Why do Consumers Contribute to Connected Goods?

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Abstract

Consumers contribute content available to their peers to social networks, which is important to ensure continued activity, and we term these contributions connected goods. Based on the properties of connected goods, we posit that consumers contribute to obtain either warm-glow altruistic benefits, compete for positional status or benefit from the experience of their peers' contributions. We develop a framework to characterize these constructs, and approximate the competition between consumers by means of a dynamic game over a social network.

We apply our model to data from a mobile phone network, with purchases of ringback tones serving as connected good contributions. We derive estimates that characterize conspicuous contribution decisions and conduct policy simulations to investigate dynamic consumer influence. We find that consumers compete for status by making contributions, but do not value the altruism benefit, and obtain a positive experience benefit from their peers' contributions. We investigate the effect of seeding a network with a new content, and find it critical to consider the dynamic state of the network to create a ripple effect. Finally, we explore whether consumers who are more central in the network are more influential, and find that this is not the case.

1 Introduction

Why do consumers use social network platforms? They visit online networks to either (a) create content, or (b) experience or consume content created by their connected peers, or (c) to communicate with their peers [Hampton et al., 2011]. At the basic level, most social network platforms themselves do not focus on providing content, but provide tools that allow their users to create, manage and disseminate content more effectively. For example, platforms like Facebook and Twitter provide tools to enable users to share posted content, but the companies rarely creates content. The main value addition of social networking sites is that they provide a social space for users that does not require synchronous or coordinated communication or presence. Rather, these sites provide a virtual location where users can connect at their convenience and still receive access to content and be able to participate in social conversations with potentially their entire social network at the same time. Practitioners understand the critical importance of networks which consumers visit regularly, and where sufficient content is created by users to ensure a critical mass of responders [Shih, 2009, Palmer, 2009, Goldenberg et al., 2009].

We abstract the content products contributed by individual consumers as *connected goods* available to their peers who are connected by a social network. Connected goods are *conspicuous contributions made by consumers, which are available to their peers who are connected to them by a social network*. A detailed discussion of connected goods is provided in §2. We begin with these properties of connected goods to understand the drivers of consumer contributions. We note that consumer contributions occur over time, and the asynchronous nature of online social networks imply that their peers could respond in the future, and not just immediately.

Our objective is to move beyond demostrating evidence of covariation of behavior across connected consumers, and to help understand the mechanisms that drive consumers to make connected good contributions to social networks that are experienced by their peers. Specifically, we address the following research questions:

- What factors drive consumers to contribute to connected goods? (How) can we empirically distinguish the degree to which each factor plays a role in contribution decisions?
- How are contribution decisions related across connected peer consumers and across time? How do the contributions differ depending on observable individual characteristics and network

positions?

- If a consumer makes a contribution, does it encourage peers to contribute in the future? Are consumers who are more central to the network also more influential in encouraging contributions from peers?

To answer these questions, we create a framework where we can incorporate multiple potential reasons that consumers make contributions to a social network. We begin with the properties of connected goods, specifically that they are *conspicuous contributions*: when a consumer contributes, her peers derive experience or consumption benefits from the contribution. These properties lead us to the reasons that consumers contribute to connected goods, as detailed in §2. First, consumers benefit from providing a new connected good to their peers due to *altruistic* reasons. Second, consumers compete with their peers for *positional status* by making more contributions, and such status could be implicit or explicit depending on the design of the social platform. Since status is inherently a relative measure, this competition for status introduces strategic interactions between consumers. Third, consumers value experiencing connected goods contributed by their peers over time, and know their present contributions might induce future contributions from their peers. In addition to these three reasons, specific settings might involve additional reasons for contributing and our framework can easily incorporate these effects.

We begin with these micro-foundations, and model contribution choices of consumers in a social network as being driven by multiple potential motivations, including altruism, status competition and experience benefits. From a practical perspective, the key advantage of modeling and disentangling the multiple benefits is that we can attribute which effects are more critical to effect continued activity in the social network, as well as understanding whether promotions like seeding content might lead to strong viral effects spreading across the network.

Our model thus recognizes not only the possibility that consumer contribution decisions are inter-related across peers within the social network, but that they are inter-temporally related as well. These considerations lead us to approximate the decision making process of consumers by modeling a dynamic game over a social network, where consumers make the key inter-temporal tradeoff deciding whether to contribute now in the current period, or defer a contribution to a future period. The tradeoff is between the cost of making a contribution in the current period, weighed against increased benefits from altruism, positional status, and expected experience utility

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as well as other potential complementary activities in the future. In this dynamic game played over a social network, consumers consider how their contribution decisions will influence the future responses from their peers, and this link induces strategic interactions between consumers. The realized utilities over time for each consumer thus depend on the strategies of *all* consumers in the network. The appropriate model for studying our framework is the dynamic game model with forward-looking agents by Ericson and Pakes [1995] (E-P), which was developed to examine the dynamic effects of competitive strategic interactions between oligopolistic firms in a marketplace. We adapt the E-P framework to our setting, overlaying the game upon a social network structure.

We operationalize and empirically demonstrate our model on a unique panel data set, which includes purchases of ringback tones offered by a global mobile phone company with a network of interconnected customers. Ringback tones are visible contributions made by consumers that are experienced by all peers who have a social connection with them. In our empirical setting, *contribution recency* serves as a state variable that is endogenously determined by the sequence of contribution decisions for all consumers. We construct the positional status of each consumer in her ego network and model it as a factor in the consumer's utility function. The recency state variable interlinks the decisions of different consumers, and positional status ensures that an increase in one consumer's status will require that other consumers decrease in status if everything else remains the same. The consumer must trade-off the corresponding benefit and costs that may be likely to result from delaying and making a contribution in the future, accounting for the likelihood that her peers may make contributions in the current and future periods.

Models of dynamic games are known to be difficult to estimate due to the challenges of computing the equilibrium value functions with large state spaces, and our setting is no exception. In fact, our inclusion of the social network structure over which the game is setup makes it even more challenging. Rather than compute the equilibrium, we estimate the model by combining Arcidiacono and Miller [2011]'s conditional choice probability (CCP) in a first stage with Bajari et al. [2007]'s use of simulated value function with their inequality-based estimation methodology. This broad approach has been used by others to alleviate the dimensionality problems inherent in estimating dynamic games [Ryan, 2012, Ryan and Tucker, 2012, Sweeting, 2009]

We find that contribution status or positional utility plays an important role in determining contribution decisions, demonstrating competitive behavior between consumers in the data. Con-

sumers value contributions made by their peers, and understand that competition for positional status enhances the likelihood of peers making a contribution when a consumer contributes. Note that the cost of contribution prevents consumers from making contributions too frequently. Consistent with our intuition, older consumers are shown to be less competitive, but receive a higher utility from contributions made by others, and tend to be more sensitive to the cost of contribution. Male consumers are more competitive and sensitive to positional status, and have higher consumption utility for experiencing contributions made by their peers, but they are less sensitive to contribution cost. Interestingly, consumers with higher centrality are more competitive, enjoy higher consumption utility, and are less sensitive to contribution cost.

We also conduct policy simulations by seeding a consumer with a new connected good, i.e. ringback tone and altering the state of the consumer. This simulation helps investigate how important each consumer is in affecting the utilities of their peers and how the decision of one consumer can motivate others to contribute. Our results show that consumers who are more competitive in making their own contributions may not be the most influential consumers in the social network. For example, consumers with higher centrality are more competitive in contributing to maintain a higher contribution status, they may not have as much impact as consumers with middle levels of centrality, whose contribution changes the ranking order or more peers. Seeding the more central consumers can encourage contributions from more peers in a faster fashion, with most of the incremental contributions made by more competitive peers.

Our contributions to the emerging literature on consumer choices in social networks are along the following dimensions. First, we address the rather poorly understood question of why individuals incur the cost to contribute connected goods in a social network when their peers experience product, and empirically distinguish between the multiple reasons. In so doing, we develop a general framework beginning from the properties of connected goods to help understand consumer behavior in social networks.

