AN EMPIRICAL INVESTIGATION OF INTRINSIC AND MONETARY INCENTIVES FOR PRODUCT REVIEW CONTRIBUTION IN A CONNECTED COMMUNITY

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Abstract

With the booming of online social networks, product reviews are increasingly generated and shared among *connected* consumers. While both intrinsic and monetary incentives are known to drive product review contributions, little is known about their effectiveness in a connected community. We bridge this gap by examining an online social shopping network, where buyers mainly draw on reviews generated within the community to evaluate sellers. We utilize a natural experiment, where the community switched from a *voluntary regime* (in which product review contributions are driven by intrinsic incentives only) to a *paid regime* (in which review contributions are driven by both intrinsic and monetary incentives). We find that (1) in the voluntary regime, the intrinsic incentive is stronger for "socialites," who have many connections, compared with "loners," who have no connections; (2) in the paid regime, the monetary incentive moderately increases loners' contributions, but dramatically *decreases* socialites' contributions. These results are robust after controlling for level of engagement and tenure, as well as unobserved heterogeneity. We also conduct simulations to show that the community can increase the overall contribution at a reduced cost by targeting the monetary incentive or by introducing monetary incentives at an early stage.

***Keywords*:** product review contribution, social network, intrinsic incentive, monetary incentive, Hierarchical Bayesian model

1. Introduction

Thanks to the proliferation of social networks in the past decade,[1] consumers can now easily use Facebook, Twitter, and so on to share product reviews through their social connections (*New York Times* 2011). Successful online review publishers have also embarked on the integration of product reviews and social networking. A salient example is Yelp.com. Aiming to build a community characterized by “authenticity, contribution and connections,” Yelp.com encourages its users to connect with each other; and to interact both online (e.g., rate each other’s comments and chat online) and offline (e.g., through social events at local venues). As a further effort to facilitate the integration, Yelp.com also collaborated with Facebook so that its contributors can share reviews with their Facebook friends.[2] The effort to combine local reviews and social networking has helped Yelp.com to quickly surpass Citysearch and Yahoo Local (both of which kept their reviewers anonymous) and draw more than 71 million monthly unique visitors for peer-contributed reviews of local businesses such as restaurants, shops and doctors (Wang 2011).

The trend of integrating product review sharing among connected consumers is unlikely to let up due to its potential benefits for buyers, sellers and online communities alike. First, such integration significantly helps to increase the reach of product reviews. Given recent evidences of the positive effect of online reviews on the sales of experience goods (e.g., Luca 2012), both sellers and consumers stand to gain from more broadly seen product reviews. Second, reviews by anonymous

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[1] A 2011 comScore report shows that social networking is among the most popular online activities, engaged in by 82% of the world’s online population (greater than the proportion of email users) and consumes nearly 20% of all time spent online

[2] http://officialblog.yelp.com/2010/04/here-at-yelp-were-always-excited-to-announce-feature-and-site-improvements-with-the-help-of-great-partners-today-weve-been.html

contributors have drawn concerns about “promotional reviews,” which are engineered by sellers themselves.[3] Sellers have a clear incentive to fake product reviews to sway consumers (Dellarocas 2006), and it is very difficult for average consumers to distinguish between real and fake reviews (*New York Times* 2012a, b).[4] Recent empirical evidence of sellers’ strategic manipulation of product reviews has led to concerns that consumers may mistrust and even disregard reviews by anonymous reviewers (Mayzlin, Dover and Chevalier 2012). In contrast, reviews by contributors who are socially connected with the reader trump anonymous reviews as more effective because of the high level of trust between the writer and the reader (Higie, Feick and Price 1987) and the personal knowledge that makes recommendations more meaningful (Brown and Reingen 1987). Finally, product reviews are a crucial type of consumer-generated content. Online communities have a serious stake in keeping a high level of product-review contributions to ensure the health and sustainability of the social communities and give them a competitive advantage over other community sites (Zeng and Wei forthcoming; K. Zhang and Savary 2011).

Despite the potential value of the integration of product review and social networks, limited consumer product-review contributions remains a major concern (e.g., Butler 2001, Hughes, Coulson and Walkerdine 2005) for two reasons. First, product reviewing entails nontrivial costs for the contributor. Direct costs include the time and effort spent writing and publishing the reviews; indirect costs include the risk associated with an early trial of an experience product (Avery, Resnick and Zeckhauser 1999). Second, it is also easy to free ride on others’ contributions. The important question is how to effectively entice consumers to contribute product reviews themselves. Observations of the

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[3] A Gartner study predicts that by 2014, 10% to 15% of social media reviews will be fake or paid for by sellers.

[4] http://www.cs.uic.edu/~liub/FBS/fake-reviews.html

current practices indicate that there is no consensus on this question. On one hand, review sites such as Yelp.com, Yahoo Local, Tripadvisor and Citysearch rely solely on voluntary contributions. On the other hand, companies such as Beso, Pose and Referly.com develop their business models on the principle of financially compensating consumers as contributors (*New York Times* 2012c). We are not aware of any existing research examining the effectiveness of intrinsic and monetary incentives in a connected community. We attempt to bridge this gap by answering two key research questions. First, which members are more likely to be driven by intrinsic incentives, which members are more likely to contribute than others? Second, to what extent can a monetary incentive complement the intrinsic incentive across different members? Answers to these questions will help communities to design and implement an effective incentive scheme - for example, whether or when the community should use the monetary incentive.

The empirical study was conducted in the context of an online social shopping network (OSSN). An OSSN connects the buyers and sellers of experience goods within a unified platform. A distinctive feature of the OSSN from traditional E-commerce sites (e.g., Amazon.com) is that it allows social connections to form among potential buyers.[5] This is in contrast to Amazon, where buyers usually remain anonymous to each other. OSSNs provide an excellent setting for an empirical investigation of the effects of intrinsic and monetary incentives in a connected network. First, since most of the products and services available from OSSNs are by nature experience goods, a major benefit that consumers derive from OSSNs is the ability to learn from product reviews created by other consumers with similar tastes. Second, social connections among OSSN members can be

[5] The fact that buyers are connected makes OSSN distinct from the social commerce network (Stephen and Toubia 2010), where sellers are connected.

directly observed. Some community members are *socialites* connected with many friends, whilst some are *loners* connected with few friends.

Our empirical analyses utilize a data set provided by an OSSN that operates in Beijing, China. The data includes detailed records of each community member's product review contributions over time. The data also includes information on the dynamics in which the connections within the community are formed, as well as the members' purchase decisions and the log-in frequencies on the community website. Importantly, the data embeds an interesting natural experiment: the company changed the incentives for product review contributions after data collection began. Specifically, the OSSN started off relying on voluntary contributions only, but then decided to provide a monetary incentive in a bid to boost review contributions. The introduction of the monetary incentive is unanticipated and affects all community members. The dataset thus allows us to examine the systematic differences in both the strength of intrinsic incentives and responsiveness to monetary incentives across community members.

