogeneity helps to identify $\sigma^2_k$. Observed state evolutions are used to identify $\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4$. $\delta_1$ and $\delta_2$ cannot be identified separately based on $\alpha_4, \alpha_2, \omega_1$, and $\omega_2$, but we can identify the ratio of $\delta_1/\delta_2$ using Equation (15). Therefore, for the component of reputation, we can get the relative coefficient of views and subscribers.

### 6.2. Results

**Table 3. Estimates for state evolution**

<table>
<thead>
<tr>
<th>Parameter (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_0$ (constant)</td>
</tr>
<tr>
<td>$\lambda_1$ (LnView$_it$)</td>
</tr>
<tr>
<td>$\lambda_2 (\text{LnView}_it^2)$</td>
</tr>
<tr>
<td>$\lambda_3 (\text{LnSub}_it)$</td>
</tr>
<tr>
<td>$\lambda_4 (a_t\text{LnSub}_it)$</td>
</tr>
<tr>
<td>$\lambda_5 (\Delta\text{LnView}_it)$</td>
</tr>
<tr>
<td>$R^2$</td>
</tr>
</tbody>
</table>

The first step in the two-stage estimation procedure is simply reduced form regression to derive the parameters for state updates. Results are presented in Table 3. All the parameters except for $\lambda_3$ are significant. For the update of $\Delta\text{LnView}_{it+1}$, parameter $\lambda_5$ on $\Delta\text{LnView}_{it}$ is more than 100 times of other parameters, indicating that there is significant serial correlation among $\Delta\text{LnView}$ across different periods. Estimate for $\text{LnSub}_{it}$ is 0.00026, suggesting that existing subscribers is also important in determining the incoming views for top providers. However, estimate for $a_t\text{LnSub}_{it}$ is much smaller (0.00007), suggesting that although top providers have much more subscribers, the probability that their subscribers watch their new videos is small.

**Table 4. Conditional choice probabilities**

<table>
<thead>
<tr>
<th>Parameter (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pr(1</td>
</tr>
<tr>
<td>$\Delta\text{LnView}_{it}$</td>
</tr>
<tr>
<td>$\Delta\text{LnSub}_{it}$</td>
</tr>
<tr>
<td>$\text{LnView}_{it}$</td>
</tr>
<tr>
<td>Constant</td>
</tr>
</tbody>
</table>
\[ \Delta \text{LnSub}_{it+1} \text{ is determined by } \Delta \text{LnView}_{it+1} \text{ to a great extent, which suggests that a larger portion of viewers of top providers would become subscribers than those of average providers. Estimates on } (\Delta \text{LnView}_{it+1})^2 \text{ is negative, 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. Positive coefficient for LnSub}_{it} \text{ implies that popular providers can attract more subscribers as existing subscribers increase. The results prove that popular providers receive general attention from the masses and thus have an expanding market. }

For conditional choice probabilities, we use logistic regression of providers’ actions on state variables. The results are presented in Table 4. 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).

In the second stage, we estimate the structural parameters involved in utility function. As we mentioned earlier, \( \alpha_1 \) is normalized to be 1 while the estimation results are presented in proportion to \( \alpha_1 \) (Table 5). \( \alpha_4 \) and \( \alpha_5 \) measure the relative contribution of daily incremental views and subscribers to current period utility respectively. Our estimates for \( \alpha_2 \) for is less than \( \alpha_1 \), 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 \( \alpha_1 > \alpha_2 \), which is equivalent to test \( \alpha_2 < 1 \), shows that the t value of is not statistically significant (0.1194).

**Table 5. Structure parameters**

<table>
<thead>
<tr>
<th>Parameter (Standard Error)</th>
<th>(*** p = 0.01; ** p = 0.05; * p=0.10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_2 )</td>
<td>0.9831 (0.1416)**</td>
</tr>
<tr>
<td>( \omega_1 )</td>
<td>1.0040 (0.0875)**</td>
</tr>
<tr>
<td>( \omega_2 )</td>
<td>1.0384 (0.0747)**</td>
</tr>
<tr>
<td>( \alpha_4 )</td>
<td>0.8114 (0.2188)**</td>
</tr>
<tr>
<td>( \sigma_k^2 )</td>
<td>1.0217 (0.0969)**</td>
</tr>
<tr>
<td>( \frac{\delta_1}{\delta_2} = \frac{\omega_1}{\omega_2} )</td>
<td>0.9792</td>
</tr>
</tbody>
</table>

\( \delta_1 \) and \( \delta_2 \) measure the relative contribution of cumulative views and subscribers to the provider’s reputation. \( \frac{\delta_1}{\delta_2} \) is calculated as \( \frac{\omega_1}{\omega_2} \), which is equal to 0.9792 (<1). The test of \( \delta_1 < \delta_2 \) is supported. This finding suggests that a top provider’s reputation is determined more by subscribers than views.

\( \alpha_4 \) measures the relative cost of posting a video, which is 0.8114. 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.

7. 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.

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, we choose top providers as our study objects because they are influenced more by revenue sharing and reputation concern than ordinary providers. We collected data on top 1000 providers on a daily basis. The results indicate that top providers’ subscribers have significant influence on incoming views, although the probability that their subscribers watch their new videos is still low. We can also see that top providers have an expanding market for subscribers that more existing subscribers can generate more new subscriptions.

Our test that daily viewers are more important than daily subscribers in terms of current period utility was rejected. 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 the
number of subscribers is more important to a top provider’s reputation than the number of views.

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.

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. Third, besides the linear function, other functional forms for utility need to be explored. 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.

8. References