Second, we make a novel identification contribution in being able to characterize the experience utility when the experiencer is different from the contributor, i.e. the person incurring the cost is different from the person experiencing the potential benefit. In traditional marketing contexts, variation of usage or sales with respect to price or other marketing variables is critical for identification of benefits. The key implicit assumption made almost always in the literature is that the

individual making purchase decisions is the same as the person obtaining the consumption or experience benefit from the product. For connected goods, this assumption does not hold, and the usual identification approach is invalid, and variation in contributor's utility cannot identify consumption or experience utility. Our approach inter-temporally links the experience utility to the positional status, permitting us to identify experience utility for these classes of goods.

Third, we characterize the network value of consumers. There are no studies to the best of our knowledge that empirically characterize the value each consumer generates within a social network. The notion that consumer actions and choices affect the utilities of their peers as well as affect their peers' decisions leads us to characterize and understand the "networked value" of consumers. We find that consumers have have both positive and negative value on their peer network, and that we must consider the dynamic state of the network when determining networked value.

This paper extends the application area of dynamic games, mostly used in the industrial organization literature with competition between firms, to the realm of consumers, who interact with their peers connected through a social network.

The present study is not without limitations, some of which we expect would be addressed with further research across a range of social network contexts. Our approach requires us to make several assumptions that would be useful to relax in future work. First, we assume that social ties between individuals are exogenous and that strong social ties do not disappear over time (consumers who maintain a minimum level of communication are in fact in a social relationship). This allows us to focus on explaining why consumers contribute to connected goods. An approach that explicitly models how and why consumers form social relationships with specific peers, and how such relationships evolve would be very helpful [Jackson and Wolinsky, 1996]. A second assumption is that individuals perfectly observe the state of each of their friends in every period, which enables them to derive the status in their local social network. This assumption may be more reasonable in settings where consumers are in regular communication or are updated fairly frequently by the network platform regarding the actions of their peers, but less tenable with weak social interactions.

2 Connected Goods and Position in the Literature

We specifically define a connected good as a *conspicuous information good contribution made by an individual, available for experiencing by the individual's peers in a social network setting.* Note that the contributor need not get an *experience* benefit from contributing the good, since she has access to the good. The peers who are connected to the contributor obtain a benefit from experiencing or consuming the good, hence we refer to them as *experiencers*. We do not think of contributors and experiencers as different sets of individuals. Rather, these are roles played by individual consumers in a social network, and each person can be both a contributor and an experiencer of connected goods. However, if there were no social connections or relationships between consumers, there would be no one to experience connected goods. Connected goods are related to but conceptually distinct from public goods, club goods or shared goods which do not share all of the above characteristics [Cornes and Sandler, 1983, Botsman and Rogers, 2010, Belk, 2010]. We build upon three properties of connected goods to draw from the literature: they are *conspicuous,* they are *contributions*, and made to others linked by a *social network*.

Conspicuous consumption, also termed Veblen effects after the early work by Veblen [1912] has developed rather well as a research area within marketing and economics. Conspicuous consumption is tightly linked with status motivations O'Cass and Frost [2004], Ivanic and Nunes [2009], with the idea that it conveys a signal about status to other consumers. Empirical evidence supports status effects in domains as diverse as cosmetics, loyalty programs and luxury goods among many others [Chao and Schor, 1998, Dreze and Nunes, 2009, Han et al., 2010]. Depending upon the context, status derived from consumption might have either intrinsic benefits for consumers, and cause them to feel unique or distinctive [Belk, 1988, Tian et al., 2001] or the act of consuming conspicuously could be a signal of wealth, of expertise, of the consumer's identity as a connoisseur that might prove economically beneficial [Bagwell and Bernheim, 1996, Corneo and Jeanne, 1997, Phau and Prendergast, 2000].

Consumers at the lower tier of consumption are known to demonstrate the effect of "keeping up with the Joneses," and in fact more equality in consumptions may increase the propensity to purchase or consume because consumers stand to gain more positional status [Ordabayeva and Chandon, 2011], an effect that we might expect to hold in the case of conspicuous contributions as well.

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However, in all cases, by definition conspicuous consumption occurs only in the presence of others and this motivation would not exist in the absence of someone to observe the consumption [Wong, 1997]. This literature has been extended to examine marketing implications for firms in settings with conspicuous consumption by considering how Veblen effects may affect segments like snobs and followers [Amaldoss and Jain, 2005], and how brands can create social value by enabling social interactions with the "right" type of consumers [Kuksov, 2007]. However, an *empirical* examination of conspicuous consumption has not been modeled and demonstrated, to the best of our knowledge.

In addition to undertaking the status-generating activity, consumers may also be involved in other *complementary activities*. Experimental evidence has demonstrated consumers receive *additional* utility from complementary activities when they have a higher status, and such activities can be economically significant [Ball et al., 2001, Ball and Eckel, 1998]. Note that such an activity may or may not be relevant depending on the institutional social network context, and is relevant in our setting detailed in §3.

There are several studies examining the reasons underlying why consumers make contributions to others, especially in the domain of charitable contributions. Pure altruism implies that individuals internalize the benefit others receive from contributions, and would not apply in most settings since the incentive to free-ride would be high when there are many agents. The 'warm-glow' impure altruism motive posits that the contributor must obtain a direct private utility from the act of giving that is also known as impure altruism, and is consistent with contributions in settings with many agents [Andreoni, 1990]. This type of altruism is significantly responsible in charitable giving [Andreoni, 2006]. It is noteworthy that although the warm-glow motive exists even when the recipient is unknown, if contributors know the identities of recipients, then they tend to give larger amounts [Rege and Telle, 2004]. In social networks, identities are often known and there are repeated interactions among individuals, making the altruism motive even more plausible.

There is a related stream of literature focsed on peer effects in social network, where the idea is that actions taken by an individual have implications for her peers, and might lead them to undertake similar actions. Such an approach has been taken in choices made by high school students involving owning cellphones or smoking [Soetevent and Kooreman, 2007], in outcomes of unemployment [Topa, 2001], activity and purchase behavior in online social networks [Trusov et al., 2009, Iyengar et al., 2009], or in choice of cars or television channels in a family [Yang and Allenby, 2003, Yang et al.,

2006]. Theoretical treatments have tried to understand how the network structure is connected with equilibrium outcomes in diverse studies motivated by conformity in social groups and how key players can have outsize influence in networks [Brock and Durlauf, 2001, Ballester et al., 2006]. To the best of our knowledge, Hartmann [2010] is the only study that aims to empirically investigate the microfoundations of how social interactions create value.[1]

3   Institutional Setting and Data Description

The data set is provided by a global mobile phone company for all customers situated in a large Asian metropolis. Cellular service providers have relied primarily on revenue from voice calling services in the past decade. However, as this revenue source saturates, they are attempting to increase revenues from data services. Data services like ringtones and ringback tones, as well as video shows and TV-enabled content are expected to demonstrate double-digit increases over the next several years according to a recent research report by IDC, and are becoming primary drivers of growth for mobile phone carriers.[2] For the mobile phone provider from whom we obtained our data, the revenue from the ringback tones represents the fastest-growing stream of data revenue (40 percent), followed closely by web services and ringtones.

Ring tones have been available for a few years, but ringback tones are more recent, and have become popular first in Asian countries before being introduced by carriers in the US. The increased adoption of data services by consumers has also been accompanied by the sales of smartphones that can access e-mail, the mobile web and other rich media content [Lawton, 2005].

Ringback tones are purchased by a subscriber to replace the standard ringing sound with a musical tune that plays for for about 20 seconds, and often features popular contemporary music.[3] Subscribers purchase ringback tones by sending a text message requesting the tone, or by calling the customer service department of the mobile company. Ringback tones are heard by the purchaser's callers, and *not* by the purchaser whereas a ringtone is heard by the purchaser or callee. We

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[1]For an overview treatment of the economics of social networks, see Jackson [2008].

[2]URL: `http://news.cnet.com/IDC-Games,-video-to-fuel-Europes-mobile-market/2100-1041_3-5217861.html`

[3]Note that ringback tone is activated at the network level, even before the call is transferred to the subscriber's phone.

demonstrate an example in Figure 1, where A is the contributor or purchaser who has incurred a cost to contribute the new ringback tone, whereas B is the caller who experiences the tone when she calls A. Thus, A makes a conspicuous contribution to his social network peers, and seldom derives consumption utility from experiencing the tone.

