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**Pay for Content or Pay for Marketing?
An Empirical Study on Content Pricing**

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Abstract

In this paper, we use unique data from a popular Chinese content provision platform to examine three issues: first, content providers' pricing strategies when each follower needs to pay an annual fee for access to content; second, content providers' trade-offs between traffic and referral marketing expenses; and third, the effect of a platform policy on the welfare of content providers and their followers. We use a structural model for a content provider's pricing and referral marketing decisions. The model estimates highlight the link between the referral effectiveness and potential revenue loss. Our counterfactual analysis shows vast difference in communities' reactions towards increased platform commissions and potential homogeneity of content provision as well as huge demand loss beyond certain commission thresholds.

Keywords: content pricing, referral marketing, platform policy, structural estimation

JEL Classification Numbers: L12, L14, L25, L51

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1 Introduction

The spread of the Internet has allowed an increasing number of people to share content online at minimal entry cost. The proliferation of content on the Internet brings these content providers not only followers but also specific commercial value. For example, bloggers with many followers can make money by displaying advertisements on their blogs (e.g., Sun and Zhu 2013), and programmers who gain enough attention in the software community for sharing code often find lucrative work as a result (e.g., Cabral et al. 2019). As the above scenarios are occurring more frequently, how to measure the exact commercial value of a content provider has become a very important and unavoidable issue. Unfortunately, as these phenomena have emerged in recent years, researchers lack detailed data. Therefore, the literature does not provide any answers to three important questions: First, if directly charging for content is possible, how do content providers make pricing decisions? Second, how much are content providers willing to pay for marketing in order to get more potential followers? Third, how can the platform policy affect the welfare of content providers and platform users?

To answer these questions, we use confidential and unique data from a popular textual content provision platform called “Little Secret Communities”,¹ with 864,543 users generating 50.30 million U.S. dollars of revenue² each year in our data. Each community consists of an owner³ and users who have paid an annual fee which is determined by the owner for access to content. The platform authorizes some community owners to customize a referral program. Users in a community eligible for this program can refer it to others via a sharing link.⁴ Every new entry arising through the link generates a referral payment, as well as a discount to the new entrant. The referral payment depends on both the annual fee and the sharing percentage, which is the share of the annual fee that an owner wants to split for each successful referral.

Given these pricing arrangements and other community features, we use a structural model to describe each owner’s pricing strategy with respect to the eligibility for the referral program. In general, an owner of a community not eligible for the referral program simply chooses a profit-maximizing price, while an owner of a community eligible for the program

¹“Little Secret Communities” can be regarded as a paid version of Reddit. Its latest version can be found on its official website.

²The amount of revenue is calculated by summing up the product of the annual fee and the number of users for all communities.

³We designate owners as female and all other users as male, and use forms of address accordingly in what follows.

⁴For example, personal chatting software, social network platforms, and other online communication websites, etc.

at first decides price, and then the sharing percentage.

In our structural model, each owner is assumed to be a “content monopolist”, which means that every paid community is considered to be an independent “content market”. The owner of a community knows her potential demand and knows that her price will directly affect demand. Unlike a typical monopoly pricing model (see, e.g., Cabral et al. 1999; Bloch and Qurou 2013; Campbell 2013; Ajorlou et al. 2016; Shin 2017), our structural model requires the owner of a community eligible for the referral program to very carefully choose both the annual fee and the sharing percentage, since – conditional on the sharing percentage – the annual fee has the opposite effects on demand. On the one hand, a higher prices lower potential demand, while on the other hand, higher referral payment (i.e., the product of the annual fee and the sharing percentage) provides existing users with stronger incentives for referrals, which brings more users to the owner.

To estimate our structural model, we start with the demand estimation. We manage the endogeneity problem using instrumental variables that exogenously affect an owner’s marginal cost of content provision. Given our demand estimation, we then estimate the cost function by incorporating marginal cost heterogeneity in order to control for an owner’s idiosyncratic cost contingent on community characteristics. Finally, we introduce a single parameter, called referral effectiveness, to explain the trade-off of the referral program on an owner’s revenue. This step-by-step estimation method promotes the computational efficiency.

The estimation of our structural model gives the following main results. First, according to demand estimation, a 1% increase in price induces a 6.7% decrease in potential demand. Existing users do not have enough incentive for referrals unless the sharing percentage surpasses 39.5%. On average, a 1% increase in referral payment induces a 1.1% demand expansion. Second, according to cost estimation, the marginal cost of each type (i.e., field of expertise) is distributed differently. Community owners of economics topics have the highest marginal cost while those of education and life-related topics have the lowest. Last, the estimation of referral effectiveness shows that the communities of fashion, art, life-related topics have a much greater proportion of users joining through sharing links, and that these owners suffer the most revenue loss from the referral program

Our paper contributes to the literature in the following three aspects.⁵ First, it significantly contributes to the literature on the incentive of online content providers. Previous literature (see, e.g., Lerner and Tirole 2002; Fershtman and Gandal 2007; Cabral et al. 2019) have both theoretically and empirically focused on why people are willing to contribute and collaborate online for free; however, few study the private capitalization behind online content provision. Our paper opens up a new angle for this thread in the literature by discussing

⁵A more detailed literature review is presented separately in Appendix A.

how content providers with different types of content and potential demand can make money directly.

Second, we are the first to empirically study the referral marketing from the content providers' perspective (in general, firms' perspective), especially when they need to decide both the price and referral reward.⁶ There have been theoretical works on the design of referral programs, i.e., how firms should set the optimal price and referral reward (e.g., Bialogorsky et al. 2001; Kornish and Li 2010; Lobel et al. 2016; Leduc et al. 2017; Yang and Debo 2019). However, due to data restriction, the empirical works focus on assessing the value and loyalty of referrers and referred customers (e.g., Schmitt et al. 2011; Garnefeld et al. 2013; Van den Bulte et al. 2018), the most effective type of ties or brands for referrals (e.g., Ryu and Feick 2007), the referrers' performance under intrinsic or extrinsic incentives (e.g., Jung et al. 2019), the referrers' response to different referral policies and corresponding impact on platform growth (e.g., Belo and Li 2019), etc. In this paper, we turn attention to the content providers' side (in general, firms' side): the referral program brings a larger number of audience to a content provider, which increases her revenue, but at the same time, she also suffers revenue loss from referral payments and discounts to new entrants. We use a simple structural model to reveal such a trade-off, and explain why some content providers can be less motivated to adopt referral marketing.

Last, this paper proffers our own opinions on platform profitability and relevant policy. In the literature (see, e.g., Zhang and Zhu 2011; Fershtman and Gandal 2011; Aaltonen and Seiler 2015; Gandal and Stettner 2016), the platform works as an intermediary and aims at facilitating the communication and cooperation between the two sides. A platform benefits from maximizing its user base, because a large user base can attract excellent cooperative developers and advertisers. Then it can realize profits from advertising. Aside from advertising revenue, a platform's income can also come from transaction or commission, and maximizing the user base may not be the top priority of a platform.⁷ In this paper we discuss this scenario, since Little Secret Communities applies a fixed 5% commission rate to all communities. From the platform's perspective, it is natural to ask: If it increases the commission rate, will this bring a higher profit to the platform? To answer this question, we conduct a counterfactual analysis in which the profit-maximizing platform has the monopolist power to choose its commission rate.

We find that the optimal platform profit-maximizing rate is 20%, far exceeding the cur-

⁶Living Social and Dropbox are typical examples benefiting from their referral marketing programs. Lobel et al. (2016) give a detailed description on the success of the referral programs that Living Social and Dropbox have applied.

⁷In Appendix B, we introduce different business models whereby content providers can make money from content provision on platforms and categorize these business models into three types.

rent 5% level. At the platform optimal rate, roughly half of the users who are supposed to join the platform are kept away. This demand loss reminds policy-makers that a competitive environment among platforms using a similar mechanism should be put into effect for social optimum; otherwise a monopolist platform may significantly reduce users’ access to content (especially of high quality) by imposing a higher transaction cost.⁸ We also observe that communities of different types react markedly differently from each other. When the commission rate is high enough, only the *Economics* and *Education* communities still have users left. Little Secret Communities loses its content provision diversity and becomes an economics/education-related platform.

The rest of the paper is organized as follows. Section 2 provides an introduction to the platform, Little Secret Communities. Section 3 introduces the data. Sections 4 and 5 show the structural model as well as the identification and estimation strategies. Section 6 presents the empirical results. Section 7 conducts a counterfactual analysis and gives policy advice. Section 8 concludes.

2 Little Secret Communities

Launched online in China in 2015, Little Secret Communities serves those who wish to provide their expertise online in exchange for income. It also helps those who want to extend their network based on the same area of interest. Up to October 2018, its total number of registered users reached 10 million. The platform consists of closed entities called communities. Each community is composed of three components: an owner, users, and content which is primarily textual.

On Little Secret Communities, owners are mostly influencers in their fields and have accumulated a certain number of loyal followers from other channels (by books, blogs, Q&A websites, etc.). These influencers direct these loyal followers from other places to Little Secret Communities. In other words, if a potential user does not know the existence of a community from the influencer he follows, it will be hard for him to join from other sources (even by a direct search on the platform). In this sense, each community can be “considered” as a relatively independent content market: the pricing strategies and potential demand of a given community does not directly affect those of other communities.

⁸Such concerns have already been seriously considered by the video game distribution platform, Steam. According to its announcement, Steam used to take 30% from the overall earning of each game, but from November 2018, it takes 25% if the sale is between 10 million and 50 million U.S. dollars, and only takes 20% for sales after 50 million U.S. dollars. According to its official announcement, Steam hopes that “this change will reward the positive network effects generated by developers of big games, further aligning their interests with Steam and the community.”

A community is categorized as either a paid community or a free community, based on whether or not users need to pay an annual fee for access to content. Whether a community is paid or free is the first decision that a potential owner has to make when she registers a community on the platform. The owner of a potential paid community has to decide the annual fee before she finalizes the whole procedure.

Little Secret Communities takes 5% of the annual fee as its commission⁹ and leaves the other pricing arrangements to owners. It makes three rules to facilitate better operation and user experience.

1. A potential owner chooses any integer between 50 to 3,000 RMB (or equivalently 7.5 to 450 U.S. dollars) as the annual fee.

This requirement makes the decision to register a paid community a prudent one: the owner must have some prediction of the potential demand. In addition, this requirement makes potential users carefully consider the benefits of joining a community and the real monetary cost for the access, particularly when the idea of “pay for expertise online” has recently emerged in the past few years. After the annual fee is appropriately chosen, the potential owner then needs to select the type of the community, thus becoming an official owner of a community on the platform.

2. There is a three-day trial period upon completion of payment. During the trial period, users can choose to redeem the annual fee at any time and quit the community. Therefore, owners of paid communities have to properly manage their communities and regularly update content, which increases operational costs and eliminates fraud.
3. The platform authorizes the referral program to some paid communities. Upon authorization, a user can send a sharing link on other platforms, and gets paid from each successful referral.

The referral program is not provided to every community. The platform operators, based on their observations of a community’s operation and quality, give some owners this authorization. An owner of a community eligible for the referral program then has a specific incentive: she is able to share some revenue with existing users for more traffic to her communities. In this case, she needs to specify both the annual fee and a sharing percentage in order to determine the referral payment.

⁹The platform provides a free transaction service so that all of the payments will be transferred directly to the community owner’s e-wallet for easy use. The e-wallet is WeChat wallet, one of the most commonly used electronic payment methods in China (the other is Alipay). In China, e-wallet can be used to buy almost any item, in almost any place.