Our main finding is that the number of friends is a significant predictor for the strength of each incentive. First, when product-review contribution is purely voluntary, the intrinsic incentive increases with the focal contributor's number of friends. The positive effect of number of friends is *inconsistent* with the free-riding hypothesis. In that literature (such as Olson 1965, Sweeney 1973), it is found that the willingness-to-contribute decreases with the number of friends due to the increasing temptation to free ride on other people's contribution. However, our finding is *consistent* with the notion that members derive social benefit from such contributions (Andreoni 2007, X. Zhang and Zhu 2011). Second, the effect of a monetary incentive is *mixed*. A monetary incentive helps *increase* the contributions of less-connected members, but dramatically *decreases* those of the more-connected members. This finding is consistent with the notion that social image concerns may "crowd out" intrinsic incentives (Benabou and Tirole 2006, Ariely, Bracha and Meier 2009). Our main results are robust after controlling for other factors that are known to affect product-review contribution, such as the likely fatigue effect induced by a long tenure with the community, group-norm effects (the frequency of contribution made by friends of the contributor), and level of engagement within the community. These findings have several implications. For example, if a monetary incentive crowds out intrinsic (such as social) motivations for some community members, the community must avoid the potential pitfalls of applying the same monetary incentive to every member. We use simulations to show that the community can mitigate the crowd-out effect by either using a targeted strategy based on the observed characteristics of the community members[6], or introducing the monetary incentives early, when the number of friends is still low for most users.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 discusses the background, the data and the natural experiment. Section 4 presents the model, estimation results and simulations that help to understand possible ways to effectively use monetary incentives. Section 5 summarizes the results, discusses our findings' implications and concludes the paper.

2. Literature Review

2.1. Overview of Previous Research on Product-Review Contributions

This study adds to the ongoing research into product reviews. The helpfulness of product reviews have been widely acknowledged: They help consumers to identify matches of products or

[6] For this simulation, we assumed the users with more friends (who potentially would demonstrate the crowd-out effect by monetary incentives) are not going to realize that some other people are provided with monetary incentives in the community.

services and make informed purchase decisions; they help sellers to boost sales.[7] The existing research has shown the effectiveness of product reviews of books (Chevalier and Mayzlin 2006), movies (Dellarocas, Zhang and Awad 2007, Chintagunta, Gopinath and Venkataraman 2010) and restaurants (Luca 2012). Product reviews have been recognized as a crucial element in the mix of customer-relationship management (Chen and Xie 2008) and the firm's strategic incentive to manipulate such reviews has been shown (e.g., Dellarocas 2006). A few studies have examined the drivers of product-review contribution in the *anonymous* context. Berger and Schwartz (2011) find that consumers are more likely to generate more immediate word of mouth (WOM) for product categories that appear interesting; but this WOM tends to be short-lived. Lafky (2009) finds that the decision to give product ratings is affected by concerns about fellow consumers and the cost of providing such ratings. None of the above studies examine product-review contribution in a connected community.

2.2. Drivers of Intrinsic Incentives in a Connected Community

Various motives have been proposed to explain the intrinsic incentives to contribute to a community; and they broadly fall into four categories: (1) self-interest, (2) altruism, (3) social image. Notably, the majority of the experimental studies focus on randomly-assigned "minimal groups" where the identities of participants are held confidential from each other. Field studies have also been limited to contexts where contributors and potential benefactors are mutually anonymous. We now examine how each of these four possible motives may affect product-review contributions in a

[7] Companies such as Office Depot and PETCO are salient examples of the benefits that can accrue from consumer-generated product reviews, Office Depot's revenue from online paid search rose by 196% after customer reviews were enabled. Following PETCO's move to add product reviews to its platform, conversion rates of top-rated products climbed 49%, and customers who relied on peer reviews spent 63% more than those using other tools (Holland 2007).

connected community, and how this influence is moderated by the potential contributor friend count.

First, the review contribution may be driven by pure self-interest if the consumer derives direct benefits from providing feedback. For example, collaborative filtering technology helps movie fans who submit more ratings to get better product recommendations, because their preferences are better understood and matched with the preferences from other viewers (Chen et al 2010). Direct benefits, however, are not always present. In the absence of direct benefits, the literature predicts undercontribution, an outcome that is individual-rational but socially inefficient (e.g., Olson 1965). Furthermore, stylized game-theoretical models have predicted that as the number of potential contributor increases, it will be more likely for an individual contributor to choose to free ride. Bliss and Nalebuff (1984) analyzed a symmetric Nash equilibrium of “waiting game” in which *one* individual must step up, incur the private costs and provide the public goods. They show that the equilibrium strategy for each individual is to wait up to an optimal duration, which is related to her private cost, before she provides. Importantly, increasing the number of participants will increase everybody’s waiting time. Experimental results have supported the idea that larger groups lead to “diffusion in responsibility” (Darley and Latane 1968). In the context of the OSSN, a necessary condition for the connection to be formed is that there is a shared interest in certain types of services (e.g., restaurants). Given the common interest, it can be rational for under-contribution to become more severe as the group size increases.

The assumption of pure self-interest as the only driver to contribute has been challenged by both experimental results and the extensive charitable giving and volunteering (e.g., Freeman 1997). Later research has proposed the altruism, or the caring of other group members’ interests, as an additional driver (Andreoni 1988, Wasko, and Faraj 2000, Charness and Rabin 2002). An important finding about the altruism is the “audience effect” (Andreoni 1990, Andreoni 2009), which hypothesizes that the intrinsic incentive increases with the number of recipients. Some of the most recent evidence of the audience effect is presented by Zhang and Zhu (2011) using a series of exogenous blockages of the Chinese Wikipedia site; they find that the contribution level is decreased by 42.8% on average due to the reduction of potential readers. In that study, the identities of the contributor and audience are unknown. Another stream of research finds that altruism is stronger among socially connected people. Andreoni (2007) finds that altruism is strengthened by the strengths of the social ties between the contributor and the potential beneficiaries. Specifically, the author finds that people give 52% more to friends than to random strangers, suggesting directed altruism in favor of friends over strangers. Adreoni’s (2007) findings are echoed in Leider et al. (2009), who find that prosocial behavior will be strengthened among friends because of expected future interactions. Similarly, Chen and Li (2009) find participants of a lab experiment donate 47% more when they were matched with an in-group member than with an out-group member.

The third potential driver of intrinsic incentives is concern about one’s social image, and more specifically, being perceived as knowledgeable and pro-social (Benabou and Tirole 2006). Wang (2011) compared data from both anonymous communities (Citysearch and Yahoo Local) and a connected community (Yelp.com); he found that connected contributors are concerned about their social image. When community members become well connected with each other, they experience a sense of belonging that leads to higher social benefits from providing product reviews (Akerlof and Kranton 2000; Ashforth and Mael 1989, Porter and Donthu 2008, Tajfel and Turner 1986).

To summarize, it is not clear *a priori* whether greater connectivity is likely to strengthen the intrinsic incentives. On one hand, if the intrinsic incentive is mainly driven by self-interest, a higher number of friends may dilute the member's incentive to contribute. On the other hand, if the intrinsic incentive is mainly driven by altruism and social-image concerns community members with larger audiences (friends) are expected to be *more* likely to contribute than members with fewer or no friends.