Figure 1: Ringback Tone: Purchased by A and Experienced by B
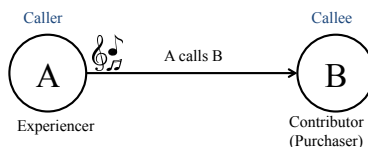
The ringback tones are varied, and include popular musical tones as well as music from different eras, and instrumental tones. Most purchases we observe are of the popular music variety, but since we do not yet have access to explicit data characterizing the genre of other details of the tones, we are unable to further build upon this dimension. For the purpose of understanding why consumers contribute to connected goods, rather than focusing on specific song choice, we evaluate the purchase / don't purchase (or contribute / don't contribute) decisions.

For the purpose of this study, the ringback tone is an ideal example of a connected good for two reasons. First, the social tie is over the phone and is likely to be stronger than designating someone as a friend in an online network. This setup provides us an offline context that may track social relationships and behavior more accurately than studies conducted with purely online data. Second, we can obtain not just communication ties between individuals but product purchase decisions that are similar to traditional marketing scenarios. This setting is somewhat different from most online studies that track *activities* like updating photographs and videos, or installing freely available applications on social platforms, which are valuable to the social network platforms due to their effect on increased traffic. Thus, our study of contributions operationalized as purchases strongly links economic factors to social networks, which has remained implicit in prior work. Our results can also be viewed as an illustration of how consumers use new data services that have a strong social component.

3.1 Data Description

Our data is a panel data with the complete calling and purchase history of all the networked customers from a large cosmopolitan city over a nearly six-month period spanning Dec 2007 – May 2008. It has the complete call records indicating the phone numbers of the calling and called individuals, along with the date, time, and duration of each call. For each consumer, we observe their purchases of ringback tones with information on date, tone downloaded, and price paid. Moreover, we also have access to demographic variables such as age, gender, geographic code, etc.

Data Sample Selection

The data sample was selcted by the company according to set of pre-determined criteria, with the objective of obtaining a reasonable sample size, the feasibility of using the data for estimation, and including a network structure with connected individuals. The following rules were used to obtain the sample.

To ensure we focus on regular consumers, we begin by randomly selecting a seed individual from subsample where consumers contribute at least 3 times, i.e. the seed customer makes at least 3 purchases during the entire panel length. Then, from the calling history, we derive the social relationship matrix R for the seed customers and their peers by using the following rule: we specify a social relationship connection between two individuals whenever each in the pair makes *at least 5 calls* to the other over the data period. We do this to focus on stronger connected ties, ignoring the weak ties that might result from occasional calls. The social network graph is detailed in Figure 4 below. Each consumer is indicated as a node, and the edges connect consumers who have a social relationship. Beginning with the seed's connected peers (ego network), we recursively obtain the network. We repeat the recursive procedure for each consumer who is included until we span a depth of three levels. To determine where to cut-off the network to obtain a reasonable sample for estimation, we used a community-detection algorithm used in communication networks. Specifically, we determine which set of peers to include in the sample by maximizing the ratio of within-sample ties to total social ties for the sample, i.e. we choose a cohesive network where an individual is included in the network sample only when they have a high ratio of the number ties to consumers in the sample to the number of ties to those outside.

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The sample data contains calling history of 197 networked customers. Table 1 below presents statistics for the social ties, network promotional exposures and purchases. Consumers make an average of around 15 calls per week to their peers, but there is a large variation in calling volume among consumers. The talk time per week, or amount of time consumers spend in voice conversations is a little more than an hour per week, and the variation in talk time is fairly large as well. Consumers purchase a ringback tone every 5 weeks on average, and again, we find a significant variation in purchase behavior across consumers. Our sample consumers have a majority of men and are mostly 20-45 years old. The summary measures from the data sample are listed in Table 1 below.

We note that ignoring the structure of the network connections, and assuming every consumer to be connected to everyone else is clearly likely to lead to biased results given the heterogeneity of the interconnection structure. The purchase pattern variation over time is detailed in Figure 2, and we note that there is significant variation both within and across consumers over time in the pattern of purchase. Consumers use the service for dyadic communication, and we see a significant but smaller variation in the aggregate dyadic communication per consumer over time, as illustrated in Figure 3.

In the network connection depicted in Figure 4, notice that there is much heterogeneity with respect to the number of links (edges), and that some consumers are very heavily connected to other peers, whereas some have few such connections. The large concentration of consumers heavily interlinked in the top half of the graph may be more central to the network, whereas the consumers in the right half are more peripheral. It is important to take into account the position of each consumer in their social network. Although the social network literature has several centrality metrics, like degree and betweenness centrality, we compute the *eigenvector centrality* for each individual in the network, which is defined as the greatest eigenvalue of the social relationship matrix, **R**. This variable has proven very appropriate because it captures not just the number of social network ties, but the importance of peers with whom the individual is connected. There is also theoretical support for this measure to be relevant when we consider the interaction between an individual and the network [Ballester et al., 2006].[4] Google's PageRank algorithm was initially based on this measure to evaluate the importance of web pages and sites. Note that the graph does not indicate

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[4]See Wasserman and Faust [1994] for a definition.

Table 1: Sample Statistics

Call and Purchase Statistics	Mean	SD
Weekly number of calls	38.81	75.91
Weekly ringback tone purchases	0.09	0.29
Weekly voice talk time (in minutes)	47.09	97.84
Demographics		
Age (in years)	36.78	13.32
Gender (1 = Male, 0 = Female)	0.93	0.24
Centrality	0.07	0.10

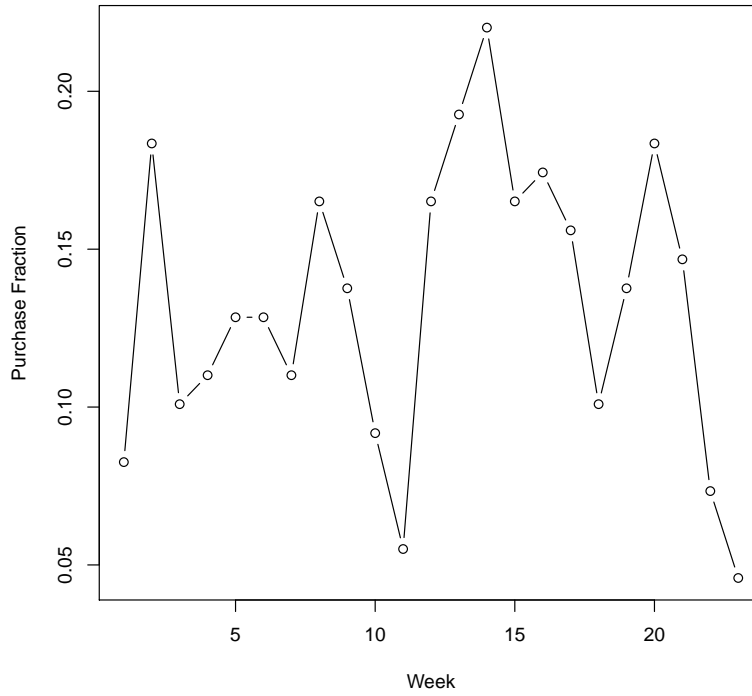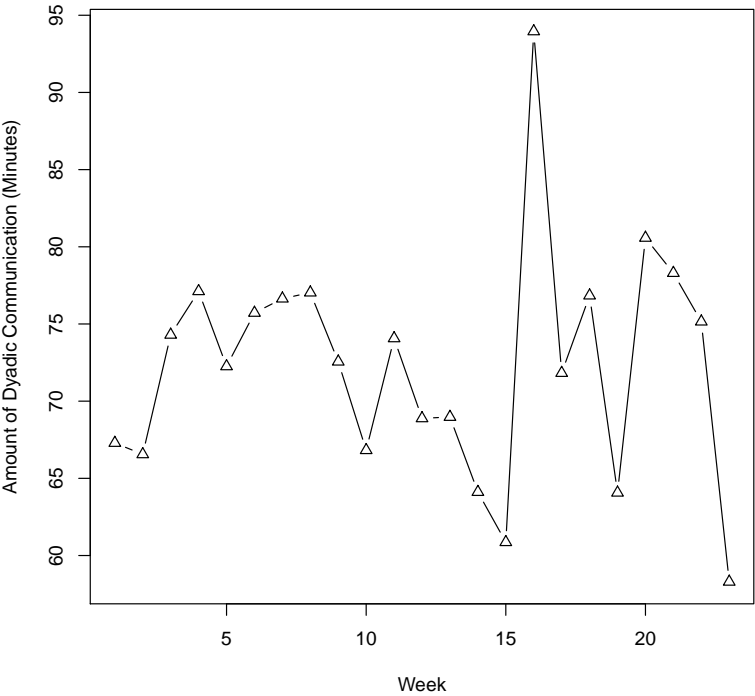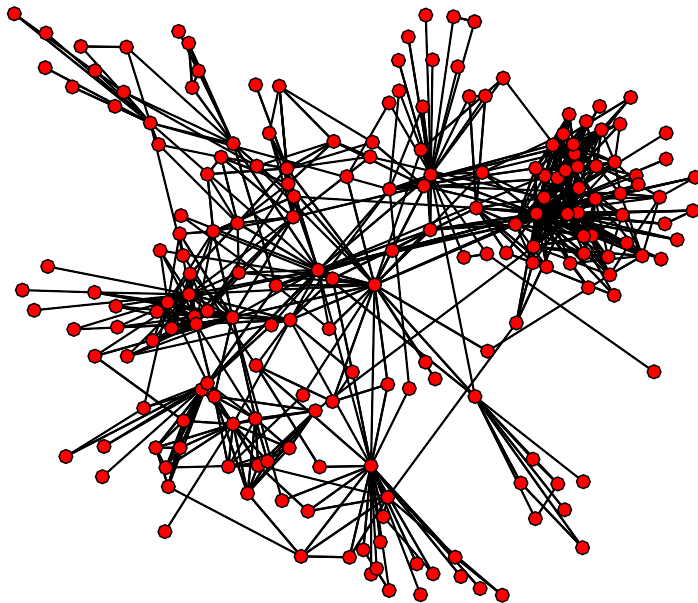Figure 2: Purchases over time