Table 1: How each party splits the \$100 annual fee, given that the sharing percentage equals 50%

	platform	owner	existing user	new user
Year 1	\$5	\$47.5	\$33.25	\$-85.75
Year 2	\$5	\$95		\$-100

An example shown in Table 1 demonstrates how the referral program works on Little Secret Communities. In this case, the annual fee stays at \$100 over two years, and the sharing percentage is 50%. Suppose that an existing user in a community posts a sharing link for referral. If a person joins the community through this link, then he pays \$100 for an annual access to content. The platform extracts \$5 as its commission. The community owner takes $50\% \times (\$100 - \$5)$. The remaining $50\% \times (\$100 - \$5)$ is further split, whereby the existing user obtains 70% as a referral payment and the new user receives 30% as a discount. After a year, when the new user wants to renew his annual access, he needs to pay \$100 again. This time the platform again extracts \$5, but the community owner takes the remaining \$95.

The referral program means that a user with enough referrals can cover his own annual fee or even make extra money. Under each post, a sharing link is clearly shown for referral to many other platforms. Little Secret Communities has a tracking system to recognize if a new user joins through the link sent from an existing user, and assigns this existing user the amount of money according to the percentage which has been set up by the owner.

Note that the referral payment is only paid once in the first year for each new user. This rules out the possibility that if a referral brings a reward to a user each year, then he will never leave the community simply because he has referred the community to many people and continues to receive money for his referrals. If this happens, there will be increasingly more people in the community simply for the referral payment, and therefore community owners will not be able to accurately predict how many people will join her community.

By deciding the sharing percentage, owners make a trade-off between marketing costs for new user acquisitions and potential profits brought by additional users. Little Secret Communities has its own recommendation of setting a 30% sharing percentage, while the whole interval is from 5% to 50%, with each 5% an incremental step.

3 Data

Our data are directly provided by Little Secret Communities. There are 1,386 communities, with 864,543 users¹⁰ generating 50.30 million U.S. dollars of yearly revenue. They are all paid communities registered from November 13, 2015 to December 17, 2018.¹¹ Given that the minimum annual fee of a community is 50 RMB, a community with 200 users without the referral program can generate 10,000 RMB revenue, which is almost 40% of the average disposable income per capita in China in 2017.¹²

A community owner can also be a user of another community(s), and a user can follow several communities at the same time if he is willing to pay. Therefore, the number of users reported above can be regarded as an upper bound of the exact number. The amount of revenue generated reflects the monetary value of content provision on a platform.

3.1 Variable Description

Our data collection period is from November 13, 2015 to December 17, 2018. For each paid community, we have eight variables in three dimensions:

1. Basic information: *id*, *time*, *count*, *type*, and *enable*;
 - *id* is the unique identifier of each community. Since there is only one owner in each community, it can also be regarded as the identifier of the owner,
 - *time* is the date when a community is registered,
 - *count* is the number of users in each community until December 17, 2018,
 - *type* includes Art, Economics, Education, Entertainment, Fashion, Health, Life and Science, which represents eight fields of expertise. As we observe from Table 2 below, the numbers of communities in each type are not identical. For example, *Economics* communities amount to 35.57% of all communities, while *Fashion* communities amount to 1.01%,
 - *enable* is a discrete variable and specifies the state of the referral program. *enable* = 0 if a community is not eligible for the referral program. *enable* = 1 if a community is eligible for the referral program and the owner applies it. *enable* = 2 if a

¹⁰In total there are approximately 10 million registered users on Little Secret Communities up to December 2018, but most users only use free communities.

¹¹December 17, 2018 is the date that we received the data set, while the latest community in our data was created on October 16, 2018.

¹²The average disposable income per capital in China in 2017 was 25,974 RMB, according to *China Daily's* report on Chinese disposable income.

community is eligible for the program but the owner chooses 0% as the sharing percentage.

Table 2: Number and percentage of communities by type for all communities

type	number of communities	corresponding percentage (%)
Art	55	3.97
Economics	493	35.57
Education	289	20.85
Entertainment	27	1.95
Fashion	14	1.01
Health	26	1.88
Life	118	8.51
Science	364	26.26
Total	1386	100.00

2. Monetary measures: *percent* and *fee*;

- *percent* denotes the sharing percentage. The first time owners make the selection, the platform recommends 30% as the default value, but this can be adjusted,
- *fee* refers to the annual fee that users need to pay for access to the content in a community, valid for one year from the date of payment. Since Little Secret Communities only provides a Chinese version, the original currency is RMB. For convenience, we transform the monetary unit from RMB to USD according to the 1:0.15 RMB-USD ratio on December 28, 2018. Note that throughout this paper, both **price** and **annual fee** is the same concept but depends on the context: **price** is used when we stand in the position of a community owner, and **annual fee** is used from a user’s perspective.

3. Quality measures: *content*.

- *content* represents the numbers of topics previously discussed or currently being discussed, uploaded files, and questions which have been answered by owners.

3.2 Summary Statistics

We show some basic yet important static facts from our data. The summary statistics of number of users, content, and monetary measures are given in Table 3.

Table 3: Summary statistics of key variables

	mean	s.d.	min	max
All communities (N=1386)				
Sharing percentage (%)	13.55	17.33	0	50
Number of users	624	1310.55	20	18309
Number of content	1585	5042.98	3	122937
Annual fee (\$)	61.27	89.96	7.20	895.20
Income (\$)	36293.00	89049.10	187.50	1335051.30
Not eligible for the referral program (N=551)				
Number of users	576	747.18	196	8563
Number of content	1107	1776.66	3	15346
Annual fee (\$)	77.66	101.09	7.35	761.25
Income (\$)	39914.00	66119.74	1552.00	846659.00
Eligible for the referral program and applied (N=643)				
Sharing percentage (%)	29.20	13.78	5	50
Number of users	693	1657.66	20	18309
Number of content	1772	4633.04	11	58684
Annual fee (\$)	48.62	77.54	7.20	895.20
Income (\$)	33409.9	94910.73	187.50	1335051.30
Eligible for the referral program but not applied (N=192)				
Number of users	530	1256.77	25	11987
Number of content	2333	10091.289	23	122937
Annual fee (\$)	56.59	87.85	7.20	469.65
Income (\$)	35557.10	120695.05	236.20	1299413.70

Note that \$ above denotes U.S. dollars. For reader’s convenience, we convert monetary unit from RMB in our original data to U.S. dollars according to 1:0.15 RMB-USD exchange rate on December 29, 2018.

We check out the relationship between the number of users per community and annual fee in Figure 1. There is a rather ambiguous relationship across eight types. We observe positive correlation between number of users and annual fee for *Art*, *Economics*, *Education*, *Fashion*, and *Science* communities. The correlation is negative for *Health* and *Life* communities. It seems that there is (almost) no correlation for *Entertainment* communities.

Figure 1: Relationship between the number of users and the annual fee. Note that the number of users and the annual fee have been taken log. The deep blue solid line represents the fitted line according to linear regression between $\log(\text{annual fee})$ and $\log(\text{number of users})$ with respect to each type.

Figure 2: Distribution of sharing percentage with respect to each type for those who set up this scheme. The orange line denotes 30%, which is the percentage recommended by the platform.

We also show how owners choose sharing percentage. As in Table 2, there are 643 communities whose owners are willing to share revenue with users for successful referrals, which amount to 46.39% of all communities. A large magnitude of sharing percentage may give users a strong enough incentive for referral, which in turn benefits the owner through more revenue from a larger group of users. Figure 2 shows how sharing percentage distributes within each type of the communities and differs across different types of communities. The feasible interval of percentage that owners can select is from 5% to 50%. The sharing percentage across eight types is not identically distributed, which implies owners of different types have different preferences of sharing revenue with users in exchange for their referrals.

4 Structural Model

We use a simple structural model to describe the pricing strategy of each community owner. At the beginning, the platform decides whether or not a community $i \in \{1, \dots, n\}$ of type $m \in \{1, \dots, M\}$ is eligible for the referral program based on its own observation. Let $\mathcal{C}_{im}^{e=1}$ denote a community eligible for the referral program, and $\mathcal{C}_{im}^{e=0}$ a community not eligible for the referral program. We assume that each community owner, as the decision taker, has no power to influence the platform’s decision.

We also assume that pricing is static; that is, the owners’ pricing strategy is invariant with respect to time.¹³ An owner of $\mathcal{C}_{im}^{e=0}$ appropriately sets up price p_{im} and maximizes her profit. An owner of $\mathcal{C}_{im}^{e=1}$ needs to decide both p_{im} and s_{im} . In addition, let ξ_s denote an owner’s specific *non-monetary* preference of sharing percentage $s \in \mathcal{S} = \{s_0, s_1, \dots, s_{max}\}$. In particular, s_0 represents “no share” (i.e., $s = 0$), and s_{max} is the highest sharing percentage allowed by the platform. In our data, an owner cannot share more than 50% of her revenue which leads $s_{max} = 50\%$. ξ_s depends neither on demand nor on cost, and is observed by owners but not by econometricians. Economically, ξ_s represents an owner’s personal *non-monetary* preference to attract people with whom she does not have a direct link but whom her users can reach through their networks.

¹³Thanks to Little Secret Communities, we obtained additional data four months after our data collection period. This gives us the opportunity to verify our static pricing assumption. For further details, please refer to Appendix F. In addition, DellaVigna and Gentzkow (2019) give two qualitative explanations to uniform pricing in US retail chains after discussions and interviews with managers, consultants and analysts: *managerial inertia* and *brand image concerns*, which fit into our context.

4.1 Timeline

For an owner of $\mathcal{C}_{im}^{e=0}$, she simply needs to determine $p_{im}^{e=0}$ which maximizes the profit, while for an owner of $\mathcal{C}_{im}^{e=1}$, we assume her timeline is as follows:

In details:

1. At $t = 0$, the platform decides the communities that are eligible for the referral program ($\mathcal{C}_{im}^{e=1}$), and those that are not ($\mathcal{C}_{im}^{e=0}$).
2. At $t = 1$, the owner of $\mathcal{C}_{im}^{e=1}$ must first decide price $p_{im}^{e=1}$. Since the referral program will appear on the platform interface only after $p_{im}^{e=1}$ is determined and ξ_s is not yet observed, the owner has to consider whether or not to maximize her potential profit:

$$\begin{aligned} & \max_{p \geq \underline{p}} \mathbf{E} \left\{ \pi^{e=1}(p, x_{im}, u_{im}) \right\} \\ &= \sum_{s \in \mathcal{S}} \pi^{e=1}(p, x_{im}, u_{im}, s, \xi(s)) \mathbf{P} \left(\arg \max_{q \in \mathcal{S}} \pi^{e=1}(p, x_{im}, u_{im}, q, \xi(q)) = s \right), \end{aligned}$$

3. After $p_{im}^{e=1}$ has been defined, ξ_s is revealed,
4. At $t = 2$, the owner chooses an appropriate sharing percentage $s_{im} \in \mathcal{S}$ according to the determined price $p_{im}^{e=1}$ and the revealed preference ξ_s , such that:

$$\pi^{e=1}(x_{im}, s_{im}, u_{im}, \xi_s | p_{im}) = D_{im}^{e=1} \times p_{im} \times \{1 - s_{im} \tau_{im}\} - \Psi(D_{im}^{e=1}) + \xi_s$$

is maximized.

We assume that ξ_s 's are independently distributed with $\xi_{s_0} = 0$ because if there is no sharing, the community owner becomes a “pure” profit maximizer: this is equivalent to considering “no share” as a outside option.

4.2 Decision of an Owner of $\mathcal{C}_{im}^{e=0}$

For such an owner, she only needs to determine the annual fee based on her prediction of the potential demand. We model the potential demand as a function of price and community characteristics and use $D^{e=0}(p_{im}, x_{im}, u_{im})$ to denote the demand function for $\mathcal{C}_{im}^{e=0}$, where x_{im} is a vector including all community characteristics observed by both owners and econometricians, and u_{im} contains all factors affecting demand that are observed only by community owners but not by econometricians.