2.3. Monetary and Intrinsic Incentives

The idea of using a monetary incentive to boost product review contributions is not new. Avery et al. (1999) is one of the first proponents of such incentive. They attribute the under provision of product reviews to two types of costs that must be solely borne by the contributor: the costs of sampling the product and the costs of writing and distributing the reviews. The authors argue that while the Internet age significantly reduces the cost of distributing the reviews, it does nothing to reduce the sampling cost. As a result, a monetary incentive is necessary to induce a socially efficient level of contribution without outside forces. Similarly, Golle et al. (2001) takes the angle of mechanism design; and demonstrates how to use payment mechanisms to overcome free-riding in peer-to-peer networks. Lending empirical support to these theoretical studies, Hennig-Thurau et al. (2004) finds that economic incentive is attractive to the potential contributors. The marketing literature has also examined paid WOM. Ryu and Feick (2007) hypothesize that a monetary incentive can complement the intrinsic incentives based on equity theory. They also find empirical support that a monetary incentive can increase the level of positive referral, especially when the tie between the sender and receiver is weak (less well-known acquaintances) rather than strong (well-known others). To the extent that connected community members still value monetary incentives, it can be argued that community monetary incentives should be effective because the resulting reviews are less likely to be discounted as not credible.

Both theoretical and empirical studies have also questioned the effectiveness of monetary incentive at increasing product reviews. It has been long recognized that monetary incentive may have a negative effect on public-goods provision due to its crowd-out effect (e.g., Deci 1975, Frey 1997, Frey and Oberholzer-Gee 1997, Reeson and Tisdell 2008). Following Benabou and Tirole's (2006) argument, if community members contribute product reviews based on their social-benefit and social-image concerns, the presence of explicit incentives may affect their judgment of other members' beliefs about their intentions (Gaechter and Falk 2002, Rodríguez-Sickert, Gúzman and Cárdenas 2007). Benabou and Tirole (2006) suggest that the reason for the mixed effect of monetary incentives may be that agents weigh the external incentive benefits and perceive that it has detrimental effects on their prosocial image and reward seeking image. Ariely et al. (2009) set up a series of field experiments with conspicuous and inconspicuous extrinsic incentives. They found a negative effect on willingness to donate to charities, consistent with the crowd-out effect demonstrated by Benabou and Tirole (2006). As far as we know, no existing studies have empirically examined the complementarity between intrinsic and monetary incentives in product-review provision in a connected community; this paper takes a first step toward that understanding.

3. Background and Data

In this section, we first present the background of OSSNs and the importance of product reviews in an OSSN. Then, we will discuss in more detail the company under study, which is an example of an OSSN. Finally, we will present some summary information about the data and describe the natural experiment occurring during the data period.

3.1. Company and Data

Examples of OSSNs include Polyvore.com, Trendme.net, Foursquare.com and Kaboodle.com.

Similar to traditional E-tailers, such as Amazon.com, sellers affiliated with an OSSN have virtual storefronts where buyers browse products and place orders. However, members of OSSNs have the option to form explicit social connections and engage in a variety of social activities, among which creating and sharing product reviews is the most common activity. Given the popularity of both online shopping and social networking among U.S. consumers,[8] it is not surprising to see the emergence of OSSNs. OSSNs grew by more than 500% between early 2007 and early 2008 (Palmer 2008). Polyvore.com now attracts more than 6 million unique visitors per month. The success of OSSNs can be attributed to their ability to significantly enhance the buyers' shopping experiences by facilitating social interactions in their communities. Member-to-member interactions are often embodied in various types of user-generated content (Olbrich and Holsing 2011), including product reviews, recommendation lists and *styles* (product assortments and combinations created by the users). Together, the user-generated contents help consumers learn about new or niche products (e.g., recommendations), share creative ideas of using the purchased products (e.g., styles) and, in the case of product reviews, to reduce risks and make more-informed purchases of experience goods. Eventually, these community interactions help members become more knowledgeable buyers and cause them to be more loyal to the shopping platform (Algesheimer et al. 2010, Nitzan and Libai 2011). Among the various types of user-generated content, sellers affiliated with an OSSN directly benefit from the buyer-generated product reviews (*New York Times* 2011). Since product reviews strongly impact others' purchases, product reviews are critical for OSSN communities' success.

[8]A recent survey shows that eight out of ten consumers shop online at least once a week (Norris, 2010). Another report shows that 47% of the American adult Internet users are members of at least one social network (Hampton et al., 2011).

3.2. Company and Data

3.2.1. Overview. Our data is provided by a company that hosts an OSSN in Beijing, China (henceforth referred to as "the company"[9]). The company positions itself as a platform that helps buyers find recreational services (e.g., ceramic studios, dance schools and DIY-cake shops), share their experiences from using these services and network with each other both online and offline. Product reviews are very important for both buyers and sellers, since most of the services are "experience goods"; and sellers affiliated with the company usually do not provide free samples. All product reviews are generated by the registered members, and sellers are prohibited from providing any incentives (e.g., discounts or free services) to users for reviews.

Each affiliated service provider has a virtual storefront (a seller portal) where the buyers can learn about the service and place orders. The layouts of these storefronts are standardized with pages for product descriptions. The buyers are also required to set up their personal portals within the website, where they can post product reviews and update their personal profiles. A member can invite another member to be a friend. The social connection is bilateral: as in Facebook, the invitation must be accepted for two members to become friends with each other. Sharing product reviews among community members is one of the major activities of users and is encouraged by the company. Once a member posts a product review on her own personal portal, the review can be accessed by all community members. Meanwhile the review is automatically "pushed" to the landing page of all her friends' personal portals; and subsequently read by the friends. In addition, members can also engage in discussions unrelated to product reviews. For each member, the company keeps a detailed record of the member's product-review contributions, non-product discussions and purchase decisions. The

[9] Due to a contractual agreement with the company, we cannot review the name of the company.

company also tracks the weekly frequency of log-ins of each member.

3.2.2. The natural experiment. The company started operation in January 2009 and data collection regarding product-review activities was not systematic until September 2009. The data we use spans an 8-month period from the beginning of September 2009 to the end of April 2010. During the first year of operation (January 2009 to January 2010), the company depended solely on voluntary contributions for product reviews. As time went by, the company became increasingly concerned about members' limited product-review contributions. The lackluster contribution level can be attributed to two factors. First, although the number of affiliated buyers increased steadily, the majority of them did not contribute any reviews. Second, among the active contributors, there was a general decline in contribution levels over time. Figure 1 shows the change in the number of users and average number of reviews over time. Being fully aware of the importance of product reviews, the company introduced a monetary reward hoping to boost contributions on January 1, 2010, by offering a community credit for each product review posted. The credit carried a cash value of approximately 0.25 USD and could be used to pay for purchases with all affiliated sellers.

[Insert Figure 1 around here]

From the perspective of an incentive to contribute, the aforementioned natural experiment divides the online community into two regimes. The *voluntary regime* is in the four-month period from September 2009 to December 2009, where contribution was purely driven by intrinsic incentives. The *paid regime* spans the next four-month period in the data from January 2010 to April 2010, where both types of incentive existed.

To obtain the estimation sample, we took two steps in eliminating data that are not suitable for our research purposes. First, the regime change may have attracted users that are more interested in the monetary rewards. Incorporating those new comers after the regime change may bias our results regarding users' response to monetary incentive. In particular, if members who are attracted by monetary incentive are more likely to be socialites/loners, including members who join the community after the introduction of monetary incentive will overestimate/underestimate the effect of such incentive. To avoid these possible biases, we chose only individuals that became members before the introduction of the monetary incentive.