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Figure 3: Dyadic communication over time

the call volume between individuals, merely the presence of a social relationship.

Figure 4: Social Network Derived from Call Patterns

The variation in the purchase patterns by consumers over time leads to different consumers having a relatively more recent contribution versus less recent contribution to the connected good. The pattern of variation in the mean state of consumers in the network, as well as the state one standard deviation above and below the mean are depicted in Figure 5 below, where a higher state is likely to correspond to a less recent contribution and a lower state a more recent contribution. We proceed next to describe the model, and then discuss how the patterns of variation in the data are useful for identification of the effects in the model in §5.

Figure 5: Consumer States over Time
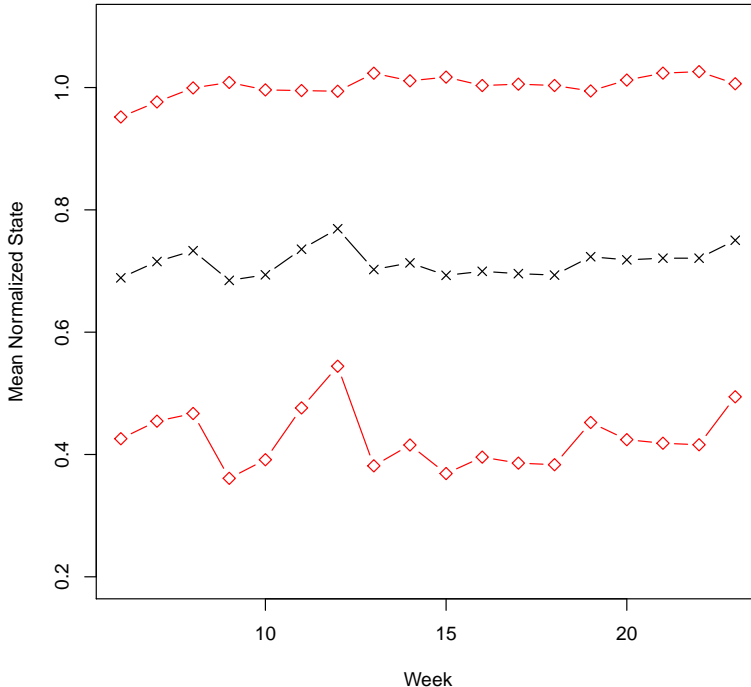
4 Model

Our model is developed with the idea of parsimoniously capturing the underlying dynamic consumer decision process. A consumer chooses to contribute whenever the current and future expected benefits from contributing. The expected benefits from contributing include an altruism benefit, higher positional status utility, higher future contribution levels by peer consumers and complementary utility. These benefits have to be weighed not only against the cost of contributing as in traditional dynamic choice models, but the expected change in the responses by peers. We use the idea from the literature that a conspicuous contribution increases positional status [Frank, 1985], which we operationalize through rank of the consumer in her local social network.

We characterize consumers as playing pure Markov-perfect strategies in a dynamic game, where our focus is on examining the equilibrium strategy profile and outcome of the game. Following the Markovian logic, we posit state variables that encapsulate in a simple manner, the history of play in the game as it influences payoffs. Consumer utilities in any period depend on the current state

and the law of motion, i.e. how endogenous states evolve over time as a result of the decisions made by consumers.

4.1 Social Structure

We use Figure 6 to demonstrate the social structure with $I = 4$ individuals. It gives us the corresponding $I \times I$ social relationship matrix below. The (i, j)-th element of the symmetric social relationship matrix $\mathbf{R}$ is 0 if i and j do not have a social relationship, and 1 if they do.

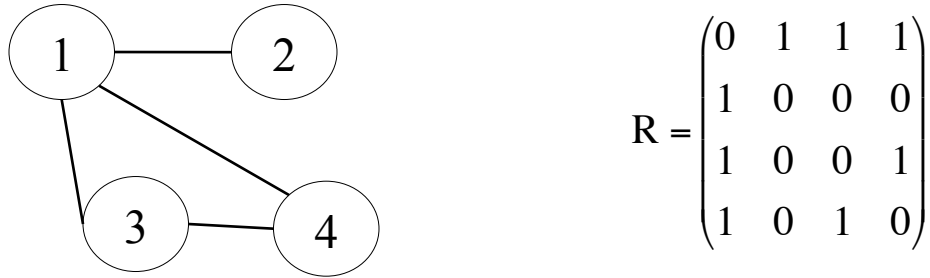$$R = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix}$$

Figure 6: Example Network and Corresponding Social Relationship Matrix

A social network can be represented as a social relationship matrix $\mathbf{R}$, and since we characterize social ties as bidirectional, the social relationship matrix will be symmetric. The matrix $\mathbf{R}$ completely captures the structure of connections, and the sum of row i (or column i) corresponds to the number of peers that consumer i is connected with. The relationship matrix is critical to our understanding of the interdependence in decisions, since a consumer can only observe the choices of peers with who she is connected, i.e. if element $R(i, j) = r_{ij} = 0$, then i and j cannot have a *direct* influence on each other, but only through other consumers. Stronger measures of social relationship will result in fewer connections between consumers, but such networks are more likely to be stable over time.

4.2 Endogenous Contribution States

We model the endogenous state s_{it} for consumer i in period t as representing the number of periods since the consumer has made a connected good contribution to the social network. The state of the consumer evolves deterministically depending on the consumer's choice in period t, indicated by d_{it}:

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$$s_{i,t+1} = \frac{s_{i,t}}{1 + s_{i,t}}[1 - d_{i,t}] + d_{i,t} \tag{1}$$

This implies that the state increases by 1 when the consumer makes no contribution, and is reset to 0 when a contribution is made. The state represents the recency of contribution, which represents how active a consumer has been in the network. If a consumer contributes regularly to the connected good, then she is likely to have a low value of the state variable, whereas a consumer who has only made a contribution a long time ago has a high value. We use a $I \times 1$ vector to denote the states of the all the I individual consumers in the social network, $\mathbf{s_t} = (s_{1t}, \ldots, s_{It})$.