There are also the costs of running a community. We assume that the cost function Ψ_{im} is a linear function of the potential demand:

$$\psi_{im} \equiv \Psi(D_{im}^{e=0}(p_{im}, x_{im}, u_{im})) = \psi_{i,D} D_{im}^{e=0},$$

where $\psi_{i,D}$ represents the marginal cost of maintaining a community i with demand $D_{im}^{e=0} \equiv D^{e=0}(p_{im}, x_{im}, u_{im})$. It can also be interpreted as the opportunity cost of online content provision. For example, the marginal cost of an *Economics* community owner can be her opportunity cost of not being able to spend as much time on stock market analysis as she did before becoming an owner on Little Secret Communities.

The problem of $\mathcal{C}_{im}^{e=0}$ is determined by maximizing profit function $\pi^{e=0}(p_{im}, x_{im}|u_{im})$:

$$\max_{p_{im} \geq 0} \pi^{e=0}(p_{im}, x_{im}, u_{im}) = \begin{cases} D^{e=0}(p_{im}, x_{im}, u_{im}) \times (p_{im} - \psi_{im}) & p_{im} \geq \underline{p} \\ 0 & p_{im} = 0 \end{cases}$$

with $\underline{p}$ representing the minimum pricing requirement set by the platform.

In this simple case, the optimal decision of a community owner is described by the first order condition:

$$\frac{\partial}{\partial p_{im}} \pi^{e=0}(p_{im}, x_{im}, u_{im}) = \frac{\partial}{\partial p_{im}} D_{im}^{e=0} \times p_{im} + D_{im}^{e=0} - \psi_{i,D} \frac{\partial}{\partial p_{im}} D_{im}^{e=0} = 0,$$

which implies that:

$$\left(p_{im} + \frac{D_{im}^{e=0}}{\frac{\partial}{\partial p_{im}} D_{im}^{e=0}} \right) - \psi_{i,D} = p_{im} \left(1 + \frac{D_{im}^{e=0}}{p_{im}} \frac{\partial p_{im}}{\partial D_{im}^{e=0}} \right) - \psi_{i,D} = 0.$$

A community owner will decide the potential optimal price such that:

$$p_{im} \left(1 + \frac{D_{im}^{e=0}}{p_{im}} \frac{\partial p_{im}}{\partial D_{im}^{e=0}} \right) = p_{im} \left(1 + \frac{1}{\varepsilon} \right) = \psi_{i,D},$$

where ε represents the expected demand elasticity and $\frac{1}{\varepsilon}$ is the Lerner Index that measures an owner's market power. The optimal price would be high when the demand is inelastic (i.e., $|\varepsilon|$ is smaller than 1), as an inelastic demand means an owner has more market power in her own "content provision market", which induces her to raise the price. An example where we assume the demand function takes a log-linear form is given in Appendix E.

4.3 Decision of an Owner of $\mathcal{C}_{im}^{e=1}$

Now consider a community eligible for the referral program. In this case, the potential demand $D_{im}^{e=1}$ becomes a function of price, community characteristics, unobserved characteristics, and referral payment:

$$D_{im}^{e=1} = D^{e=1}(p_{im}, r_{im}, x_{im}, u_{im}) = D^{e=1}(p_{im}, s_{im}, x_{im}, u_{im})$$

with $r_{im} = s_{im} \times p_{im}$. Note that r_{im} is the referral payment that a user can receive when he posts a sharing link through which someone pays price p_{im} and joins the community $\mathcal{C}_{im}^{e=1}$.

The price now has two opposite effects. On the one hand, a higher price lowers demand. On the other hand, given a sharing percentage s_{im} , the owner can use a higher price to stimulate existing users for referrals. Therefore, a higher price can also lead to faster network expansion and more potential demand.

Under the referral program, a proportion τ of total users in a community comes from existing users' sharing links. Assume τ is a function of referral payment r_{im} . We then specify $\tau_{im} = \Lambda(r_{im})$. Note that τ_{im} is bounded above and below. $\Lambda(r_{im}) = 0$ if no referral is allowed (i.e., $r_{im} = 0$); $\Lambda(r_{im}) = 1$ if $r_{im} \rightarrow \infty$, because if the referral payment becomes too high, any existing user is going to refer the community, and almost all new users would come through a sharing link. In the rest of this paper, we assume that τ_{im} takes an exponential form:

$$\Lambda(r_{im}) = 1 - \exp\{-\lambda_{im} \log(1 + r_{im})\}.$$

This functional form implies that τ_{im} is positively correlated with λ_{im} . We interpret λ as the referral effectiveness with respect to the network structure of each community type.¹⁴ Note that $\lambda_{im} = \lambda_m$, or in other words, λ is a type-specific parameter, which combines both the popularity of a certain type of content among the general population and people's willingness to pay through a sharing link.

Figure 3 illustrates two different roles of referral effectiveness (λ). First, as the blue arrows

¹⁴Han and Xu (2018) empirically identify the effect of different network structures on the technology diffusion process. They show that without using a detailed structural model, it is difficult to fully reveal such an effect. In this paper, λ 's roughly capture this effect.

in panels 3a and 3b shows, λ influences an owner's network expansion, since higher referral effectiveness means higher popularity of the content and easier mental accounting users make to pay for the community. Second and more importantly, as the red arrow in panel 3b shows, λ influences how users who have been in the owner's network join the community. If λ is high enough, some users who should have paid the full annual fee join through sharing links: in panel 3b, user 2 have been in the owner's network and could have paid the full annual fee. However, user 2 eventually joined the community via user 1's referral. In this case, the owner needs to provide user 1 with a referral payment, and provide user 2 with a discount.

Note: in each subfigure, the black line represents the owner's network with users; the red diamond represents a community owner and blue circles represent potential users; the blue arrow represents λ 's role in network expansion, and the red arrow represents additional role of λ in affecting users who have been in an owner's network. In this case, $\lambda_a < \lambda_b$ and $\tau_a = \frac{1}{3} < \frac{2}{3} = \tau_b$.

Figure 3: Roles of network expansion and λ

Network structure and λ . Different types of community can have different network structures. For owners of some types, they are connected with all of her potential users. In this case, it is more likely to join the community directly by paying for the owner. However, if an owner is linked with a limited number of her potential users, then she will appeal more to referrals. Therefore, the referral effectiveness (λ) in the second kind of network structure can be larger than that in the first one. We should be aware that the network structure in reality can be more complicated than any one of the scenarios here.

λ , τ , and revenue loss. The larger λ is, the easier a type of content can be disseminated by referrals. The more users who are supposed to fully pay the annual fee will join through sharing links (i.e., the larger τ is), the more revenue loss there will be.

The potential income of a community $\mathcal{C}_{im}^{e=1}$ is:

$$\begin{aligned} D^{e=1}(p_{im}, s_{im}, x_{im}, u_{im}) &\times \left\{ \underbrace{(1 - \tau_{im}) p_{im}}_{\text{without sharing}} + \underbrace{\tau_{im} (1 - s_{im}) p_{im}}_{\text{with sharing}} \right\} \\ &= D^{e=1}(p_{im}, s_{im}, x_{im}, u_{im}) \times p_{im} \times (1 - s_{im} \tau_{im}). \end{aligned}$$

In this particular case, “choosing a sharing percentage” becomes a very sophisticated decision. Conditional on p_{im} , sharing more ($s' > s$) provides a possible demand expansion through a user’s network and therefore brings potential demand:

$$D^{e=1}(p_{im}, s', x_{im}, u_{im}) - D^{e=1}(p_{im}, s, x_{im}, u_{im}) \geq 0.$$

Sharing causes some potential demand loss for those who could have paid fully, which amounts to $\tau_{im} D^{e=1}(p_{im}, s_{im}, x_{im}, u_{im})$.

The cost function remains unchanged because the referral program does not directly affect the cost of community operations. We can express $\mathcal{C}_{im}^{e=1}$ ’s profit function by:

$$\pi^{e=1}(p_{im}, x_{im}, s_{im}, u_{im}, \xi(s_{im})) = D_{im}^{e=1} \times p_{im} \times (1 - s_{im} \tau_{im}) - \Psi(D_{im}^{e=1}) + \xi_{s_{im}}.$$

4.4 Backward Induction

We adopt the backward induction method to solve the decision of an owner of $\mathcal{C}_{im}^{e=1}$. At $t = 2$, given a price p_{im} , this owner chooses the optimal sharing percentage s_{im} according to:

$$\max_{s_{im} \in \mathcal{S}} \pi^{e=1}(x_{im}, s_{im}, u_{im}, \xi_s | p_{im}) = D_{im}^{e=1} \times p_{im} \times \{1 - s_{im} \tau_{im}\} - \Psi(D_{im}^{e=1}) + \xi_{s_{im}},$$

where p_{im} denotes the price under the referral program. If s_{im} has been chosen, it must at least satisfy the following condition:

$$\forall s \in \mathcal{S} \text{ and } s \neq s_{im}, \pi^{e=1}(x_{im}, s, u_{im}, \xi_s | p_{im}) \geq \pi^{e=1}(x_{im}, s_{im}, u_{im}, \xi_s | p_{im}).$$

An alternative way to express the condition above is:

$$\begin{aligned} \forall s \in \mathcal{S} \text{ and } s \neq s_{im}, v(x_{im}, s, u_{im}, \xi_s | p_{im}) &\geq v(x_{im}, s_{im}, u_{im}, \xi_s | p_{im}), \text{ with:} \\ v(x_{im}, s, u_{im}, \xi_s | p_{im}) &= \frac{\pi^{e=1}(x_{im}, s, u_{im}, \xi_s | p_{im}) - \pi^{e=1}(x_{im}, s_0, u_{im}, \xi_{s_0} | p_{im})}{|\pi^{e=1}(x_{im}, s_0, u_{im}, \xi_{s_0} | p_{im})|} \\ &= v(x_{im}, s, u_{im} | p_{im}) + \tilde{\xi}_s, \end{aligned}$$

where:

$$v(x_{im}, s, u_{im}|p_{im}) = \frac{\pi^{e=1}(x_{im}, s, u_{im}, \xi_s = 0|p_{im}) - \pi^{e=1}(x_{im}, 0, u_{im}, \xi_s = 0|p_{im})}{|\pi^{e=1}(x_{im}, 0, u_{im}, \xi_s = 0|p_{im})|},$$

$$\text{and } \tilde{\xi}_s = \frac{\xi_s}{|\pi^{e=1}(x_{im}, 0, u_{im}, \xi_s = 0|p_{im})|}.$$

We assume that $\tilde{\xi}$ is logistically distributed such that:

$$\mathbf{P}(s_{im} = s|p_{im}, x_{im}, u_{im}) = \begin{cases} \frac{\exp\{v(x_{im}, s_{im}, u_{im}, \xi_s|p_{im})\}}{1 + \sum_{s \in \mathcal{S} \text{ and } s \neq s_0} \exp\{v(x_{im}, s, u_{im}, \xi_s|p_{im})\}} & \text{if } s_{im} \neq 0 \\ \frac{1}{1 + \sum_{s \in \mathcal{S} \text{ and } s \neq s_0} \exp\{v(x_{im}, s, u_{im}, \xi_s|p_{im})\}} & \text{otherwise} \end{cases}.$$

Therefore, at the first period, the optimization problem can be rewritten as:

$$\max_{p_{im} \geq \underline{p}} \mathbf{E} \{ \pi^{e=1}(p_{im}, x_{im}, u_{im}) \} = \sum_{s_{im} \in \mathcal{S}} \pi^{e=1}(p_{im}, x_{im}, u_{im}, s_{im}, \xi_{s_{im}} = 0) \mathbf{P}(s_{im} = s|p_{im}, x_{im}, u_{im}).$$

5 Identification and Estimation Strategy

Let $\theta = (\beta^{demand}, \psi^{cost}, \lambda^{share})'$ be a vector of parameters of interest, where β^{demand} affects the demand function, ψ^{cost} affects the cost function, and λ^{share} influences revenue loss from referral payment. In this section, we focus on how to identify and estimate θ from data.