Second, as mentioned previously, many individuals did not contribute at all in the 8-month period in our data – it is likely that these users simply did not care to contribute at all, regardless of the incentives available. As our purpose is to examine the effect of intrinsic and monetary incentives on users' contributions to the online social community, we focus our attention to the active contributors, defined as members who contributed at least once in the observation period. Consequently, members with zero reviews were considered as peripheral and excluded from the estimation sample. As a validation check, we also estimated the model including all inactive users with qualitatively similar results. Thus, from now on, we focus on presenting and discussing results from the sample of the active contributors.

The final estimation sample contains 10,008 observations from 335 active contributors. The summary statistics are presented in Table 1. The overall average number of reviews provided per week is 0.10 with a standard deviation 0.30. Seventy-two percent of all the observations took place after the monetary incentive was introduced. At the time of the regime switch, community members had an average of 4.88 friends, and there was a great deal of variance for the number of friends (standard deviation 10.61). Before the monetary incentive was introduced, the average number of non-product discussions was 1.24, the average number of purchases was 0.07 and the weekly log-in ranges from 0.03 to 268.5, with an average of 6.32.

[Insert Table 1 around here]

4. Model and Results

This section presents the model-free evidence, our model and the estimation results. In the model setup, based on the literature, we hypothesize that the number of friends could influence both the level of the intrinsic incentive and the response to the monetary incentive. To demonstrate the validity of this setup, before presenting our full model, we first present some model-free evidence demonstrating that these two factors do influence both incentives.

4.1. Model-Free Analysis

Given the previous discussions, we would like to see model-free evidence regarding whether the number of friends and level of engagement affect intrinsic and monetary incentives. Members of the online community can be classified into two subgroups by their friend count at the time the monetary incentive was introduced: members who had at least one friend (the *"socialites"*) and member with no friends (the *"loners"*). In our data, there are 139 socialites, and 196 loners. When the natural experiment occurred, all community members were simultaneously exposed to the same unanticipated introduction of the monetary incentive. Figure 2 demonstrates that there is a notable difference in the average contribution level in a two-month period around the regime change. We further compute for each of the subgroups the average contribution levels during the voluntary and paid regimes in the spirit of traditional difference-in-difference (DID) analysis. The results are summarized in Table 2.

[Insert Figure 2 around here]

[Insert Table 2 around here]

Comparing the simple average contribution level across these subgroups reveals several clear patterns. First, before the introduction of the monetary incentive, the socialites on average contributed 0.379 reviews per week, significantly more than the average number of reviews provided by the loners (0.005). After the monetary incentive was introduced, the community saw an increase in the average contribution level by the loners (0.005 to 0.054). However, contrary to the company's expectations, the socialite's contribution level suffered a dramatic decrease (from 0.379 to 0.040). These results clearly show that the contribution behaviors of the two groups differ systematically in the two regimes. Next, we present the full model.

4.2. Full Model

In each period t, each member i decides whether to provide a product review, denoted d_{it}:

$$d_{it} = \begin{cases} 1 & \text{if member } i \text{ provide a review at time } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Following the standard latent utility model for the product-review decision, $d_{it} = 1(U_{it} > 0)$, where U_{it} is the latent utility for making a positive contribution at time t, compared to making none.

We cast the individual-level discrete choice model in a Hierarchical Bayesian (HB) framework. Users are different in the strengths of their incentive to contribute. For example, some members are by nature more expressive and *ceteris paribus* more likely to express their opinions by writing a product review. Past research has found that individuals do differ in their willingness to contribute. For example, Leider et al. (2009) used a random-effects model and found significant differences in agents' baseline altruism. Fischbacher, Gächter, and Fehr (2001) find that a third of their experiment subjects can be classified as free-riders whereas the others are cooperators. Moreover, it is important to understand the relative strengths of both types of incentive. For example, Benabou and Tirole (2006) theorize that at the individual level, whether the monetary incentive complements or crowds out the intrinsic incentive depends on which effect is stronger. To sum, the inherent individual-level heterogeneity necessitates a model that fully accounts for unobserved heterogeneity. The HB framework allows individual members' responses to intrinsic and monetary incentives to be a function of the observed individual-level characteristics (e.g., number of friends) and provides a natural approach to relate these individual-level characteristics to members' responsiveness to incentives. The individual-level estimates help us evaluate the effectiveness of monetary incentive and require an understanding of the *joint distribution* of both incentives at the aggregate level and across all individuals.

There are two levels in this HB model. The top-level model captures the drivers of each member's decision about contributing a product review in each week, while allowing for the parameters to be individual specific. The latent utility for product review contribution is specified as

$$U_{it} = \beta_{0i} + \beta_{1i} AfterIncentive_t + \beta_{2i} PropContributingMembers_t + \beta_{3i} Tenure_{it} + \epsilon_{it} \qquad (2)$$

In equation (2), β_{0i} is an individual-specific intercept, representing the level of contribution when everything else is zero: in this case, there is no monetary incentive, no social norm influence, and no experience with the community. This individual level intercept measures each individual's basic intrinsic incentive for contributing product reviews. $AfterIncentive_t$, a dummy variable, takes the value 1 if the monetary incentive is in place at week t and 0 otherwise. Conceptually, β_{1i} is the individual-level change in contribution in the paid regime; and captures individual i's responsiveness to the monetary incentive.

Besides the intrinsic and monetary incentives, there are other factors that would influence each member's product-review contribution. An important control factor is the social norm, or how active the peers are in making contributions. Models of conformity (e.g., Akerlof 1982, Jones 1984, Bernheim 1994) assume that individuals care about status and recognize that departing from the social norm will diminish their status, thus knowledge about others contributions can influence their beliefs about the norm, inducing a positive relationship between others' contributions and one's own. In the context of online communities, Chen et al. (2010) conduct a randomized field experiment to study the effectiveness of social comparisons for users at MovieLens.com, an online community that aggregates movie ratings and makes recommendations. They found that information on the median contribution level led less-active contributors to increase contribution by 530%; whereas more active contributors were unaffected. Thus, we include a measure of social norm in expectation that the level of community engagement increases with identity-related motivation to contribute product reviews. Specifically, we created the variable $PropContributingMembers_t$ computed as the ratio between the number of *other* users who contributed at least one product review in week *t* and the total number of registered users in that week. Its parameter β_{2i} captures each individual's differential responses to peer influences.

Previous research (e.g., Figuieres, Willinger, and Masclet 2009), has identified that, in general, product-review contributions decline over time. To account for this *fatigue* effect, we include $Tenure_{it}$, which counts the number of weeks member *i* has been registered by week *t*. Its parameter β_{3i} captures individual-level changes in contribution intentions over time. This parameter could be negative, demonstrating a fatigue effect as found in the literature mentioned above; it could also be positive, demonstrating a *strengthening* effect over time.