The vector of contribution states of consumers in the social network $\mathbf{s_t}$ is the primary variable that relates the decisions and utilities of the consumers, not only across consumers in a specific period, but over time and is critical to the underlying inter-temporal tradeoff. At each time period, consumers derive utility based on their own state as well as the states of their connected peers. In turn, the decisions made by each consumer affect their own state. The state of the network $\mathbf{s_t}$ serves as endogenous state variables that drives all the dynamic effects in the model.

We focus on strongly connected social networks where consumers know the states of their network peers with whom they are connected. When consumers are in contact with their peers fairly regularly, it is reasonable to assume that they are able to identify the contributions made by their peers.[5]

4.3 Period Utility Function

We model consumer i's utility in period t as depending on the consumer's self-state, the resulting positional status (or contribution status), consumption utility, the cost of contribution and an unobservable error term. More specifically, the utility function is defined as:

$$u(\mathbf{s_t}, d_{it}, \epsilon_{it}, \nu_{it}) = \underbrace{\theta_{1,i} s_{it}}_{Altruism} + \underbrace{\psi(i, \mathbf{s_t}; \mathbf{R}, \theta_{\mathbf{2,i}})}_{Positional\ Status} + \underbrace{\theta_{3,i} \chi(i, \mathbf{s_t}; \mathbf{R})}_{Experience\ Utility}$$
$$+ \underbrace{\hat{u}(\mathbf{s_t}, \nu_{it}; \mathbf{\Gamma_i})}_{Complementary\ Activity} + \underbrace{\theta_{4,i} d_{it} p}_{Price} + \epsilon_{it}(d_{it}) \tag{2}$$

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[5]However, in a setting where consumers are in contact only rarely, such an assumption would be untenable, and we would expect knowledge about peers' states to be imperfect at best. If we do not observe the pattern of communications over time, inference may require such uncertainty to be built into the model.

In the per-period utility function, we allow the following factors to affect consumer contribution decisions: The first component is the utility derived from *warm-glow* altruism, where the contributor receives utility from making a contribution to connected goods, depending on the recency of their prior contribution, and captures an absolute effect that is independent of the decisions of peers. The second component, the positional status, is relative, where an individual consumer's utility could be impacted if she makes more contributions or more frequent contributions *when compared to her peers*. Each individual can observe their peers' contributions and the relative positional status affects utility. The third component is experience utility, where the consumer obtains utility depending on new contributions to connected goods made by her peers. The fourth component denotes the utility from complementary activities that have an *interaction* with positional status. Finally, we have the "price effect," which includes monetary, cognitive and search costs to select an appropriate connected good that will be experienced by the contributor's peers.

In the above utility function, all parameters are common knowledge, and the unobservables ϵ_{it} and ν_{it} are *private* shocks observed by each consumer and are *iid* across consumers and periods. The distribution of ϵ_{it} is type-I extreme value, whereas ν_{it} is distributed log-normally. Below, we explicate on the different terms in the consumers' period utility function.

'Warm-glow' Altruism or Self-expression

The state of the consumer i in period t, s_{it}, captures how the consumer's utility depends on the consumer's own state, and ignores the effect of other consumers. This can be interpreted either as a warm-glow altruism or as a consumer's need for self-expression as discussed in §2. The key is that the consumer's utility for making a contribution depends on the length of time that has passed since the previous contribution made by the consumer. These two alternative theories are observationally equivalent in our setting.[6]

The parameter θ_1 represents this overall effect, and a more negative value for θ_1 indicates that consumers more self-expression or altruism, whereas a positive value suggests that inertia to make a contribution increases when more time has passed since the previous contribution.

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[6]The reader is referred to §5 for further details on identification of the effect.

Positional Status

We formalize the idea that consumers value not just a higher level of absolute consumption but specifically value achieving higher positional status than their peers [Frank, 1985]. To do so, we extend a simple ordinal measure of status proposed by Hopkins and Kornienko [2009] (HK, hereafter) to our dynamic setting. This positional status term $\psi(s_{it}, \mathbf{s_{-i,t}}; \theta_{\mathbf{2,i}})$ depends on the state of the consumer i as well as the state of all i's other peers in the network ($\mathbf{s_{-i,t}}$).

More specifically, the positional status of consumer i is determined by how many other peers of i have a lower status (and state) than i, and is operationalized by the empirical CDF of the states in each period:

$$\Phi_{\mathbf{s_t}}(i, \mathbf{s_t}; \mathbf{R}) = \frac{|\{m: \quad r_{im} = 1 \wedge s_{mt} \leq s_{it}\}|}{|\{m: \quad r_{im} = 1\}|} \tag{3}$$

where r_{im} is the element in the ith row and m-th column of the relationship matrix $\mathbf{R}$ (see Figure 6). This empirical CDF construct represents the fraction in i's local network who have made a more recent contribution to the connected good than i. The positional status of consumer i in period t is the fraction of peers with a less recent contribution than i, or $\Phi_{\mathbf{s_t}}(i, \mathbf{s_t}; \mathbf{R})$. Specifically, it is the fraction of i's peers who have a lower state than i in the period. Note that one consumer's relative position can improve only when another person's position declines.

The empirical PDF given by $\phi_{\mathbf{s_t}}(i, \mathbf{s_t}; \mathbf{R}) = \frac{|\{m: \quad r_{im} = 1 \wedge s_{mt} = s_{it}\}|}{|\{m: \quad r_{im} = 1\}|}$ indicates the fraction of i's peers who have exactly the same state as i in period t. It denotes positional ties in the state as well as contribution status. We treat positional ties separately to account for consumers' preference for equality of state (and hence status) or aversion to such an effect.

Thus, we employ the following function form to capture the positional effects:

$$\psi(i, \mathbf{s_t}; \mathbf{R}, \theta_{\mathbf{2,i}}) = \theta_{21,i} \left[1 - \Phi_{\mathbf{s_t}}(i, \mathbf{s_t}; \mathbf{R})\right] + \theta_{22,i} \phi_{\mathbf{s_t}}(i, \mathbf{s_t}; \mathbf{R}) \tag{4}$$

Using the empirical CDF and PDF allows us to characterize a measure that is invariant to network density, i.e. both dense networks where consumers have several connected peers, and sparse networks can be accommodated because of the implicit normalization. It is also useful to note that the rank is a rather general positional measure, invariant to additon or multiplication of

each state by a constant term. We model the effect of ties on the utility separately to allow the flexibility for consumer utility to be affected by the number of peers in the same state.

The coefficient $\theta_{21,i}$ captures the effect of status of consumer i, which is determined by how many other consumers have a lower status (or a higher state) than i. If $\theta_{21,i}$ is determined to be positive and significant, then consumers value having a higher status among their peers. If $\theta_{22,i}$ is significant and determined to have a lower magnitude than $\theta_{21,i}$, then consumers place a lower value on being tied with their peers compared with being more current. We use parameter vector $\theta_{2,i} = (\theta_{21,i}, \theta_{22,i})$ to denote the components associated with positional status based utility.[7]

Experience Utility

In period t, consumer i has access to $\sum_{m \neq i} r_{im} d_{m,t-1}$ new connected goods, i.e. contributions made by her peers ($\{m : r_{im} = 1\}$) in the previous period, accounting for the presence of a social relationship. Unlike most marketing purchase decisions, where the person purchasing obtains experience (or consumption) utility, with connected goods, the person incurring the cost of contribution (contributor) is different from the person obtaining experience or consumption utility. Consumers value the amount of *new* connected goods available for consumption in each period, which can be viewed as an approximation that also captures declining utility for observing older contributions over time.