Our demand equation contains many parameters, and the cost function for each community owner can be non-identical due to the existence of heterogeneity. Given these estimation challenges, we provide a novel method to estimate the model, which dramatically improves the speed of estimation, especially in the case when θ has a large dimension. Compared with the ordinary GMM or likelihood method, which have been extensively used in the existing structural model estimation literature,¹⁵ our method has depicted a step-by-step road-map to avoid the “computational complexity” and “overcomplicated and unwieldy models” discussed in Low and Meghir (2017).

¹⁵Gourieroux and Monfortand (1996) mention GMM in Section 2.2, as well as Simulated Maximum Likelihood and Pseudo-Maximum Likelihood in Section 3 by a simulation-based approach. Low and Meghir (2017) also provide a comprehensive discussion on structural model estimation. In particular, they discuss in detail the use of GMM in the section *Using Method of Moments for Estimation of Structural Models*.

5.1 Model Identification

5.1.1 Demand Equation (β)

The demand equation $D(p, s, x; \beta)$ is a function of price $p \in \mathbf{R}_+$, sharing percentage $s \in [0, 1]$, and a vector of control variables x . We use several control variables to capture the demand of content of different types and qualities, including type of community, duration of existence of community, and quality of the community represented by the average content updating frequency. We assume that the demand function $D(p, s, x; \beta)$ is a rich log-linear function, which takes the following form:

$$\begin{aligned} \log D(p, s, x; \beta) = & \beta_{price} \log p + \beta_{reward} \log(1 + p \times s) + \beta_{share} s + \beta_{share^2} s^2 \\ & + \beta_{price \times duration} (\log p \times \log(\text{duration})) + x' \beta_x + \eta, \end{aligned}$$

where β_{price} captures the price elasticity of demand; β_{reward} ¹⁶ captures the pure effect of network expansion. For communities not eligible for the referral program, we set $s = 0$ which leads directly to $\log(1 + p \times s) = 0$; β_{share} and β_{share^2} allow the possibility that consumers are sensitive to relative sharing percentages rather than to absolute sharing amounts. We also allow that price elasticity of demand can be time-varying and use $\beta_{price \times duration}$ to capture the effect. This essentially allows for the possibility that long-lived communities could have stronger market power by capturing as many loyal followers as possible, which would be one important source of heterogeneity. η is an error term that is assumed to be normally distributed with mean 0 and variance σ^2 .

5.1.2 Our Solution to Endogeneity Problem

Owner-determined prices and sharing percentage in our demand equation are endogenous. The same endogenous problem also applies to all interaction terms using these two variables. This is not usual since in general we rarely allow more than one endogenous variable when estimating a reduced form model. Multiple endogenous variables will cause greater difficulty in identification and interpretation of the model. To deal with this problem, we use many instruments (at least more than one) to fix the problem. In our data, a set of relevant instrumental variables is derived from the owners' cost function. Specifically, we consider the user's satisfaction rate and regret rate based on their user experience in a community.

At a certain point in time, the platform sent a questionnaire to users in all communities, asking whether or not they were satisfied with the community and whether or not they

¹⁶Note that the subscript "reward" is equivalent to referral payment hereafter, especially in equations.

regretted joining the community. Survey results were not made public (in particular, confidential to owners) since the purpose of this survey was to understand the operational quality of each community. A potential user yet to join was also not aware of such information. To a great extent, the survey results also reflected the communities' operating costs. As many users declined to complete the questionnaire, those satisfied with a community were those who were "extremely" satisfied, while those who regretted joining the community were those who felt "extremely" disappointed. From an owner's perspective, they would need to incur higher marginal cost to make users feel satisfied.

We apply a validity check by considering one more instrumental variable in the new data provided courtesy of Little Secret Communities. This new data set covers 791 common communities as in our main data. It extends until April 17, 2019, which is four months after our data collection period. The additional instrumental variable from the new data is the number of words per post in each community. It shows an owner's effort when writing each post, while it does not affect the demand side. We add the number of words per post in our demand equation as the *third* instrumental variable besides the satisfaction rate and the regret rate. In this case, since we have more instrumental variables than endogenous variables, we run the Sargan test of over-identification. The p-value of the Sargan test statistic is not even significant at 10%, which means that *all* instruments are uncorrelated with the error term in our demand equation. This proves the validity of our original set of instrumental variables: the satisfaction rate and the regret rate. The detailed analysis is in Appendix H.

In order to fix the endogeneity problem, we identify the demand equation by using the satisfaction and regret rates. Once the demand equation is identified, we estimate the cost equation based on the identified demand equation and compute the optimal price for each community. We take the estimated price and marginal cost as new instrumental variables and substitute them into the demand equation again, with the same steps followed. We conduct the weak instrument test and Wu-Hausman test which show that our instrumental variables are feasible and robust. The detailed test results are in Appendix G.

Let z denote the set of original instrumental variables. Together with x and (p, s) , θ would be identified.

5.1.3 Marginal Cost (φ) and Its Heterogeneity

The cost function, for simplicity, is assumed to be a linear function of demand:

$$C(D; \varphi) = \varphi_i D,$$

where φ_i represents the marginal cost of each owner. This linear setting means that there is no fixed cost of community registration, since the registration procedure on Little Secret Communities is free and takes less than 10 minutes. Marginal cost here mainly captures two sources of heterogeneity: first, the owner’s idiosyncratic preference for “niceness”; and second, the different opportunity cost that community owners may have. To identify the cost function, we apply the following strategies.

For communities not eligible for the referral program, the demand function can be simply expressed as:

$$\log D(p, s = 0, x; \beta),$$

and the demand elasticity is captured by:

$$\varepsilon = \beta_{price} + \beta_{price \times duration} \times \log(\text{duration}).$$

In addition, the model’s first order condition ensures that the optimal choice follows:

$$p \left(1 + \frac{1}{\varepsilon} \right) = \varphi.$$

Given p and ε , we can compute the value of $p \left(1 + \frac{1}{\varepsilon} \right)$ and are able to identify φ_i as a function of selected instrumental variables z : $\varphi_i \equiv \varphi(z_i)$. Note that the cost function is only related to the demand equation, and therefore it is not directly related to whether or not to choose to share. Once (φ_i, z_i) is obtained, we are able to generalize the cost function to all communities based on the cost function identified by $\mathcal{C}_{im}^{e=0}$.

5.1.4 Revenue Loss from the Referral Program (λ)

Once the demand equation and cost function are identified, we now identify the revenue loss by the referral program. Our model assumes that given the price and costs, different sharing percentage $s \in \mathcal{S}$ may bring different levels of potential profits $\pi_s(p, \varphi_i, \beta, \lambda)$. The community owner compares the percentage increase in profit under different choices of sharing percentage s with that under no sharing at all (i.e., $s = 0$):

$$\nu_s(p, \varphi_i, \beta, \lambda) = \frac{\pi_s(p, \varphi_i, \beta, \lambda) - \pi_{s_0}(p, \varphi_i, \beta, \lambda)}{\left| \pi_{s_0}(p, \varphi_i, \beta, \lambda) \right|}.$$

Combining their own preferences for different sharing percentages, they are able to make a decision on s .

Given the price, cost, and instrumental variables (p_i, φ_i, z_i) , λ influences the probability that owners of different types choose a particular sharing percentage. So it can be at least locally identified by observing the selection probability of different levels of sharing $\mathbf{P}(s|p, \varphi; \lambda)$ in the data.¹⁷

5.2 Estimation Strategy

Based on the identification of the model, we estimate θ . Compared with the simulated moment method or likelihood method, we provide a novel estimation method which incorporates both endogeneity and marginal cost heterogeneity.¹⁸ The whole estimation process is specified in the following steps:

1. Based on the observations $(p_i, s_i, x_i, z_i)_{i=1, \dots, n}$, we use all data to estimate the log-demand function $\log D(p, s, x; \beta)$ according to the Two-Stage Least Squares (2SLS) method. The estimation gives $\hat{\beta}_{IV}$;
2. Using $\hat{\beta}_{IV}$, we can calculate the elasticity of demand $\hat{\varepsilon}_i$ for different communities;
3. The first order condition allows us to obtain the marginal cost φ_i of each owner of $\mathcal{C}_{im}^{e=0}$ according to $(p_i^{e=0}, \hat{\varepsilon}_i^{e=0})$;
4. Using non-parametric estimation,¹⁹ we can get $\hat{\varphi}_i(z_i^{e=0}|\hat{\beta}_{IV})$ as a function of z_i ;
5. Since we assume that the cost function is only related to the demand and the instrumental variable z does not affect the eligibility for the referral program, we can extrapolate $\hat{\varphi}_i$ to $\mathcal{C}_{im}^{e=1}$, we then obtain $\hat{\varphi}_i(z_i^{e=1}|\hat{\beta}_{IV})$. Let $\hat{\varphi}_i = \hat{\varphi}_i(z_i^e|\hat{\beta}_{IV})$ for $e \in \{0, 1\}$;
6. Given $\hat{\varepsilon}_i$ and $\hat{\varphi}_i$, we calculate the optimal price $\hat{p}_i$ assuming $s = 0$ for *all* communities; in other words, even for $\mathcal{C}_{im}^{e=1}$, we assume $s = 0$ and then calculate the optimal price accordingly;
7. Let $z_i^* = (\hat{p}_i, \hat{\varphi}_i)$ be a new instrumental variable into and replace z_i in Step 1. We re-estimate the demand function to see whether or not the instrumental variables are valid and robust;

¹⁷McFadden (1984) introduces this method in detail.

¹⁸Han and Xu (2018) use a similar estimation method.

¹⁹In practice, we use a kernel regression estimate of a one dimensional dependent variable on p-variate explanatory data (see Li and Racine 2007), and bandwidth is specified by using the method of Racine and Li (2004) and Li and Racine (2004). In fact, parametric estimation or any other type of non-parametric estimations (e.g., sieve estimator) could be used in this step.

8. If Step 7 proves that instrumental variables are valid and robust, we use the estimates of Step 7 as a reinforced estimation of the demand function $\hat{\beta}_{IV}^r$. In fact, one can redo Step 1 to Step 7 several times to get an even more “powerful” set of instrumental variables;²⁰
9. Based on $\hat{\beta}_{IV}^r$, redo Step 2 to Step 5, we obtain $\hat{\varphi}_i(z_i^e|\hat{\beta}_{IV}^r)$ for $e \in \{0, 1\}$. Now $\hat{\varphi}_i = \hat{\varphi}_i(z_i^e|\hat{\beta}_{IV}^r)$;
10. Based on $\hat{\beta}_{IV}^r$ and $\hat{\varphi}_i$, for all $\mathcal{C}_{im}^{e=1}$, we can compute their predicted profit under different sharing percentages:

$$\pi_s(p_i, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda), \text{ for } s \in \mathcal{S},$$

which provides the percentage increase in profit compared to the benchmark case (no sharing at all, i.e., $s = 0$):

$$\nu_s(p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda) = \frac{\pi_s(p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda) - \pi_0(p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda)}{|\pi_0(p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda)|} \text{ for } s \in \mathcal{S};$$

11. Compute the conditional probability of observing $\mathbf{P}(s_i = s | p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda)$ by:

$$\mathbf{P}(s_i = s | p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda) = \frac{\exp\left\{\nu_{s_i}(p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda)\right\}}{1 + \sum_{q \in \mathcal{S}} \exp\left\{\nu_q(p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda)\right\}};$$

12. Since λ changes with the type of community (i.e., $\lambda_{im} = \lambda_m$ for community i providing content of type $m \in \{1, \dots, M\}$), we estimate different λ 's. The corresponding log-likelihood function is:

$$\sum_{m=1}^M \sum_{i \in \mathcal{G}_m^1} \log \mathbf{P}(s_i = s | p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda = \lambda_m)$$

where $\mathcal{G}_m^1$ represents the group including all communities of type m and $e_i = 1$. Rather than jointly estimate λ_m 's, we can estimate λ separately for each type of community. For $m \in \{1, \dots, M\}$:

²⁰This is inspired by Heckman and Urzua (2010).

$$\hat{\lambda}_m \in \arg \max_{\lambda} \sum_{i \in \mathcal{G}_m^1} \log \mathbf{P} \left(s_i = s | p_i^{e=1}, x_i; \hat{\beta}_{IV}^r, \hat{\varphi}_i, \lambda \right).$$

The above estimation process is depicted in the following algorithm tree in Figure 4.