Another variable that could influence a user's review contribution is *number of friends* at each week. There are three reasons to consider incorporating this variable. First, the model-free analysis demonstrates that users' responses to the monetary incentive vary depending on their number of friends (see Figure 2). Second, as mentioned earlier in our empirical setting, when a product review is posted, friends are informed. As a result, the user's number of friends can be also considered as the size of the user's key audience. Using a natural experiment, Zhang and Zhu (2011) has found that the size of the audience positively influences the intention to contribute to the Chinese Wikipedia website. Finally, Leider et al. (2009) has found the prospects of future interactions are much stronger among friends than with strangers. In a connected community, the product reviews' main audience is the contributor' friends. This leads to a similar question – what is the audience effect in a connected community? *A priori*, it is unclear whether a member with a large number of friends will tend to contribute more or less. The effect of connectedness is ambiguous due to the opposing free-ride and social-benefit forces. First, the free-riding behavior is likely to be weaker with friends: As Leider et al. (2009) found, an important difference between friends and random strangers is that the prospects of future interactions are much stronger among friends, such that socially efficient outcomes are more likely to be induced among the friends. In the context of an OSSN, interactions among friends are more likely to result in more review contributions that enhance the total benefits for mutually connected friends. Second, the "warm-glow" effect is likely to be stronger among friends.

However, there are two problems with treating this variable as dynamic. First, in the context of our social network, members do not have the option to "defriend". As a result, the number of friends in our data for each individual is non-decreasing. This ever increasing pattern will not explain the variations of the reviews provided within each individual. The second problem with this variable is that the data are collected during the first year of operation of this website, and it is relatively a small site (unlike Facebook) in terms of number of users. Change in the number of friends within each individual is not very frequent during the observation period. In fact, among all the 335 users included in our estimation sample, 233 (83.5%) of them never added any additional friends during the period from the beginning of the data to the week when monetary incentive was introduced. About 95% of them added 2 or fewer friends during this period. Due to the lack of variation in the number of friends over time, we treat it as a static, cross-sectional variable, similar to a demographic variable. The static nature of this variable is actually helpful for studying our research question, where we try to understand how the level of connectedness in a social network moderate the "crowd-out" effect of monetary incentive. If the number of friends demonstrated more variations over time, it would have been necessary to tease out the drivers of the changes in this variable, before we can evaluate its moderating effect monetary incentive. Later, we will provide more details regarding how this variable is calculated and used in the hierarchical model.

The final term in equation (2) is the additive error term ϵ_{it}, which captures all other time-variant factors that might influence *i*'s product review contribution decision in week *t*. We assume these factors are not correlated with any of the explanatory variables captured in the model (2), after allowing for individual-specific parameters. We allow ϵ_{it} to follow the extreme value distribution, and the probability of contributing follows the standard logit model:

$$P(Contribute = 1) = \frac{\exp(V_{it})}{\exp(V_{it}) + 1} \tag{3}$$

Here $V_{it} = U_{it} - \epsilon_{it}$, representing the observed part of the latent utility in equation (2).

In this model, all the model parameters are allowed to be individual specific in order to capture the unobserved heterogeneity. All these individual-level parameters are assumed to follow a multivariate normal (MVN) distribution, allowing them to be correlated. In addition, these individual-level parameters could be shifted by the two factors discussed above.

The first factor is the level of connectedness in the community, measured by the number of friends, or the size of the audience for the product review. As discussed earlier, number of friends for an individual does not vary much over time in our data, so we treat it as a cross-sectional variable that captures the cross-sectional differences. We measure number of friends at a common time period across everyone in the data, which is the week right before the monetary incentive was introduced.

A second factor that might shift the individual-level parameters represents each user's level of engagement with the community. Highly engaged community members are more likely to develop a more salient identity, leading to more contributions to the community (Porter and Donthu 2008). Two additional variables are introduced to control for the level of overall engagement of each member. They are computed based on the weekly average before the monetary incentive was introduced. $AvgLogin_i$ is the average number of log-ins made by member i, $AvgPurchase_i$ is the number of times member i made purchases from the sellers affiliated with the community.

Thus, the second level of the model consists of a multivariate normal regression, with the individual-level parameters from the top-level choice model as the dependent variable and the three factors mentioned above as the explanatory variables:

$$\begin{bmatrix} \beta_{0i} \\ \beta_{1i} \\ \beta_{2i} \\ \beta_{3i} \end{bmatrix} = \begin{bmatrix} \delta_{01} & \delta_{02} & \delta_{03} & \delta_{04} \\ \delta_{11} & \delta_{12} & \delta_{13} & \delta_{14} \\ \delta_{21} & \delta_{22} & \delta_{23} & \delta_{24} \\ \delta_{31} & \delta_{32} & \delta_{33} & \delta_{34} \end{bmatrix} \begin{bmatrix} 1 \\ \ln(Friends_i) \\ \ln(AvgLogin)_i \\ \ln(AvgBuy)_i \end{bmatrix} + \begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \\ \zeta_{2i} \\ \zeta_{3i} \end{bmatrix}, \tag{4}$$

where $\ln(Friends_i)$ is the logarithm transformation of the number of the friends at the regime switch, to allow for possible diminishing returns. $\ln(AvgLogin)_i$ and $\ln(AvgBuy)_i$ are the logarithm transformations of the average number of member i's log-ins and purchases before the monetary incentive was introduced. Conceptually, such a model specification is similar to adding the interactions between these explanatory variables in the model explaining the latent utilities in the first level (Rossi and Allenby 2003).

In matrix notation, (4) can be rewritten as:

$$\beta_i = \Delta D_i + \varsigma_i, \varsigma_i \sim MVN(0, \Psi), \tag{5}$$

Where D_i is the 4 x 1 vector $[1, \ln(Friends_i), \ln(AvgLogin)_i, \ln(AvgBuy)_i]$ and Δ is a 4 x 4 matrix of coefficients. Conceptually, parameters in Δ are similar to the coefficients of the interaction terms in the DID analyses used in the previous literature (e.g., X. Zhang and Zhu 2011). For example, a positive δ_{02} implies that the intrinsic incentive increases with the (log) number of friends; and vice versa. Finally, Ψ is a 4 x 4 variance–covariance matrix that accounts for unobserved variables that could influence the effects of the main drivers of review contributions.

In this HB model, equation (5) utilizes cross-sectional data and provides the *prior* distribution of the parameters β_i, which are incorporated when obtaining the posterior distribution of the individual-level parameters specified in equation (1).

To complete the model setup, we assume the following diffuse and conjugate priors for the parameters in equation (5). The prior of Δ is specified as a MVN distribution with mean zero and covariance matrix $100I$, where I is a 4x4 identity matrix. The prior for the covariance matrix Ψ is Inverse-Wishart with degree of freedom $n_0 = 6$ and the scale matrix $V_0 = 6I$:

$$\Delta^{prior} \sim MVN(0,100I)$$
$$\Psi^{prior} \sim IW(6,6I)$$

We employ Gibbs sampling and data-augmentation techniques to estimate this model (Gelfand and Smith 1990, Tanner and Wong 1987). The Markov Chain Monte Carlo (MCMC) approach is used to draw all the model parameters, including the individual-level parameters from the choice models β_i and those from the hierarchical regression model, Δ.

4.3. Estimation Results

The model is estimated using the MCMC method. The MCMC chain was simulated for 50,000 iterations; and the last 20,000 draws were used to obtain the statistics for the posterior distributions of the model parameters. Examining the MCMC plots and testing with different starting values ensured convergence of the parameter estimates. The estimation results are presented in Table 3. The first column lists the results from the top-level heterogeneous choice model (1), which are the mean values of the estimated β_i. The results represent the average effects of the intrinsic incentive, the monetary incentive and the control variables, including tenure and social norm considerations. The next four columns present the elements of Δ: these parameters explain how number of friends and engagement level affect the response parameters in the choice model among the users, which are the values of β_i. We next present the model results by rows: We first discuss the average effect and then the drivers of the individual differences.