Thus, the third term in the utility function represents the utility obtained in the current period from consuming these new connected goods contributed by peers during the previous period:

$$\chi(i, \mathbf{s_t}; \mathbf{R}) = \sum_{m \neq i} r_{im} d_{m,t-1} = \sum_{m \neq i} r_{im} \mathbf{I}(s_{m,t} = 1) \tag{5}$$

Note that the experience utility only depends on the contributions made by consumer i's peers,

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[7]There are three significant modeling differences between HK's setup and ours. First, consumers in HK's model choose from a set of continuous levels, which makes it easy to rank them, whereas in our model consumers can only choose from two levels (contribute or don't contribute) in each period. We consider status to be based on the consumer's state (the number of periods since the consumer has made a contribution) to capture a more fine-grained notion of status, allowing the effects of contributions to persist beyond across periods. This characterization derives from the idea that a newer contribution is indicative of a higher level of contribution to the network. Second, HK's focus is on examining the comparative statics of the equilibrium of the static game, whereas our primary interest is in the dynamic effects of status-based competition between consumers. Third, we explicitly incorporate the network structure in the status competition, whereas HK implicitly assume a *complete* network, in which each individual is connected to all others.

and not by any current decisions i makes in the current period. However, i's current period contribution ($d_{it} = 1$) may induce i's peers to contribute in future periods, e.g. $d_{m,t+1} = 1$, where i and m are peers. Consumer i can thus derive higher expected future experience utility by making a contribution in the current period t. The experience effect is represented by the parameter $\theta_{3,i}$ and a larger positive value indicates that the consumer has a higher experience utility for contributions made by her peers.

Complementary Activity - Dyadic Social Communication

In our setting, we model the possibility of interaction between status and dyadic communication. Consumers could derive additional interaction utility from dyadic social interactions when they have a higher positional status, consistent with the theory in §2. To capture this interaction between the positional status and dyadic communication, we model the utility for the latter flexibly with a simple non-linear formulation, with interaction effects between status and the utility of dyadic communication captured in a multiplicative manner. The decision on the *aggregate* amount of dyadic communication x is made every period, and consumers receive utility for dyadic communication given by:

$$\tilde{u}_i(x, \mathbf{s}, \nu; \Gamma_i) = \left(\gamma_{1,i}x + \gamma_{2,i}x^2\right) \cdot \nu \cdot [1 + \gamma_{3,i}(1 - \Phi_s(s_i))] - c \cdot x, \qquad \log(\nu) \sim N(0,1) \qquad (6)$$

We choose a relatively simple and flexible functional form $\left(\gamma_{1,i}x + \gamma_{2,i}x^2\right)$ that allows for concave or convex utilities from dyadic communication, i.e. $\gamma_{2,i}$ can be positive or negative. This could be regarded as an approximation to more a detailed specification of utility for dyadic communication. The factor $\gamma_{3,i}(1 - \Phi_s(s_i))$ represents the interaction between the dyadic communication and positional status. The cost of communication, c is a constant marginal cost and reflects both monetary as well as opportunity costs. We collect the coefficients corresponding to dyadic communication in $\Gamma_i = (\gamma_{1,i}, \gamma_{2,i}, \gamma_{3,i})$.

Thus, in the above equation, the coefficients $\gamma_{1,i}$ and $\gamma_{2,i}$ capture the non-linear utility of dyadic communication, and ν is a log-normally distributed error term, and $(1 - \Phi_s(s_i))$ represents positional status. Its coefficient $\gamma_{3,i}$ measures whether having a higher status offers consumer additional

instrumental utility from dyadic communication. Note that the consumer obtains utility through dyadic communication of amount x even when there is no interaction with status, i.e. when $\gamma_{3,i} = 0$.

We interpret the amount of time the consumer spends on communicating with peers as the amount for which marginal benefits of communicating further will equal the marginal costs. The marginal benefits are affected by the unobservable term ν. Thus, consumers may value dyadic communication more in some periods and less in others, and ν rationalizes the decision. We expect that calling behavior is less indicative of status because it is dyadic communication, with only the caller and callee involved in the interaction, whereas markers of status are conspicuous and made visible to everyone in the reference group. This reasoning would imply that dyadic communication is not a critically important construct for the present study, and it less likely to have dynamic effects, so we approximate the decision using a static decision that aggregates all such dyadic communication that a consumer is involved in. The optimal amount of dyadic communication and the corresponding utility are then denoted formally by the following:

$$
\begin{aligned}
x^*(\mathbf{s}, \nu; \Gamma_i) &= \arg\max_x \tilde{u}(x, \mathbf{s}, \nu; \Gamma_i) \\
\hat{u}(\mathbf{s_t}, \nu_{it;}; \Gamma_i) &= \tilde{u}(x^*(\mathbf{s}, \nu), \mathbf{s_t}, \nu_{it}; \Gamma_i)
\end{aligned}
\tag{7}
$$

Note that after choosing the optimal aggregate dyadic communication, x^*, the instrumental utility $\hat{u}$ only depends on the state and the current period realization of the random variable, indicated by ν_{it}. Note that the instrumental decision (dyadic communication) is affected by the state and status, but does not influence the dynamics of the model through the state. Thus, it is purely a 'static' decision, similar to prices set in each period in the oligopoly market competition among firms in Ericson and Pakes [1995]. In principle, multiple complementary factors can easily be incorporated in the model.

Equilibrium

The methods for dynamic games have evolved from the algorithms used to estimate single-agent dynamic discrete choice models.

Consumer i's decision problem in the dynamic game can be represented as:

$$\max_{(d_{it})_{t=1}^{\infty}} \mathbf{E}\left[\sum_{t=1}^{\infty} \beta^t u\left(s_t, d_{it}, \epsilon_{it}\right)\right]$$

In a Markov Perfect Equilibrium (MPE), consumers choose their best response based on the strategies adopted by their peers in the network, with all consumers conditioning strategies only upon the state vector ofc the network in the corresponding period. The state variable is modeled to capture the entire history of the game, and the aspect not captured in the state is not relevant to consumer strategies. For a focal consumer i in our setting, the decision in each period is "should I contribute?" The consumer i has a strategy $\sigma^{(\mathbf{i})} : \mathbf{S} \times \mathbf{\Omega} \times \epsilon \to \{0,1\}$ based on the observable state $\mathbf{S}$ and unobservable state Ω, and the outcome corresponding to this strategy is the decision to contribute. Given the strategy profile $\sigma = \left(\sigma^{(\mathbf{1})}, \ldots, \sigma^{(\mathbf{N})}\right)$, we can write the Bellman equation as:

$$V(\mathbf{s}, \omega, \sigma_{i}, \sigma_{-i}; \theta) = \max_{\sigma_i}\left[u\left(\mathbf{s}, \omega, \sigma_{\mathbf{i}}, \sigma_{-\mathbf{i}}\right) + \beta \int V\left(s'|s, \sigma_i, \sigma_{-\mathbf{i}}\right) \quad dP\left(s'|s, \sigma_i, \sigma_{-\mathbf{i}}\right)\right]$$

The MPE is then characterized by the equilibrium strategy profile σ^* defined so that the value functions corresponding to those strategy profiles for any consumer i are the maximum attainable if every consumer other than i plays the equilibrium strategy. Thus, a unilateral deviation by consumer i from σ_i^* to σ_i' will not be profitable. We can formally write this condition as follows:

$$V\left(s, \omega, \sigma_i^*, \sigma_{-\mathbf{i}}^*\right) \geq V\left(s, \omega, \sigma_i', \sigma_{-\mathbf{i}}^*\right) \qquad \forall \sigma_i'$$

An alternative approach to equilibrium play in games with a large number of agents involves using the notion of Oblivious Equilibrium (OE), suggested by Weintraub et al. [2008]. OE is a different equilibrium concept that characterizes the long-run states of the dynamic game, and is presented as an approximation to MPE, and converges to the MPE with a large number of agents. OE relies on the essential idea that agents may not react significantly to deviations by any one agent, since each agent's effect is small.[8] In an Oblivious Equilibrium, each agent is assumed to play the best response to the *long − run* strategies of the other agents, and agents only keep track of the aggregate state of other agents. Although this approach is very attractive for settings like the present one with a

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[8]OE relies on a light-tailed condition on the distribution of the agents' states to achieve this.

large number of agents, OE lacks the ability to appropriately model the experience utility in our setting, i.e. to incorporate the idea that consumers make contributions to increase the likelihood that their peers contribute in future periods leading to a higher experience utility, which is a key contribution of our model and analysis. Therefore, we cannot use the OE method in our setting. Moreover, OE cannot easily incorporate arbitrary dependence structures that we require to model relationships in social network settings.

5 Identification and Estimation

We describe the empirical issues that arise in the estimation of the model described in Section 4. We begin by specifying how to characterize the computational issues that arise in the equilibrium of the dynamic game played between the individuals over a social network. We then proceed to discuss how the specified model is identified from variations in contribution patterns observed in the data. Finally, we discuss the estimation process for dynamic games in general and the two-step approach of Arcidiacono and Miller [2011] and Bajari et al. [2007] that we adopt.