Figure 4: Visualization of estimation process

The next section shows the results of model estimates. We show that our proposed method not only presents an exponential improvement in computational speed but also well explains the data we see in reality.

6 Results

When going through the estimation strategy step by step in practice, we eliminate the communities which were registered less than 75 days before December 17, 2018, when the data collection ended. Such elimination ensures that the included communities have had a stable number of users, while a recently registered community usually undergoes a flood of new users who have been loyal to the owner on other channels. It turns out that only one

community²¹ is eliminated. We also conduct robustness checks that remove communities which were registered less than 50, 125, and 150 days before December 17, 2018. The results are reported in Appendix I.

6.1 Demand estimations

Columns (1), (2), and (3) in Table 4 show the regression results of demand estimation using OLS, 2SLS, and the reinforced IV method, respectively. Under the simplest OLS specification, the coefficient of price is slightly negative but not statistically significant at all. With our instrumental variables (i.e., the satisfaction rate, the regret rate, and relevant interaction terms), the 2SLS specification corrects the slope of the demand equation and makes the estimates look more reasonable. We now have a negative and statistically significant effect of price on the demand.

To better filter out endogeneity, we construct a set of reinforced instrumental variables from the satisfaction rate and the regret rate. As discussed in Subsection 5.1.2, we use the estimated marginal cost ($\hat{\varphi}_i$) and optimal profit-maximizing price ($\hat{p}_i$) as the reinforced instrumental variables.

Column (3) reports the results of this reinforced IV method. Comparing columns (2) and (3), we observe that our key variables including price, sharing percentage and its squared term, reward, and the interaction term between price and duration are both qualitatively and quantitatively similar. We conduct several diagnostic tests on the validity and robustness of our reinforced instrumental variables, including the weak instrument test, the Wu-Hausman test, and the Sargan test. All test results support the validity of instrumental variables and superiority of using $\hat{\varphi}_i$ and $\hat{p}_i$. The detailed results can be found in both Appendix G and Appendix H.

The influence of price on demand is significant: on average, a 1% increase in price induces a 6.7% decrease in demand. The effect of sharing percentage on demand depends on its relative magnitude. According to the coefficient of sharing percentage and its squared term, users do not have enough incentive for referrals unless the sharing percentage surpasses 39.5%, which is relatively high given the range from 0% to 50%. This implies that users may enjoy the exclusiveness of content provision within a community unless the sharing percentage is high enough to provide a concrete monetary reward. The magnitude of the reward reflects the effect of owners' network expansion through users' referrals. Note that

²¹The eliminated community is an *Economics* one with 285 people, opened on October 6, 2018. As a comparison, the second latest community in our data is also an *Economics* one, opened on September 5, 2018; however the number of its users is 18,309 – 64 times more than the eliminated community of the same type.

this effect is only statistically significant at 10%, since it takes time for a community to be eligible for the referral program, which is not observed by users when they decide to join a community.

Table 4: Demand estimation results

	(1) OLS	(2) 2SLS	(3) Reinforced IV
(Intercept)	17.797*** (3.374)	32.709** (12.244)	47.507** (15.371)
Price	-0.650 (0.412)	-4.690 [†] (2.775)	-6.688* (3.405)
Sharing Percentage	-0.018* (0.009)	-0.233** (0.075)	-0.237* (0.094)
Sharing Percentage ²	0.000 (0.000)	0.003* (0.001)	0.003 [†] (0.001)
Reward	0.010 (0.061)	1.520** (0.556)	1.101 [†] (0.599)
Duration	-1.573*** (0.452)	-3.487 [†] (1.784)	-5.582* (2.243)
Price×Duration	0.100 (0.067)	0.634 (0.431)	0.974 [†] (0.532)
Type: Economics	0.103 (0.135)	0.179 (0.198)	0.043 (0.217)
Type: Education	-0.086 (0.138)	-0.110 (0.189)	0.017 (0.207)
Type: Entertainment	0.751*** (0.221)	0.485 (0.315)	0.427 (0.360)
Type: Fashion	-0.307 (0.283)	-0.305 (0.407)	-0.032 (0.445)
Type: Health	-0.364 (0.224)	-0.546 (0.352)	-0.410 (0.383)
Type: Life	0.033 (0.155)	-0.221 (0.217)	-0.259 (0.248)
Type: Science	0.154 (0.136)	0.189 (0.196)	0.304 (0.212)
Updating Frequency	0.388*** (0.021)	0.443*** (0.037)	0.490*** (0.046)
Num. obs.	1385	1385	1385
RMSE	0.933	1.193	1.318

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$.

In all three specifications, we include both month and year for time fixed effect. Notice that from 2SLS to reinforced IV method, the estimates are almost all qualitatively alike with similar magnitude.

The highly statistically significant estimate of update frequency proves the importance of high quality content provision on demand. The statistical insignificance of all types implies that most users join for specific community owners, and type is not as important as monetary factors (price, sharing percentage, and reward) and quality measure (updating frequency).

6.2 Cost function estimation

We assume the cost function is a linear function of demand, and focus on the marginal cost of each community. The marginal cost of most communities (regardless of their types) is around 30 U.S. dollars, which is much higher than the average price of all communities at 61.27 U.S. dollars.²²

The dashed line in Figure 5 shows the mean of marginal cost of each type. The average marginal cost of *Economics* communities is much larger than any other type, while that of *Education*²³ and *Life* communities is the smallest among all types. Detailed statistics of marginal cost are reported in Appendix J.

Figure 5: Opportunity cost of content provision

A higher marginal cost represents: first, a higher opportunity cost for the community owner; and/or second, a stronger preference to keep her community “niche” by setting a higher price accordingly. The “niceness” (or being very specialized) reflects the value of information or expertise that owners provide.

Economics community owners have the highest opportunity cost to provide high quality content since they are usually active in their own business operations, consultancy services,

²²The average price of all communities and the relevant subgroup of communities are shown in Table 3.

²³Note that the maximum estimated marginal cost of *Education* communities is the second largest among all communities. Although its average marginal cost is the smallest, the range is large.

and other economic or financial related highly paid jobs. This generates more income than posting content in their communities. In addition, *Economics* community owners are more interested in making their communities “niche”. For example, an experienced broker has spent a considerable amount of time and effort on stocks in a certain industry. This makes her information and analysis highly valuable, which adds to the marginal cost for her to share with others.

Education community owners have the lowest marginal cost. This is consistent with the social phenomenon in recent years whereby Chinese are willing to invest in education for their own and, more importantly, for their children. In response to this trend, *Education* community owners focus more on making their own experience or expertise become the mainstream, and are therefore less interested in making their expertise “niche”. In addition, *Education* community owners are often teachers at test-prep corporations, such as Kaplan. They can easily “copy and paste” their own teaching materials in the classroom to communities and therefore have negligible opportunity costs.

We do not use any information about the type of a community when estimating cost function. However, as indicated in Figure 5, our cost function estimation results are consistent when we take type into consideration. This verifies this important technical advantage of our cost function estimation.

6.3 Revenue Loss from the Referral Program

Given estimated demand and marginal cost, we now determine the revenue loss from the referral program. The revenue loss comes from a referral payment and a discount to those who should have paid a full annual fee but ultimately joined through sharing links. From Equation 4.3, we know that the proportion of users joining a community through a sharing link (i.e., τ) is positively correlated with the referral effectiveness (i.e., λ). We assume that λ is a community-specific parameter. It is then in our interest to estimate the referral effectiveness of each type of the communities, and use this as a guide to trace revenue loss.

Table 5 reports the estimated referral effectiveness for each type of the communities. Figure 6 shows the relationship between the referral payment (after taking log) and demand loss through simulations. Our estimation of the referral effectiveness is to find the maximizer of the probability of choosing a specific profit-maximizing sharing percentage.

The magnitude of referral effectiveness reveals the popularity of certain types of content among the general mass and people’s willingness to pay through the sharing link. As we observe from Table 5, *Fashion*, *Art*, and *Life* communities have a much larger referral effectiveness than other types. Note that these communities are easier to refer since these three

Table 5: Estimated referral effectiveness (λ)

	λ	p-value
Fashion	0.3859	0.980
Art	0.3346	0.980
Life	0.3137	0.000
Health	0.0608	0.000
Entertainment	0.0433	0.701
Economics	0.0239	0.000
Education	0.0205	0.000
Science	0.0200	0.000

types of information are usually the most popular on social media, and these communities have relatively low annual fees compared with other types, which makes it easier for potential users to perform mental accounting. As a result, some people who should have paid the full annual fee directly to the owners are now joining through sharing links.²⁴ In addition, community owners lose money for referral payments. However, the platform benefits as more users bring more commission regardless of whether they join directly or by referral.

The associated p-value of one specific type is jointly influenced by two factors: first, the uniformity of the community owner’s network structure; and second, a rational prior of existing users’ network structure. The referral effectiveness will be statistically insignificant if community owners of one type have various network structures, and/or they cannot form a rational prior on their existing users’ network structure.

If the community owners of one type have similar network structures but disagree on the network structure of their users, then λ is also going to be statistically insignificant. *Art* and *Fashion* community owners are likely to be in this scenario. *Art* community owners are often famous artists and art critics who, by means of offline activities, form an inter-connected network structure. However, it would be more difficult to infer their users’ network structure. *Fashion* community owners are often popular makeup vloggers²⁵ and key opinion leaders on luxury goods, and they usually form a tree-like network structure. But their users can have different backgrounds and therefore different network structures. For example, a white collar work and a college student may follow the same makeup vlogger, but are very likely to have different network structures.

If the community owners of one type have a rational prior on their users’ image but

²⁴In other words, τ is large.

²⁵Vloggers are those who record themselves talking about their life and upload it to video sites. “Vlog” stands for Video blogs.

very different network structures, then λ is also likely to be statistically insignificant. *Life* community owners are likely to be in this scenario. *Life* community owners cover a much wider range of topics compared with other types. For example, an interior designer and a master of floriculture, though both being *Life* communities owners, are very likely to have different network structures. However, since the expertise covered in *Life* communities is largely niche, it would not be hard for owners to infer their users' network structure.

Figure 6 illustrates the connection among λ , τ , and revenue loss. Given the same amount of reward, the higher λ is, the more easily the content can be disseminated. The more people who are supposed to pay the full annual fee now join through sharing links, the more revenue community owners lose. In this sense, *Fashion*, *Art*, and *Life* community owners suffer the most revenue loss from the referral program.

Figure 6: Effectiveness of the referral program

6.4 Goodness of Fit of Structural Model

After estimating our price, cost, and revenue loss, we double check the performance of our estimations with all of our estimates combined. In Figures 7 and 8, we compare our predicted

sharing percentage and optimal price with their true counterparts, respectively, in each type of the communities.