The first row is associated with the estimates of the individual-level intercept β_{0i}, which measures the level of the intrinsic incentive for each individual in the choice model. The mean intercept (mean of β_{0i}) is –3.647 and statistically significant, indicating that the baseline intrinsic incentive is weak. This is consistent with the overall low average contribution level observed in Table 1. The later columns demonstrate how the three factors (number of friends, average frequency of log-ins and average purchase frequency) influence the level of the intrinsic incentive. The results show that members with more friends tend to have a higher level of the intrinsic incentive in contributing product reviews. This is consistent with the positive "audience effect" identified by X. Zhang and Zhu (2011). Similarly, members who are more engaged with the OSSN (with higher levels of $\ln(AvgLogin)_i$ and $\ln(AvgBuy)_i$) exhibit a stronger intrinsic incentive in contributing product reviews.

The second row reports the estimates for the effect of the monetary incentive, which is measured by the dummy variable $AfterIncentive_t$. The first column of the hierarchical results shows that when the monetary incentive is introduced, on average, the users are more likely to contribute product reviews ($\text{mean}(\beta_{1i}) = 1.173$), and the effect is statistically significant. The parameter estimate for the logarithm-transformation of number of friends is negative and statistically significant ($\delta_{12} = -2.418$), which implies that monetary incentives are much less effective for people with more friends compared to those with fewer friends. On the other hand, the marginal effect of the monetary incentives is higher for users who log in the website more frequently ($\delta_{13} = 0.383$) or purchase more often from sellers affiliated with the OSSN ($\delta_{14} = 0.468$). Comparing the first two rows in this table, we notice that interestingly, number of friends has the *opposite* effect on the level of the intrinsic incentive compared to the monetary incentive.

The third row lists the parameters associated with $Tenure_{it}$ the first of the additional control variables. The parameter estimate listed in the first column shows that on average, the longer a user has been with the online community, the less likely she is to contribute product reviews ($\text{mean}(\beta_{2i}) = -0.688$), which demonstrated the “fatigue” effect. According to the estimates in the later columns, this “fatigue” effect is even more pronounced for less connected members. In particular, as time goes by, users with fewer friends are more likely to lose interest in contributing than those with more friends ($\delta_{22} = 0.254$). This demonstrates that a high level of connections within the community has a long-lasting effect of motivating product-review contributions. The level of engagement, however, does not have significant effect on reducing the fatigue effect ($\delta_{23} = -0.109$

and $\delta_{24} = 0.003$).

The last row is associated with the estimates for the effect of the last control variable of group norm, measured as the percentage of other users who provided product reviews in the same week. Overall, the norm effect is positive ($\mathrm{mean}(\beta_{3i}) = 0.634$), and statistically significant, indicating the positive peer-influence effect in the connected social network, which is consistent with the findings in the previous literature (e.g., Chen and Xie 2008). The results from the hierarchical model indicate that this effect is not significantly moderated by number of friends ($\delta_{32} = -0.109, \mathrm{n.s.}$) Log-in frequencies has a positive and marginally significant effect ($\delta_{33} = 0.165$), while the effect of past purchase is also positive but not significant ($\delta_{34} = 0.021, \mathrm{n.s.}$).

[Insert Table 3 around here]

4.5. Robustness Check

One of the main research questions of this paper is to analyze the effect of introducing monetary incentive on members' production review provisions (β_{1i}), and the moderating effect of the number of friends for each member. In our main model specification (equation 2), we capture this effect through an dummy variable $AfterIncentive_t$, indicating whether the monetary incentive was already in place or not at time *t*. In addition, we use the variable $Tenure_{it}$ to capture the individual specific time trend effect in an additive way. To ensure the results we found are not due to the specification of the model, in an alternative model, we let the time trend to interact with the incentive dummy, to capture the effect of the monetary incentive in addition to the time trend. The alternative model is specified as

$$\begin{aligned} U_{it} = \beta_{0i} + \beta_{1i} AfterIncentive_t \times Tenure_{it} \\ + \beta_{2i} PropContributingMembers_t + \beta_{3i} Tenure_{it} + \epsilon_{it} \end{aligned} \tag{3}$$

The estimation results from this model are qualitatively very similar to those as specified in equation (2). In particular, in this model, the estimate for the interaction variable β_{1i} is positive and statistically significant. This indicates that similar to the result in the base model, the overall average effect of monetary incentive across everyone is positive. In addition, we find that people with more friends demonstrate lower increase in product review after introducing monetary incentive. This indicates that our results are robust to these alternative specifications. Since the specification from the main model (equation 2) has slightly higher Log-Marginal-Likelihood (-2202.5) compared to this alternative specification (-2205.4), we use the former one as the base model. The simulation results discussed in the following are all based on the analysis from the main model.

4.6. Simulations

4.6.1. Targeted offering of monetary incentives. The HB framework we use extends the conventional DID analysis used in early studies (e.g., Zhang and Zhu 2011). This framework not only provides a more nuanced understanding of the unobserved heterogeneity by estimating individual levels of the intrinsic incentive and responses to monetary incentives (e.g., Benabou and Tirole 2006), but also opens up the possibility of targeted monetary incentives. Results from the preceding section demonstrate the nontrivial effect of monetary incentives on product reviews by mutually connected members of an OSSN. We next simulate the dynamics of overall product-review contributions under three alternative scenarios, where the OSSN uses different incentive schemes. In the first scenario, the OSSN chooses to stick with the voluntary contribution by the users: No monetary incentive is introduced at all. In the second scenario, monetary incentives are offered, but are targeted to a fraction of the users. The targeting strategies are based on the level of connection and commitment by each user, measured as number of friends. First, the incentive is offered only to users without any friends.

As a comparison, the second scenario describes when the incentive is offered only to users with more than the average number of friends, which is about 4 (see Table 1).

In these simulations, we assume that (1) buyers' decisions to join the OSSN and (2) the formation of buyers' local social network within the OSSN are exogenous to the specific types of operating incentives for product-review contributions and (3) a targeted monetary incentive will not induce extraneous effects such as fairness concerns[10]. We focus on two outcome variables, the total monetary costs (if OSSN decides to use a monetary incentive) and the net addition of product reviews in a four-month period. Table 4 summarizes the simulation results.

[Insert Table 4 around here]

The first column of Table 4 lists the average number of product reviews after week 16 when the monetary incentive was introduced for some scenarios. It shows in the baseline case, the average number of product reviews provided by each user after week 16 is 1.06. If the incentive was not introduced at all, the average product reviews will drop slightly to 1.00. When targeted incentive schemes are employed, the numbers changed much more dramatically. In particular, if the incentive is targeted only to people with no friends, the average number of product reviews will increase to 1.54, or a 45% gain compared to the base line scenario. However, if the incentive is targeted to users who have many friends (more than the average), the number of product reviews will actually drop to 0.32, a 70% drop. To summarize, the simulation exercise shows that a targeted strategy that selectively

[10] Our simulation reflects an ideal situation where the extraneous effect is non-existent. There are ways by which community may prevent such extraneous effects from happening. For example, the community may offer the monetary incentive in the form of coupons; but limit the availability of these coupons to service categories where members tend to be less connected. Another possibility is that the company can allow the members to self-select into whether they would like to be compensated financially. If the socialites are concerned about their images; they are likely to choose to provide review without monetary incentives; and vice versa for the loners.

provides a monetary incentive would likely have been much more effective and less costly than what happened in reality.