Identification

The identification of static and dynamic parameters (Γ and θ) are in general intuitive but important to understand. The social network structure as well as dynamic contribution decisions lead to state changes, which provide the variation across individuals and over time necessary to ensure identification. We consider the identification of each effect for a focal consumer i.

For the first effect, i.e. self-expression or altruism, the coefficient $\theta_{1,i}$ is identified from how the likelihood of purchase (contribution) depends on the recency of purchase (state variable), holding the state of peer consumers constant. This is similar to hazard rate models and the identification is rather straightforward. Note that we could have alternatively operationalized altruism as occuring whenever a consumer makes a contribution, i.e. independent of the consumer's state, but absent price varition, such an effect would be subsumed with the price effect since the consumer would obtain a benefit as well as incur a cost for each purchase (contribution) occassion, and our setting would not permit us to distinguish these alternative explanations. This limitation would be shared in most social network settings since in fact there is often no explicit price paid for making a contribution.

The positional status effect, modeled by the two coefficients $\theta_{21,i}$ and $\theta_{22,i}$ are identified from changes in the contribution recency rank of the focal consumer, holding the state of consumer i constant. To fix ideas, we illustrate the argument with a simple example. Consider the case A where i's state is $s_{it} = 5$, and i has 10 peers, and the positional status (or rank) of i is $(1 - \Phi_{s_t}) = \frac{7}{10}$, and the fraction of peers tied with i is $\frac{1}{10}$. Now, consider another situation B, where the i's state is the same, but the positional status is $\frac{5}{10}$ rather from $\frac{7}{10}$. If consumer i is more likely to contribute when faced with situation B as compared to A, then the positional status coefficient $\theta_{21,i}$ would be positive, and have a higher value if the likelihood of contribution is more sensitive to the postional status. The coefficient of positional ties, $\theta_{22,i}$ is similarly identified by the variation in the likelihood of contribution with respect to the fraction of peers tied.

The coefficient of *experience utility*, $\theta_{3,i}$ is identified due to a combination of forward-looking behavior and the positional status interactions. Consider again the experience utility effect, say when $\theta_{3,i}$ is positive and has a high value: consumer i makes a contribution in period t if that contribution is more likely to result in future contributions by i's peers. If consumer i makes a contribution, then i's positional status rises to the top, but i's peers will find their positional status decreased a little. The probability of contribution by i's peers in turn depends on how much they value positional status, and the number of peers they have. If more of i's peers are likely to contribute as a result of i's contribution than when i chooses not to contribute, this will be a stronger effect. Thus, a consumer with a high value of experience utility will be more likely to contribute when it makes a higher marginal difference to the likelihood of peers contributing in future periods.

For the complementary utility from dyadic communication, the coefficients $\gamma_{1,i}$, $\gamma_{2,i}$ are identified by the variation in communication patterns over time. For $\gamma_{3,i}$, the variation in the amount of dyadic communication as a function of positional status identifies the effect, and consumers whose communication is more sensitive to their positional status will have a higher value of $\gamma_{3,i}$. The cost parameter c in the dyadic communication or instrumental benefit equation, given by (6) is not separately identified, so we normalize it by setting $c = 1$.

Having detailed the sources of variation that help identification, we note that absent the data on social connections, we would be unable to identify either the experience utility or the positional status utility; in case the social network is not observed, the approximation that every consumer is connected with all others must be used to provide identification. In a model with myopic consumers

($\beta = 0$), the consumption utility coefficient $\theta_{3,i}$ will not be identified. The reason is that consumers will not value expected future consumptions, and will not account for this effect when making their contribution decisions. Therefore, while consumers will obtain experience utility in the current period, their actions will not affect the future actions of their peers, and we will be unable to identify this dimension of utility. While we provide the above intuitive arguments to clarify the identification of the effects in the model, we emphasize that in practice, all the variation in the data is used to identify the effects in totality.

Computational Approach

The basic approach to estimating single-agent settings, detailed in Rust [1987], is to compute the optimal value function given a set of parameter values using an 'inner loop', and search over the parameter space in an 'outer loop'. This approach is feasible in a dynamic game only with special structural properties when the number of players is very small and depends on the state space [Gowrisankaran and Town, 1997]. Despite advances in computing technology and methodological developments in optimally reducing the computation like Pakes et al. [2004], our setting with a large number of players and a large state space is likely to remain very much beyond the reach of these methods.

Due to the intractability of explicitly computing the Markov perfect equilibrium, which grows exponentially with the number of consumers, we adopt the multi-step approach advocated by Bajari et al. [2007] (BBL, henceforth). There are several recent advances proposed to alleviate the unique computational difficulties posed by dynamic games, and other algorithms that break the estimation down into steps include Aguirregabiria and Mira [2007] and Pesendorfer et al. [2008]. The BBL approach is prominent among the recent methodological advances that involve breaking down the estimation into multiple steps, and builds on the *conditional choice probability* (CCP) method developed by Hotz and Miller [1993] and the value function simulation method of Hotz et al. [1994], extending the applicability to dynamic games. The primary benefit of this two-step method in estimating dynamic games is that we do not need to compute the equilibrium. Indeed, in our setting, computing the equilibrium even once is intractable due to the large number of agents. Another benefit specific to the Bajari et al. [2007] approach not shared by the other two-step estimators is the ability to handle a continuous state space without discretization. The trade-off

with BBL and other two-step procedures when compared with explicit equilibrium computation is that the two-step procedures do not incorporate all of the information, resulting in a loss of efficiency with small samples. Arcidiacono and Miller [2011] have recently demonstrated how to incoporate unobservable individual heterogeneity into the CCP framework using the expectation maximization algorithm [Dempster et al., 1977], and such an approach can be used either by itself or in conjunction with two-step estimators like BBL. We choose to use CCP in conjunction with BBL because it allows us to accomodate unobservable heterogeneity, and retains the computational advantages of a simulation method without computing the equilibrium.[9]

In our context, the first step involves recovering the contribution policy of consumers as a function of the state of the social network. This is a reduced-form process of mapping the equilibrium strategies that are represented in the data to a policy function. The second step recovers the structural parameters of the model that affect the consumer's dynamic inter-temporal considerations.

Estimation

The overall goal is to estimate both the static parameters as well as the dynamic structural parameters of the model. We denote the set of dynamic parameters by $\theta = (\theta_{1,i}^k, \theta_{21,i}^k, \theta_{22,i}^k, \theta_{3,i}^k, \theta_{4,i}^k)_{k=0}^{N_D}$. We have $5 \times N_S \times (1 + N_D)$ parameters to estimate, where N_D is the number of individual-level demographic variables, and N_S is the number of latent consumer segments. The static parameters are collected in the vector $\mathbf{\Gamma} = (\gamma_{i,1}, \gamma_{i,2}, \gamma_{i,3})$. Note that the static variables are separately estimated, and used as input to the estimation process for the dynamic parameters.

Static Parameters

The static parameters corresponding to the instrumental benefit affect only the period utility functions, and do not affect the dynamics of the game between consumers. We estimate the static parameters by MLE, but alternative approaches like GMM can be used. The static parameter estimates are used as an input to the dynamic estimation procedure. The expected period utility for dyadic communication can be mapped onto the state variable, and determined uniquely from the state of the consumer. We estimate the consumers' dyadic communication by maximum likelihood. The utility for x amount of dyadic communication is given by equation (6). Maximizing this utility

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[9]See Bajari et al. [2007] for Monte Carlo evidence on the point of efficiency.

as a function of the state variable $\mathbf{s}$ and the unobservable ν gives us the optimal amount of dyadic communication chosen by the user. We use the data to perform an inverse mapping to the realized value of the random variable denoted as v_{it} and estimate the parameters $\mathbf{\Gamma_i} = (\gamma_{1,i}, \gamma_{2,i}, \gamma_{3,i})$ by maximum likelihood. This mapping is derived from the FOC of (6) and is given by:

$$v_{it}(\mathbf{s_t}, x_{it}; \Gamma_i) = \frac{c}{(\gamma_{1,i} + 2\gamma_{2,i}x_{it})\left[1 + \gamma_{3,i}\left(1 - \Phi_{\mathbf{s_t}}(s_{it})\right)\right]} \tag{8}$$

The likelihood for dyadic communication is then specified as:

$$L_{DC}(\gamma) = \prod_{i=1}^{I}\prod_{t=1}^{T} f_V(v_{it}|\mathbf{s_t}, x_{it}; \Gamma_i) \tag{9}$$

where f_V is the density function of the random variable V with log-normal distribution, $\log V \sim N(0,1)$. Since the current consumption of dyadic communication does not affect the state variable in future periods, we first estimate $\mathbf{\Gamma}$ and treat it as known in the algorithm for recovering the structural parameters.