Figure 7: Goodness of fit of sharing percentage

Figure 8: Goodness of fit of optimal price

In both figures, red bars represent our predicted results and blue bars represent the true data. The sections where red and blue bars do not overlap with each other are what cannot be captured by our model. The non-overlapping sections also imply that these community

owners do not follow the profit maximization principle in their pricing strategy. Among all eight types of communities, *Economics* and *Science* communities have the best fit between our predicted sharing percentage and optimal price and their true counterparts. This indicates the rationality of the owners of these two types. Our predicted sharing percentage and optimal price of *Entertainment* and *Fashion* communities suffer from their observation deficiency compared to other types. The fewer overlapping sections also indicate that *Entertainment* and *Fashion* community owners are not purely for profit maximization but also for other purposes that are beyond our consideration in our model.

7 Counterfactual Analysis

In the above discussion, we have shown how community owners make decisions on both price and sharing percentage in order to maximize their profits given the infrastructure of the platform. From the moment an influencer first registers on Little Secret Communities, the platform primarily plays several roles: first, as a provider of a digital marketplace that facilitates the exchange of information; second, as the provider of secure monetary transactions with the annual fee in and out of owners' pocket; and third, as a careful investigator of any content which may pose a legal risk. However, this infrastructure is not provided free of charge. In reality, Little Secret Communities collect a fixed 5% commission from the entry of each new user. The community owners, regardless of the type of content they provide, have to internalize this sunk cost into their pricing consideration. In this sense, the platform's commission rate provides an excellent opportunity to examine how a profit-maximizing platform can influence the pricing decision of a group of profit-maximizing community owners (in general, content providers), and therefore shift the general welfare of all users on this platform.

Consider the scenario in which Little Secret Communities has monopolistic power on deciding the commission rate upon all communities. The higher the commission rate, the less a community owner can extract from the annual fee of a new user. This leads to a systematic adjustment of her decision on both the amount of annual fee and the sharing percentage. Now, we allow the platform to choose a commission rate between 0% and 95%, with each 5% an incremental step. Using the same definition of parameters in our model, we estimate the optimal commission rate which maximizes the platform profit. The result is 20%, much higher than the *de facto* 5%. Then two questions of interest remain to investigate given different levels of commission rate: first, How will the profit of communities of each type change? second, How will the number of users of each type change?

Table 6 and Figure 9 describe the profit change of the communities of each type with

Table 6: Profit change with respect to different commission rates

%	Art	Economics	Education	Entertainment	Fashion	Health	Life	Science
0	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	23.23	66.19	65.02	23.33	66.92	99.33	87.02	63.58
15	31.84	110.85	113.73	83.84	72.46	121.23	112.54	89.69
20	75.61	114.25	136.13	-1.22	-16.14	57.04	161.07	81.85
25	117.24	138.87	105.23	-37.05	-100.00	15.45	141.60	74.68
30	97.56	147.38	66.95	-24.46	-100.00	38.53	138.70	56.45
35	68.64	148.96	70.84	-100.00	-100.00	61.62	125.18	53.43
40	92.73	155.23	53.83	-100.00	-100.00	84.71	157.34	36.91
45	116.82	102.92	41.32	-100.00	-100.00	107.80	51.55	11.89
50	35.44	71.20	38.18	-100.00	-100.00	130.89	-47.31	-13.11
55	48.98	-12.60	-1.39	-100.00	-100.00	-100.00	-100.00	-38.38
60	-100.00	-61.62	-24.84	-100.00	-100.00	-100.00	-100.00	-81.86
65	-100.00	-91.82	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
70	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
75	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
80	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
85	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
90	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
95	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00

Note: The first column shows different levels of the platform’s commission rate from 0% to 95%. All other columns show the profit change in percentage. The default rate is 5% which makes no change on the profit of each type of the communities. As the rate increases, profits increase and then decrease until vanishing. The change from profit boost to profit decline happens at different commission rates across different types. We denote the occurrence of the first profit decline in **bold** typography for each type (except for the cases with a 0% commission rate).

respect to different levels of commission rate from 0% to 95%. Communities of different types face profit decline at different commission rates. *Entertainment* and *Fashion* community owners experience profit decline at 20%, which is the optimal commission rate that maximizes the platform’s profit, while other types of communities face the same issue when the rate hits 50% or higher.

Communities of different types also hit zero-profit at different commission rates. *Fashion* communities reach this turning point at the 25% rate, while *Economics* communities reach the threshold at 70%. Since the absolute profit of different types vary considerably, the order of hitting zero-profit informs us of the owners’ sensitivity to the change of commission rate with respect to type. For *Fashion* community owners, they may react to the commission rate increase by setting up a higher annual fee, but this may easily drive users away. *Economics* community owners may take more action to retain at least the same amount of profit as that at the 5% rate, since their users are resilient to a possible annual fee increase.

In Figure 9, note that the red dashed line on the left indicates the *de facto* 5% commission rate, which is the basis of all our analyses in the previous sections. The red dashed line on the right indicates our estimated optimal commission rate of 20%, which brings the platform the highest profit. It is clear that communities of each type react quite differently towards the increased commission rate.

Figure 9: Profit change with respect to different commission rates

Figure 14 in Appendix K illustrates the profit change by type with respect to different commission rates. *Art* and *Health* communities show a clear “M” curve. This implies the expertise that these community owners provide are polarized. Some of them are providing hard-core professional knowledge that keeps attracting people even if they raise the annual fee in response to a higher commission rate, while others are mediocre content providers such that users do not find it worthwhile to continue when annual fee increases beyond expectations. Consider two doctors who run *Health* communities and raise their annual fee under the pressure of higher commission rates. Users would like to pay a considerable amount of the annual fee to Dr. Meredith Grey, since she has cutting-edge knowledge and rich experience in the division of gastroenterology, and writes posts on topics such as the diagnosis and treatment of gallstones. In contrast, users would be more reluctant to pay even five extra dollars per year to Dr. Neville Longbottom since he primarily discusses why calendula works as an effective herbal treatment as in Kiehl’s Calendula herbal-extract toner.

Table 7 and Figure 10 show the effect of the different commission rates on the number of users, which affects the owners’ demand expectation as well as their propensity to share.

Table 7: Demand loss with respect to different commission rate

%	Art	Economics	Education	Entertainment	Fashion	Health	Life	Science
0	25.51	21.88	32.73	59.04	0.00	16.66	57.45	28.65
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	-45.22	-19.49	-20.63	-42.42	-20.00	0.00	-7.96	-20.72
15	-63.48	-33.84	-33.81	-42.72	-45.60	-33.34	-33.72	-41.43
20	-63.48	-51.55	-46.40	-77.25	-80.12	-66.67	-40.71	-60.79
25	-63.69	-56.95	-66.05	-88.48	-100.00	-83.33	-60.23	-70.93
30	-72.61	-64.42	-78.86	-88.48	-100.00	-83.33	-66.86	-79.52
35	-81.74	-70.50	-81.80	-100.00	-100.00	-83.33	-73.49	-83.39
40	-81.74	-74.04	-86.72	-100.00	-100.00	-83.33	-73.49	-87.30
45	-81.74	-82.45	-89.66	-100.00	-100.00	-83.33	-86.75	-91.28
50	-90.87	-87.07	-90.96	-100.00	-100.00	-83.33	-95.92	-94.27
55	-90.87	-94.11	-94.39	-100.00	-100.00	-100.00	-100.00	-96.53
60	-100.00	-97.45	-96.19	-100.00	-100.00	-100.00	-100.00	-99.08
65	-100.00	-99.13	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
70	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
75	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
80	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
85	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
90	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00
95	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00	-100.00

Note: The first column shows different levels of the platform’s commission rate from 0% to 95%. All other columns show the demand loss in percentage. The default rate is 5% with no demand change. As rate increases, demand is lost at different rates with respect to the different types of communities, and eventually vanishes. We highlight in **bold** typography the demand loss at 20%.

At the optimal commission rate of 20%, *Fashion* communities encounter the largest demand loss compared with other types. On average, communities of six types lose half of their demand at 20%, and all communities suffer from losing more than half of their demand at 25%. Figure 10a indicates that an increase in the commission rate unanimously lead to a drop in the number of users who are supposed to join. At the optimal rate of 20% which maximizes the platform’s profit, communities lose approximately 40% ~ 80% demand. In Figure 10b, we pool all communities together. At the optimal rate of 20%, the platform as a whole loses around half of its potential users. We use the bandwidth to indicate total demand on the platform, as the thinner the band is, the more demand is lost. We also categorize the platform according to the severity of demand loss. It is “healthy” if the demand loss is less than 50%, “alertly” if the demand loss is between 50% and 75%, and “moribund” otherwise.

To summarize, our counterfactual analysis gives a profit-maximizing platform the flexibility to choose its commission rate. The optimal 20% rate exceeds the original 5% rate considerably. The discrepancy between 5% and 20% has implications to community owners,

Figure 10: Demand loss with respect to different commission rate

the platform, and policy makers.

For community owners. On the one hand, if a community owner does not adjust the annual fee accordingly, then she will have fewer incentives to provide content of the same quality and updating frequency, since given the same annual fee, she earn less, no matter whether or not she is eligible for the referral program. This will inevitably result in fewer users who are supposed to be willing to renew their access to her community. On the other hand, if a community owner responds to the increase of the commission rate, then she is forced to increase the annual fee in order to receive the same amount of profit. This may prevent potential users from joining her community given a higher price beyond expectation.

For the platform. Although at the 20% rate all communities would lose around half of their demand compared to the status quo, they encounter a different profit change, and in particular, may even experience a profit increase when the rate is lower than certain thresholds. The platform may then set up different commission rates according to type and therefore enlarge the total revenue of both the platform and community owners.

The platform should also be aware that its policy may cause unexpectedly homogeneous content provision. As observed in Tables 6 and 7, when the commission rate increases to 20%, there are many more users who may choose to stay in *Economics*, *Education*, and *Life* communities. As the rate keeps increasing, basically only *Economics* and *Education* communities have users left. In the end, Little Secret Communities would lose its diversity of content provision and become an economics/education-related platform.

For policy makers. When the rate increases from 5% to 20%, half of the users who should have access to the content are now kept away. This clearly shows that by imposing a higher transaction cost, a monopolist platform of this kind will significantly reduce people’s access to online content (especially that of high quality). Policy-makers should remove the monopolistic power of a platform in our counterfactual analysis to charge commission for its own profit maximization while putting social welfare at stake. As content providers find a means by which to make money from sharing their expertise on another platform with a similar infrastructure, policy-makers need to establish rules so as to include room for platform competition, and find a balancing point between users’ easy access to content, content providers’ strong incentive to post high-quality posts, and platforms’ socially optimal business model.

8 Conclusion

In this paper, we examine – for the first time – the important issue of the commercial value of online content providers. Studying such issues is not an easy task. On the one hand, while the phenomenon of charging for online content becomes widespread, access to data is not readily available. On the other hand, even if some data can be directly gathered from the Internet, in most cases, due to the absence of some important variables, the data is not enough for us to draw decisive conclusions.

Using confidential data directly provided to us by the platform, Little Secret Communities, we have a unique opportunity to reveal the pricing strategies of online content providers with different fields of expertise through structural model estimation. In particular, our structural model shows that the pricing strategy becomes increasingly sophisticated when the price maker shares a portion of the revenue in exchange for additional users.

Our results have important policy implications. We show that when a platform that makes profits by charging commissions has monopoly power, the platform will charge high commissions. This makes some content providers refuse to provide (high quality) content, while others increase their annual fees accordingly. As a result, half of the consumers in the market who are supposed to enjoy the content will lose access to the content. It is also possible that the platform will wipe out some types of communities and make content provision homogeneous. Such results suggest that in order to maximize social welfare, the government should prevent the emergence of such a platform as a monopoly, and encourage several platforms with similar functions to compete in the market.