4.6.2. Timing of Monetary Incentives

The above section shows the potential benefit of a targeted monetary incentive. However, it is possible that a targeted compensation scheme may bring up unintended consequences such as consumers' fairness concerns (e.g., Bolton and Ockenfels 1997), which may negate the intended benefits. Next, we explore another counterfactual where the monetary incentive is offered to every community member, but the community must decide on *when* to use the monetary incentive. This counterfactual is motivated by our finding that the effect of monetary incentive varies from period to period, and as the OSSN community becomes increasingly connected. In this analysis, we assume that the users' decisions of making friends are independent of the timing of the monetary incentive. To conduct this counterfactual, we examined each of the 70 weeks, treating each week as a potential time when the monetary incentives could be either introduced or retired. This is illustrated in Figure 3. The blue line in the middle shows the average percentage of members in the estimation sample (a total of 335) who will respond positively to monetary incentives when introduced in each week. The green line below and the red line above are created using the lower and upper 95^{th} percentile of the parameter estimates; they can be seen as conservative and optimistic estimates of the percentage of members for which the net effect of monetary incentive is positive. Based on our findings, when people have fewer friends when monetary incentive was introduced, more members are more likely to respond to it positively. However, as time goes by, members grow their friend base, and will be less likely to respond to the monetary incentive positively. Consequently, the percentage of members with a positive response will decrease with time. This is true especially at the beginning of the period, when members are growing their friend base dramatically, until week 30. If the monetary incentive were introduced in week 30–60, the percentage of members who will respond positively to monetary incentive does not vary much. A caveat of this analysis is that it is based on the assumption that the introduction of monetary incentive does not influence users' decision of getting friends.

[Insert Figure 3 about here]

To summarize, the above simulation results suggest that it will be more effective for the community to introduce a monetary incentive in the early stage of the social network, when the community is less connected. The company may also want to consider retiring the monetary incentive when the online community becomes more strongly connected, when the crowd-out effect of the monetary incentive becomes stronger. In retrospect, our finding is not inconsistent with the practices of major online review sites in the United States. For example, Yelp.com used to offer reviewers cash incentives for writing reviews during the beta version of the website; but later decided to retire such incentive completely. Yelp.com now resorts to a reputation-based reward system, which provides "Elite" status to the most popular and prolific contributors.

5. Discussions

Our research is motivated by the recent surge of integration between online product-review sharing and social networking. Such an integration bears great promise for companies who would like to leverage the power of product reviews among connected consumers, underprovision of such reviews remains a serious challenge as long as long as potential contributors continue to bear the costs, which involve not only publishing the product review, but also the risk of early trials. A natural experiment embedded in the data allows us examine the nontrivial interactions between intrinsic and monetary incentives on product-review contributions and presents fresh empirical evidences regarding boundary conditions that make monetary incentives complement intrinsic incentives.

Our findings suggest that designing an effective incentive mechanism is a nontrivial task. First, consumers who are well connected within the community have a stronger intrinsic incentive to contribute, which implies that if the community decides not to use monetary incentives it should focus on ways that increase the level of connectedness of the community, as Yelp.com does. On the other hand, monetary incentives do not necessarily complement intrinsic incentives, especially for well-connected consumers. A possible explanation is that the monetary incentive crowds out pro-social intentions for some of the most active community members. This finding is in contrast to evidence from earlier studies showing the positive effect of monetary incentives (e.g., Brachta, Figuieres and Ratto 2007, Lacetera, Macis and Slonim 2009, Neckermann and Frey 2008, Hennig-Thurau et al. 2004). Thus, online communities must be fully aware of the undesirable consequences of using such incentives. Our simulations further suggest that the monetary incentive works best when the community is still growing and the level of connectedness is relatively low. Finally, it may also be possible for the company to rely on both intrinsic and monetary incentives even if the community is full developed. In that case, monetary incentive must be effective for at least some of the consumers. Then, by using a sophisticated targeting strategy, the community can avoid the pitfall of a “blanket” monetary incentive. Apparently, to implement a targeted strategy, the community must first gain an understanding of the joint distribution of the strengths of intrinsic and monetary incentives at the individual level. This can be achieved using the HB model controlling for consumer heterogeneity.

There are a few limitations of our study, which opens up future research directions. First, we study a monetary incentive provided by the community itself. A practical question regarding the use of monetary incentive is *who* will make the payments to early contributors. We argue that this role can be naturally taken by the community website, not only because it has the incentive to do so (the revenue model is usually based on commissions of sales, which can be helped by the reviews), but also because its perceived objectivity. Attribution theory (e.g., Folkes 1988, Mizerski, Golden, & Kernan 1979) suggests that consumers are suspicious: if an endorser has an incentive to recommend a product, they discount such recommendations. Alternatively, sellers could directly provide monetary incentives, similar to the practice of using paid referral programs to encourage earlier users to spread positive WOM (Ryu and Feick 2007). However, sellers must be aware of lack of trust in seller-provided product reviews (Mayzlin et al. 2012).

Second, in our study, the monetary incentive is public knowledge. Although FTC provides specific guidelines that bloggers should make self-disclosure for whether they are being paid for product reviews and posting product links,[11] the disclosure of paid referrals and product links has not been perfectly enforced. So an interesting question is whether this ambiguity leads to more or less crowd-out effect of the monetary incentives. Third, we focus on enticing consumers to write product reviews because of its popularity, the significant costs of production as well as the extensive positive externality (Avery et al. 1999). Future research can shed light into other types of public goods (e.g., knowledge). Similarly, OSSN is one of many social communities; and it will be important to validate our findings in the contexts of other communities such as Enterprise 2.0 platforms. Fourth, our results may be sensitive to cultural differences: Consumers from different cultural backgrounds may differ systematically in their relative strengths of responsiveness to intrinsic and monetary incentives. For example, in some cultures, friends may not mind at all that their friends are getting paid for what they review. Therefore, the crowd-out effect of monetary incentive is expected to be less severe. Future

[11] http://ftc.gov/os/2009/10/091005revisedendorsementguides.pdf

research could apply our methodology to different cultural contexts. Fifth, while we treated the social network among community members as exogenous, future work could endogenize the formation of such social networks. Sixth, while we focus on audience size and social identity, future studies can take a more nuanced view of the intrinsic incentives, such as status-seeking and uniqueness-seeking (e.g., Mcquarrie, Mcintyre and Shanmugam 2012, Zeng and Wei forthcoming), which helps to further explore the interactions between intrinsic and monetary incentives. Finally, it will be natural to further examine the effect of these reviews on subsequent purchase decisions. Future research could examine the effectiveness of such reviews in conversion and payment. It is particularly interesting to see whether product reviews provided in the paid regime are more or less effective than those in the voluntary regime.