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Appendices

A Literature Review in Details

A.1 The Impact of Monetary Rewards on Individual’s Incentive for Content Provision

The incentives to provide content online have been mostly investigated by literature in the context of open source software. Lerner and Tirole (2002) examine open source software developers’ incentive to share codes on online communities for free. From a theoretical perspective, they propose that providing high-quality codes can be a good signal of skills for venture capital or future employers. Due to the lack of relevant data, empirical studies have just tested this career concern hypothesis in recent years. Using Stack Overflow data, Cabral et al. (2019) show that after finding a new job, users contribute considerably less in reputation-generating activity than their non-reputation-generating activity. This suggests that users contribute to Stack Overflow in part because they perceive it as a way to improve future employment prospects.

However, content providers need to show their ability and skills until they are noticed by either venture capitalists or better employers. In this sense, immediate monetary reward becomes a less risky and strong enough incentive for individual’s content provision, but there have been limited discussions on capitalization of online content provision. The major reason lies in the lack of data on price, sales, and other monetary measurements of content provision. Instead, the literature seek to use proxies of monetary measures to show its incentive role. Fershtman and Gandal (2007) use the commercial potential under three levels of (relative) license restrictiveness as a proxy for the financial incentive that drives owners’ effort, and find the threshold level to which owners contribute in the context of restrictive licensing in open source software. The more restrictive a license is, the less possible a project can be commercialized, the less effort owners exerts, and the lower the output per owner in end-user-oriented project is.

An alternative way to show the relationship between content provision and monetary incentive is through ad-revenue-sharing program initiated by platforms where owners post content shares revenue with them. Related literature mainly focus on how content providers adjust their behaviors in order to generate more income through such programs. For example, Tang et al. (2012) use data from YouTube to show that ad-revenue-sharing is a major incentive for content contribution. Content providers who join ad-revenue-sharing program pay more attention to the total number of views of their videos because this determines

their income from video-embedded ads. Capturing the same effect of ad-revenue-sharing program on content providers’ income, Sun and Zhu (2013) find out that in order to attract more visits to their blogs on a major Chinese blogging site, bloggers who participate in this program are more willing to write on popular content.

Our data show that content providers can make profits immediately by charging their audience for access to the content. The pricing-related data allow us to measure the exact commercial value of content providers with different fields of expertise, without indirectly measuring through ad-revenue-sharing programs.

A.2 Social Network Effects in Online Content Provision

Zhang and Zhu (2011) find that individual contributors decrease their contribution following the shrink of their readership after Chinese government blocked Wikipedia in mainland China. They emphasize that contributors obtain social benefits from increases in not only the amount of contribution but also audience size. Aaltonen and Seiler (2015), also using Wikipedia data, show that past edits make cumulative benefits and promote future edits of the same article. This suggests a “virtuous circle” which enlarges the overall owner base (Goldfarb and Tucker 2019).

In this paper, we show another mechanism by which content providers would be able to expand their audience size. Our mechanism focuses on the marketing cost that content providers are willing to spend in order to obtain more audience. By adopting the referral program, content providers can share certain percentage of revenue with their audience who refer their content to others. With the data of sharing percentage, type of content, and other monetary measures, we are able to identify the trade-off between the referral payment from content providers to their audience and the potential revenues generated from market expansion.

B Business Models of Content Provision on Platforms

We summarize in details, from managerial perspective, three principal business models that content providers earn money and categorize them accordingly. The first business model captures the free access to content. The other two are based on the fact that people need to pay for access to the content, which we refer to as “direct payment model”, but the scope of content that people can reach makes the two direct payment models different from each other.

Content providers on Wikipedia, YouTube, Q&A websites, and some other similar platforms do not charge for access to the content. People can read articles, watch videos, post questions and have problems solved without making any financial transactions for access. However, this does not mean that people are not making any payments at all - they are simply paying by other means. Wikipedia as a platform raises donations from its users who may not pay specifically for the article that they are currently reading but for the accumulated experience and for continuous operation of this online encyclopedia. YouTube makes money in a “three-party market” (Anderson 2009): content providers can upload videos free-of-charge to consumers, but advertisers pay for InVideo ads to YouTube in the hope that they can sell the advertised products or services to video audience. YouTube also sets up ad-revenue-sharing program by which video owners can also benefit from their uploads. Q&A websites have more sophisticated ways of making money while keeping the basic question-posting and problem-solving functions free, by combining “third-party markets” and “direct cross-subsidies”.²⁶

Online education platforms usually charge for access to the content posted on them and share revenue with content providers. Further investigations reveal two different types of this direct payment model. MOOC²⁷ websites represent one type of direct payment to content. People need to pay certain amount of money for one content in a period of time. For example, Udacity, a MOOC website mainly designed for people who seek knowledge on programming, artificial intelligence, data science, etc., charges \$999 for a 4-month-long Deep Learning

²⁶Jeff Atwood, the co-founder of Stack Overflow, lists four ways as a somewhat “official answer” to the question “What is Stack Overflow’s business model”: (1) Job listings, (2) CV Search, (3) Traditional display advertising on Stack Overflow, Server Fault, and to a lesser extent Super User, and (4) Stack Overflow for Teams service. For complete answer, please refer to What is Stack Overflow’s business model? According to the official introduction of StackExchange network, Stack Overflow is a Q&A site for professional and enthusiast programmers; Server Fault is a Q&A site for system and network administrators; Super User is a Q&A site for computer enthusiasts and power users. They are all members of the StackExchange network.

²⁷MOOC refers to “massive open online course”. It is an open-accessed online course which usually provides filmed lectures, reading materials, homework assignments, and other interactive content that help registered students in many areas of traditional offline education. Some MOOC websites include Coursera, Udacity, edX, etc.

class,²⁸ but as the session ends, users will not be able to access to the course materials again. Some other MOOC websites apply similar variants of this “course/certificate subscription” fee. Online education platforms such as Course Hero and Chegg are examples of another way of direct payment to content. People need to pay certain amount of money for different kinds of content in a period of time. For example, Chegg charges \$14.95 for three resources and service including textbook solutions for over 34,000 ISBNs,²⁹ ask questions for help 24/7, 30 minutes free online tutoring, and millions of homework answers posted by users.³⁰

Little Secret Communities, the focal platform in this paper, applies similar payment method as the above online education platforms, but it also allows social network expansion and supports rating systems to promote interactions between content providers and audience. Table 8 compares the above platforms with Little Secret Communities while a detailed introduction to it is given below. Note that by “(social) network expansion”, we simply mean a content provider can obtain followers and build up links with each other on platforms/websites since they share similar interests.³¹

Table 8: Comparison among major content provision platforms and Little Secret Communities

platform/website	Social network		content	
	network expansion	like/upvote & comments	direct payment for content	major type(s) of content
Wikipedia				textual
Facebook	✓	✓		all kinds
YouTube	✓	✓		videos
Quora	✓	✓		textual
Reddit		✓		textual
Coursera			\$ for 1 content in a period	all kinds
Course Hero			\$ for multiple content in a period	textual
Little Secret Communities	✓	✓	\$ for multiple content in a period	textual

²⁸For a full list of prices of Udacity courses, please refer to Udacity’s pricing charts of courses and nanodegrees.

²⁹ISBN stands for International Standard Book Number. It is an identifier that shows the uniqueness of a book. Each variation or edition of a book is assigned an different ISBN.

³⁰For further information, please refer to Chegg membership web page.

³¹Reddit is of a special kind in terms of social network expansion. As “an American social news aggregation, web content rating, and discussion website” according to Wikipedia, it allows a user to follow others, but the followers remain anonymous and therefore we do not categorize it as a website that has “social network expansion” function. For details, please refer to this post on Reddit “How to see your followers?”.

C Registration and Function of a Community

Figure 11 shows step-by-step procedure when someone registers a community on Little Secret Communities. The first step is to choose whether she wants the community free or paid. If choosing a free community, this potential community owner will jump to the third step which allows her to give a name to the community, add some community descriptions, and specify a type. After selecting the type, she will be able to run the community immediately. However, if choosing a paid community, this potential community owner will have to decide the price before selecting the type.

(a) Step 1: Free or paid? (b) Step 2: Price set-up (c) Step 3: What is the type?

Figure 11: Create a community

The owner can post articles and answer questions asked by users. In Figure 12a, we show various functions under a post about gallstones and its treatment. Users may like, save, comment, or give tips to the owner for the usefulness of this specific post. They can also refer this community to others for referral payment. In a paid community, a user may have the chance to earn a portion of owner's revenue by the the referral program. This program is not available to all communities. The platform operators, based on their observations of a community's operation and quality, give some owners the authorization of the referral program.

Given the referral program, as long as a user can attract enough users by sharing, he can cover his annual fee and may even earn extra money. As we can see from Figure 12a, under each post, users can refer this post to other platforms in order to obtain certain amount of money. A pop-up reminder as in Figure 12b will also be shown to emphasize the benefit of referral. Little Secret Communities has a tracking system to recognize if a new user joins in a community through clicking the link generated by an existing user within this community,

and assign this existing user the amount of money according to the percentage which has been set up by the owner.

(a) Referral hyperlink is shown in orange color under the main body of content

(b) Pop-up window for the benefit of referral

Figure 12: User console from user's perspective

D The Referral Program Q&A by Little Secret Communities

1. What is the referral program?³²

It is a promotion that encourages users to pay for the content in paid communities.

2. How to benefit from the referral program as a user?

After logging in to the Little Secret Communities, you can share the paid communities which applies the referral program. After a new user pays through the link you share, you will receive a referral payment (70% of the annual fee) and the new user will receive discount (30% of the annual fee).

3. As an owner, how can I set up the referral program?

This program is in the internal testing stage, and only open to some communities.

4. How to calculate the owner's income from the referral program?

A paid communities that applies this function will display a certain amount of referral payment (i.e. reward). After someone else has successfully purchased through your sharing link, you will receive the amount of the reward. Example: You share a paid community with 100 RMB annual fee and 30% sharing percentage. You can get a 21 RMB reward and the new user gets a 9 RMB discount.³³

5. What is the maximum amount of sharing percentage?

The sharing percentage is set from 5% to 50%.

6. If the invited user withdraws from the community and refunds, how will the reward be processed?

Little Secret Communities supports full refund within three days of payment. If the invitee withdraws within three days, the reward will be refunded to the invited user. If the user asks for refund after three days of joining, the reward will not be refunded.

7. Why didn't I get a reward after someone else joint the community through my sharing link? The main reason may be:

- The one who posts the sharing link is the community owner;

³²This Q&A is translated from the official Chinese version.

³³Note that in this example, platform's commission is not considered for simplicity.

- Owners stop using the referral program;
- Owners change the community to free;
- The platform administrators determines that this specific order is abnormal and cancel the processing of this order;
- The existing user posting the sharing link has withdrawn from the community;
- The new user applies to withdraw from the community during the payment period;
- Other circumstances as specified in the complete agreement.³⁴

³⁴The complete agreement can be found in this link.

E The Optimal Pricing Strategy of an Ordinary Community Owner

When the demand function takes a log-linear form as:

$$D_{im}^{e=0}(p_{im}, x_{im}, u_{im}) = \exp \{ \beta_{price} \times \ln p_{im} + x'_{im} \beta_x + u_{im} \}$$

where u_{im} is normally distributed with mean 0 and variance σ^2 . We have³⁵:

$$\begin{aligned} \mathbf{E} D_{im}^{e=0}(p_{im}, u_{im} | x_{im}) &= \exp \left\{ \beta_{price} \times \ln p_{im} + x'_{im} \beta_x + \frac{\sigma^2}{2} \right\}, \\ \text{and } \frac{\partial}{\partial p_{im}} D_{im}^{e=0} &= \frac{D_{im}^{e=0}}{p_{im}} \beta_{price}. \end{aligned}$$

The optimal solution is then described by:

$$p_{im}^{e=0} = \begin{cases} \frac{\psi_{i,D}}{1 + \frac{1}{\beta_{price}}} & \text{if } \frac{\psi_{i,D}}{1 + \frac{1}{\beta_{price}}} \geq \underline{p}, \\ 0 & \text{otherwise.} \end{cases}$$

The community owner decides to register a paid community to commercialize the content, and to charge higher than $\underline{p}$ because the potential profit is high enough to cover the cost of community operation.

³⁵Notice that

$$\begin{aligned} \mathbf{E}(e^u) &= \int e^u \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{u^2}{2\sigma^2}} du = \frac{1}{\sigma\sqrt{2\pi}} \int e^{-\frac{u^2 - 2\sigma^2 u}{2\sigma^2}} du = \frac{1}{\sigma\sqrt{2\pi}} \int e^{-\frac{(u - \sigma^2)^2}{2\sigma^2} - \sigma^2} du \\ &= \frac{1}{\sigma\sqrt{2\pi}} \int e^{-\frac{(u - \sigma^2)^2}{2\sigma^2}} e^{-\sigma^2} du = e^{-\frac{\sigma^2}{2}}. \end{aligned}$$

F Robustness Check on the Static Pricing Assumption

In our structural model, we assume that owners’ pricing strategy is static. We use a new data set given by courtesy of Little Secret Communities to prove the validity of this assumption. This new data set is referred to as “new data” and our original data as “main data” what follows.

The new data include 791 communities in the main data, matched by community-specific *id*’s. The 7 other variables (*time*, *count*, *type*, *enable*, *percent*, *fee*, and *content*) are also included. Our data collection period ends at December 17, 2018, and the new data extends until April 17, 2019, so we have additional 4-month window to check each community’s activities.

Table 9: Number and percentage of communities by type for all communities in new data

type	number of communities	corresponding percentage (%)
Art	33	4.17
Economics	316	39.95
Education	148	18.71
Entertainment	14	1.77
Fashion	7	0.88
Health	14	1.77
Life	52	6.57
Science	207	26.17
Total	791	100.00

Firstly, we compare the composition of communities by type in the new data and in the main data. As shown in Table 9, it is clear that both the number and corresponding percentage of communities in each type are similar to those in Table 2.

Then we check whether some key variables have changed drastically during this additional 4-month period. The eligibility for the referral program is in our first interest. In the main data, we define a new binary variable *eligible* and let $eligible = 0$ if $enable = 0$, and $eligible = 1$ otherwise. In the new data, we have a specific binary variable $eligible_{new}$ to record such eligibility. We then calculate the difference between $eligible_{new}$ and *eligible*. As in Figure 13a, the eligibility for the referral program does not change for almost all communities during 4 months.

(a) Density of change in eligibility

(b) Density of *percentage* change in number of users

(c) Density of *percentage* change in annual fee

(d) Density of change in sharing percentage

Figure 13: How do the new data and our data differ?

In Figure 13b and Figure 13c, we calculate the percentage changes in number of users and in annual fee between the main data and the new data, respectively. It is immediate to show that over the 4-month window, neither number of users nor annual fee have changed in most communities.

For each community, we then compare the sharing percentage in the main data and the new data. As shown in Figure 13d, most owners do not change their sharing percentage from December 17, 2018 to April 17, 2019.

The time-invariance of these 4 key variables proves the validity of our static pricing assumption.

G Diagnostic Tests on Demand Estimation by 2SLS and Reinforced IV in Table 4

The weak instrument test and Wu-Hausman test show the validity of our instrumental variables both in 2SLS and in reinforced IV specification.

Table 10: Diagnostic tests

test	2SLS		Reinforced IV	
	statistic	p-value	statistic	p-value
Weak instrument: $\log(\text{Price})$	10.431	$< 2 \times 10^{-16}***$	9.305	$< 2 \times 10^{-16}***$
Weak instrument: Sharing Percentage	4.161	$1.50 \times 10^{-7}***$	2.670	$8.97 \times 10^{-5}***$
Weak instrument: Sharing Percentage ²	2.779	0.000292***	2.177	0.001968**
Weak instrument: $\log(\text{Reward})$	4.726	$5.66 \times 10^{-9}***$	2.711	$6.86 \times 10^{-5}***$
Weak instrument: $\log(\text{Price}) \times \log(\text{Duration})$	10.838	$< 2 \times 10^{-16}***$	9.586	$< 2 \times 10^{-16}***$
Wu-Hausman	4.301	0.000692***	4.131	0.000998***

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$.

Weak instrument tests show that all our instrumental variables have low correlations with the endogenous explanatory variables. According to p-values, the null is rejected in each case, so we conclude that our instrumental variables are sufficiently strong.

Wu-Hausman (or Durbin-Wu-Hausman) test show that our instrumental variables are just as consistent as OLS, and in this case OLS is more efficient. The null hypothesis is that either 2SLS or reinforced IV estimator are equally consistent as OLS estimator. As we can see from Table 10, the test statistic is significant at the 0.1% level in each case. This implies both 2SLS and reinforced IV estimators are consistent while OLS estimator is not.

H Validity of Our Instrumental Variables Using New Data

In Subsection 5.1.2, we discuss how to use the new data to check the validity of our instrumental variables (i.e., the satisfaction rate and the regret rate). Here we provide more details on the construction of instrumental variables from the new data, regression results using these new instrumental variables, and related diagnostic test results.

In the new data, we have the total number of posts (i.e., *content* in our main data) as well as the total number of words in all posts in each community. The number of words per post, i.e., the *third* instrumental variable mentioned in Subsection 5.1.2, is constructed by $\frac{\text{total number of words in all posts}_i}{\text{total number of posts}_i}$ for each community i .

Table 11 reports the regression result using the same demand equation in Subsection 5.1.1, instrumented by the satisfaction rate, the regret rate, and the number of words per post. When comparing the results here with those of the 2SLS specification in Table 4, we observe quantitatively similar coefficient of price.

Table 11: Regression results using new data

	Model 1
(Intercept)	35.8046* (14.7524)
Price	−3.6550 (2.3664)
Sharing Percentage	0.0235 (0.0699)
Sharing Percentage ²	−0.0002 (0.0010)
Reward	−0.1983 (0.5662)
Price×Duration	0.5569 (0.3700)
Num. obs.	791
RMSE	0.8981
Monthly Fixed Effect	YES
Yearly Fixed Effect	YES
Control Community Types	YES

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$

Note that in this case, we have two endogenous variables price and sharing percentage, while three instrumental variables. We conduct both weak instrument test and the Sargan test of over-identification to check whether these instrumental variables are valid. The test results are reported below in Table 12.

Weak instrument tests show that all our instrumental variables have low correlations with the endogenous explanatory variables. According to p-values, the null is rejected in each case, so we conclude that our instrumental variables are sufficiently strong.

The Sargan test checks overidentification restrictions. It tests that all exogenous instrumental variables are in fact exogenous, and uncorrelated with the model residuals. As we observe in Table 12, the p-value in each case is not even significant at 10% level, and therefore we cannot reject the null hypothesis that over-identifying restrictions are valid.

The results of both tests prove the validity of our instrumental variables (i.e., the satisfaction rate and the regret rate) which we use in our main regression in Subsection 6.1.

Table 12: Diagnostic tests using new data

test	Model 1	
	statistic	p-value
Weak instrument: $\log(\text{Price})$	6.854	$1.57 \times 10^{-15***}$
Weak instrument: Sharing Percentage	5.882	$8.08 \times 10^{-13***}$
Weak instrument: Sharing Percentage ²	5.383	$1.97 \times 10^{-11***}$
Weak instrument: $\log(\text{Reward})$	3.947	$1.59 \times 10^{-7***}$
Weak instrument: $\log(\text{Price}) \times \log(\text{Duration})$	7.007	$5.88 \times 10^{-16***}$
Sargan	12.779	0.3853

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$.

I Robustness Check on the Consistency of Demand Estimation with respect to Duration

We test the consistency of our demand estimations according to different length of duration. In our main result Table 4, we remove one community which was created less than 75 days before the date when the data collection ends (i.e. December 17, 2018). In this section, we consider the following three cases where communities which were created less than 50, 125, and 150 days before December 17, 2018 are eliminated. Note that the case when duration is ≥ 100 days is identical to the main result in Table 4 since the same community is eliminated. As we observe from Tables 13, the results of demand estimations are similar to our main results in Table 4 both qualitatively and quantitatively. This shows the consistency of our main results of demand estimations with respect to duration.

Table 13: Demand estimations with different durations

	duration ≥ 50 days			duration ≥ 125 days			duration ≥ 150 days		
	(1) OLS	(2) 2SLS	(3) Reinforced IV	(4) OLS	(5) 2SLS	(6) Reinforced IV	(7) OLS	(8) 2SLS	(9) Reinforced IV
(Intercept)	17.135*** (3.337)	35.391** (13.678)	53.096** (17.485)	17.100*** (3.672)	32.322* (13.251)	47.605** (16.214)	13.232** (4.104)	25.399† (13.688)	43.278** (16.304)
Price	-0.814* (0.393)	-4.713† (2.700)	-7.307* (3.405)	-0.673 (0.413)	-4.657† (2.775)	-6.398† (3.319)	-0.582 (0.423)	-4.209 (2.764)	-6.200† (3.253)
Sharing Percentage	-0.019* (0.009)	-0.232** (0.074)	-0.240* (0.095)	-0.019* (0.008)	-0.227** (0.074)	-0.220* (0.090)	-0.019* (0.008)	-0.217** (0.073)	-0.224* (0.092)
Sharing Percentage ²	0.000 (0.000)	0.003* (0.001)	0.003† (0.002)	0.000 (0.000)	0.003* (0.001)	0.003† (0.001)	0.000 (0.000)	0.003* (0.001)	0.003† (0.001)
Reward	0.014 (0.061)	1.517** (0.553)	1.143† (0.613)	0.010 (0.061)	1.489** (0.550)	0.975† (0.578)	0.007 (0.061)	1.462** (0.538)	0.983† (0.577)
Num. obs.	1386	1386	1386	1380	1380	1380	1370	1370	1370
RMSE	0.933	1.192	1.352	0.928	1.179	1.277	0.926	1.163	1.275
Monthly Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
Yearly Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control Community Types	YES	YES	YES	YES	YES	YES	YES	YES	YES

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

For each duration specification, we include the OLS, 2SLS, and reinforced IV results.

The case when duration is ≥ 100 days is identical to the main result in Table 4 since the same community is eliminated.

J Marginal Cost of Communities with respect to Type

It is clear from Table 14 to see that

1. Communities of different types have different average marginal costs. *Economics* communities have the highest average marginal cost while *Education* communities have the lowest.
2. The range of marginal cost for each type of communities differs a lot. *Economics* communities have the largest range with an enormous maximum of marginal cost. *Fashion* communities have the smallest range.

Table 14: Key statistics of marginal cost with respect to type

Type	Min	Median	Mean	Max
Art	29.83	36.94	41.86	106.55
Economics	11.04	43.29	49.97	473.21
Education	28.19	36.89	40.73	131.06
Entertainment	29.37	34.69	44.24	126.11
Fashion	30.68	37.78	42.70	78.76
Health	28.62	35.29	42.04	104.04
Life	28.25	37.21	40.93	95.62
Science	28.44	38.75	43.31	114.92

K The Effect of Platform's Policy on commission Rate

The patterns of profit changes and demand loss with respect to each type of communities are different from each other, as seen in Figure 14 and Figure 15 below.

Figure 14: Profit change with respect to different commission rates by type

Figure 15: Demand loss with respect to different commission rates by type