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Table 1 Summary Statistics

	Mean	**St. Dev.**
Number of product reviews provided	0.10	0.30
Number of friends	4.88	10.61
Tenure	18.36	9.63
Monetary incentive is available	0.72	0.45
Weekly average number of log-ins before monetary incentive	6.32	24.06
Weekly average number of non-product discussions before monetary incentive	1.24	3.06
Weekly average number of purchases before monetary incentive	0.07	0.15

Table 2 Product-Review Contributions Before and After Introduction of the Monetary Incentive

	Before the monetary incentive	After the monetary incentive
Members with no friends	0.005	0.054
Members with at least one friends	0.379	0.040

Table 3 Estimation Results from the Base Model

	Results for the choice model β_i	Results for the hierarchical model $\Delta = \{\delta_{ab}\}$			
		Intercept	ln(*Friends*)	ln(*AvgLogins*)	ln(*AvgBuy*)
Intercept (β_0)	–3.647 (–4.97, –2.89)	–4.784 (–6.26, –3.75)	1.488 (1.00, 2.18)	0.289 (–0.15, 0.67)	–0.452 (–1.07, –0.04)
Incentive dummy = 1 if monetary incentive is provided (β_1)	1.173 (0.70, 1.84)	2.650 (2.09, 3.51)	–2.418 (–2.96, –2.04)	0.383 (0.16, 0.60)	0.468 (0.07, 0.83)
Number of weeks being a user on this website/10 (β_2)	–0.688 (–0.91, –0.46)	–0.827 (–1.12, –0.55)	0.254 (0.11, 0.42)	–0.109 (–0.27, 0.06)	0.003 (–0.13, 0.14)
Percentage of other users who provided product reviews in the same week * 10 (β_3)	0.634 (0.31, 1.05)	0.605 (0.18, 1.08)	–0.109 (–0.27, 0.06)	0.165 (0.01, 0.34)	0.021 (–0.16, 0.26)

Table 4 Simulation: Targeted Monetary Incentives

		Average number of reviews added after week 16	Percentage change in average number of reviews	Number of individuals receiving incentives	Percentage change in monetary cost
Current		1.06	–	340	–
No monetary incentive		1.00	–6%	0	–100%
Targeted incentive scheme					
Number of friends	No friends	1.54	45%	198	–42%
	> 4 friends	0.32	–70%	75	–78%

Figure 1 Dynamics in number of users and average number of reviews

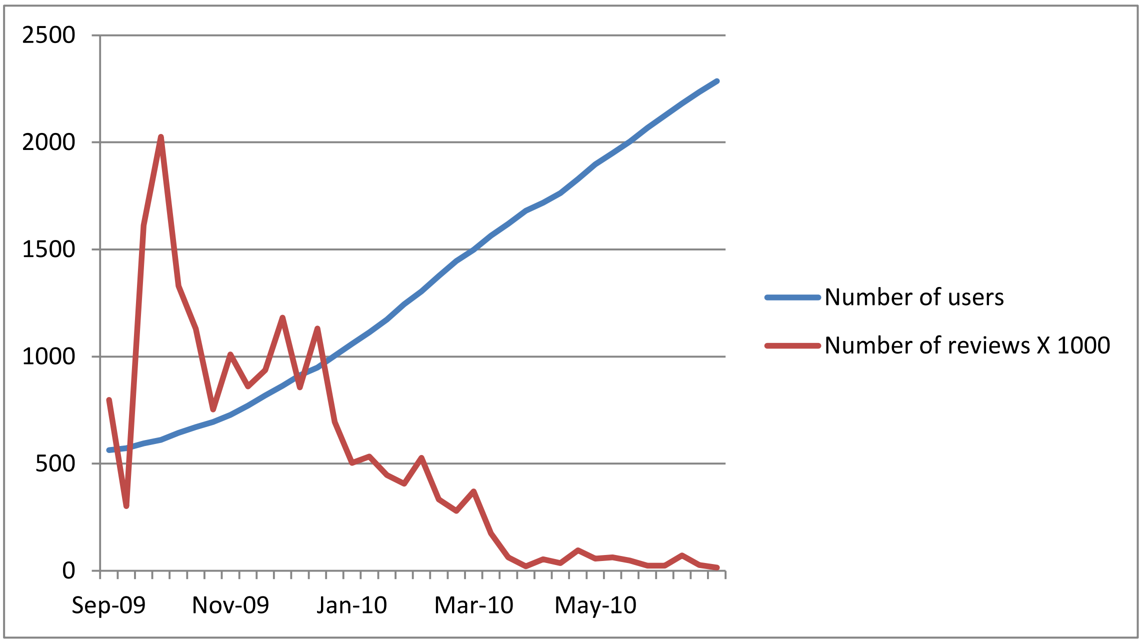

Figure 2 Average number of reviews, before and after the regime change

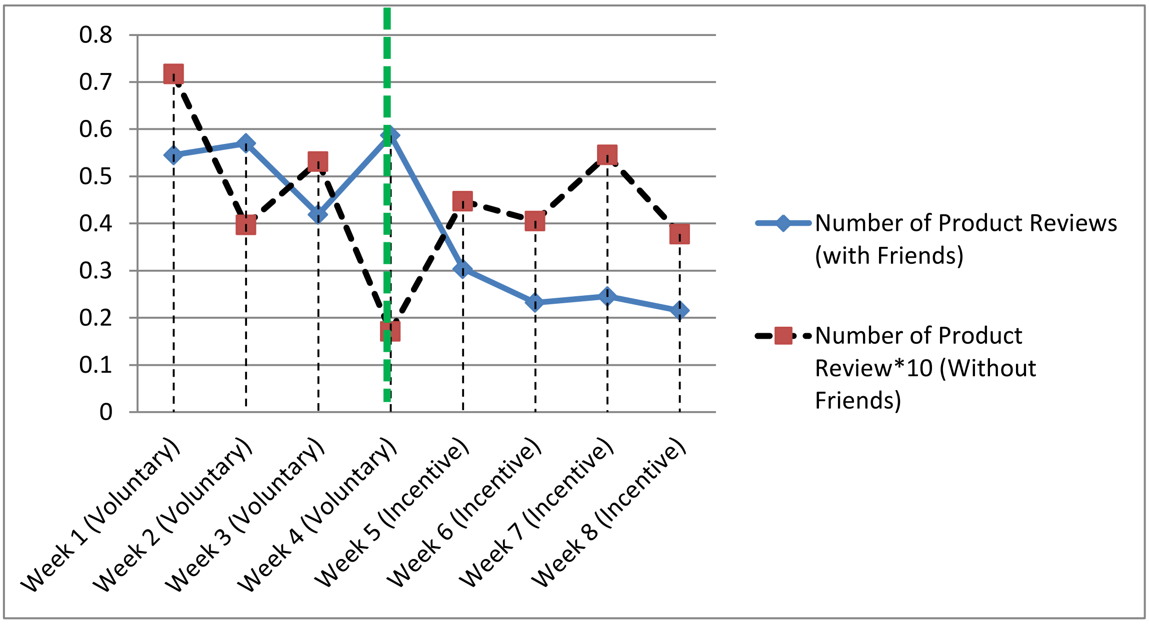

Figure 3 Simulation: Effectiveness of monetary incentives over time