Dynamic Parameters: First-step Policy Function

The first step recovers the policy function from data and is used as an input to compute the value functions via simulation. We use a logit model to characterize the choices of consumers as a function of the state of the consumer, the positional status of the consumer among his peers, the number of peers the consumer is tied with for status, and the consumer's characteristics. If the amount of data were not an issue, we could consider a non-parametric approach to estimating the first step.

Dynamic Parameters: Second-step

In the second step, we utilize the recovered policy functions $\hat{\sigma}$ from the first stage to determine the estimates of the structural parameters. This second step consists of several stages, and we describe them in turn below.

In the first stage, the estimates of the policy functions along with the period utilities is used to obtain the value function by forward simulation as detailed in Bajari et al. [2007]. This is designed to recover the value function for a specific consumer i beginning with an observed state $\mathbf{s_0}$, and is denoted by $V_i(\mathbf{s_0}|\sigma, \theta, \beta)$ for a policy σ. The value function thus depends upon the policy, the

dynamic parameters represented by θ and the 'true' first-stage parameters, β. We linearize the value function in terms of the parameters, so that the computation of the inequalities can proceed independent of the parameter values. Thus, we represent the value function in the form of the dot product of the parameter-free vector W_i and the augmented parameter vector $[\theta, 1]$:

$$V_i(\mathbf{s}|\sigma,\theta,\beta) = W_i(\mathbf{s}|\sigma;\beta) \cdot [\theta, \mathbf{1}]$$

We can only consider the parameter-free representation of the value function because the period utility function in (2) is linear in each of the "dynamic" parameters. For most of the estimation process, we are concerned only with the parameter-free value function $W_i(\mathbf{s}|\sigma)$. The key advantage of working with parameter-free value functions, as Bajari et al. [2007] point out, is that these value functions do not have to be recomputed for each value of the parameter vector, and hence the minimization of the objective function can proceed in a more tractable manner.

Value Function Simulation

The process of computing the value function by forward simulation involves the following computations performed for $t = 1, \ldots, T_S$ periods:

1. Draw a private vector of unobservables $\epsilon_{\mathbf{kt}}$ for each consumer $k \in \mathbf{I}$.

2. Determine the choices for each consumer according to the specified policy $d_{kt} = \sigma^{(\mathbf{k})}(\mathbf{s_t}, \omega_{\mathbf{k}}, \epsilon_{\mathbf{kt}})$.

3. Obtain the state in period $(t+1)$ using the transition rule in equation (1) for each consumer.

4. Calculate the period utility components for consumer k.

This forward simulation procedure gives us the value function for a consumer k corresponding to any specified policy $\sigma^{(k)}$, including the optimal policy and any deviation from the optimal policy.

In the second stage, we need to perform forward simulation to determine the value function *under two different policy functions*. The first policy $\hat{\sigma}$ is recovered from data in the first step and is treated as the solution to the consumers' problems, i.e. the equilibrium strategy profile. Note that since our dynamic decision is binary (contribute or do not contribute), we can interpret $\hat{\sigma}$ as corresponding to specifying a threshold error $\hat{\epsilon}_i(\mathbf{s}, \omega)$ for each state, so that $\hat{\sigma}(\mathbf{s_t}, \omega, \epsilon_{it}) = 1 \iff \epsilon_{it} > \hat{\epsilon}_i(\mathbf{s_t}, \omega)$.

The alternative policy is a perturbation of $\hat{\sigma} = (\hat{\sigma}_{\mathbf{i}}, \hat{\sigma}_{-\mathbf{i}})$ for a focal consumer i that we denote as $\sigma' = \left(\sigma'_i, \hat{\sigma}_{-i}\right)$. In practice, we construct the perturbed policy σ' from $\hat{\sigma}$ by adding a random disturbance to the threshold $\hat{\epsilon}_i(\mathbf{s}, \omega|)$ for consumer i. We determine the value function $W_i(\mathbf{s_0}, \omega||\sigma', \beta)$

corresponding to the alternative perturbed policy using the procedure detailed in the first stage above, using the same error draws as for the optimal value function, which reduces the variance introduced by simulation.

In the third stage, we draw from a set of inequalities $\mathcal{H}$, each element of which corresponds to a tuple $(i, \mathbf{s}, \omega, \sigma')$, i.e. a specific consumer i, a starting state for the network, $\mathbf{s}$, an unobservable consumer state ω and an alternative (perturbed) policy σ'. The difference between the value function corresponding to the optimal policy and the value function corresponding to the perturbed policy, $W_i(\mathbf{s}, \omega || \hat{\sigma}, \beta) - W_i(\mathbf{s}, \omega | \sigma', \beta)$, must in theory always be positive: there are no profitable deviations from $\hat{\sigma}$, since it is an equilibrium strategy. Therefore, whenever the difference is negative, the equilibrium condition is violated, and we include the degree of violation captured by the difference between the value functions. The violation function is defined as:

$$g(i, \mathbf{s}, \omega, \sigma'; \beta) = \min\left[\left(W_i(\mathbf{s}, \omega | \hat{\sigma}, \beta) - W_i(\mathbf{s}, \omega | \sigma', \beta)\right)[\theta, \mathbf{1}], \quad 0\right]$$

The objective function is defined as:

$$Q(\theta, \beta) = \int g(i, \mathbf{s}, \omega, \sigma')^2 d\mathcal{H}$$

The value of the above objective at the true parameters is zero, since there will be no violations of the equilibrium conditions when consumers play the equilibrium strategy. To calculate the objective in practice, we obtain N_I inequalities from the set of inequalities, drawing $(i, \mathbf{s}, \omega, \sigma')$ and computing the associated value functions for consumer i_k. The sample analog of the objective function generated from inequalities is represented by the function $\tilde{Q}$ and used as the actual objective for estimation:

$$\tilde{Q}(\theta; \hat{\beta}) = \frac{1}{N_I} \sum_{k=1}^{N_I} \min\left[\left(\tilde{W}_{i_k}\left(\mathbf{s}^\mathbf{k}, \omega^k | \hat{\sigma}(\hat{\beta})\right) - \tilde{W}_{i_k}\left(\mathbf{s}^\mathbf{k}, \omega^\mathbf{k} | \sigma'^{(k)}(\hat{\beta})\right)\right)[\theta, \mathbf{1}], \quad 0\right] \quad (10)$$

where i_k represents the consumer chosen in the k-th inequality draw, and $\mathbf{s}^\mathbf{k}$ is the starting state for that draw, and $\sigma'^{(k)}$ is the perturbed policy corresponding to that draw. The sample value functions $\tilde{W}$ correspond to the equilibrium value functions W and $\hat{\beta}$ represents the parameters for

the first-step policy function estimation. The objective function is then defined as:

$$\hat{\theta} = \arg\min_{\theta} \tilde{Q}(\theta, \hat{\beta}) \tag{11}$$

The estimation procedure detailed above does not have a closed form for the asymptotic variance for the BBL estimator, because the variance depends on the inequality sampling procedure, and this makes the computation of standard errors difficult. To compute standard errors corresponding to the inequality estimator, Bajari et al. [2007] suggest the use of bootstrap or subsampling methods. Such resampling methods require the repeated estimation of hundreds, if not thousands of subsamples and are computationally intractable in our setting, since each estimation takes several hours. To overcome this hurdle, we therefore use the Laplace-type Estimator (LTE) proposed by Chernozhukov and Hong [2003], who prove that an MCMC approach can be effective in recovering the parameters of a generalized criterion function even in the absence of a likelihood function. The LTE essentially involves constructing a quasi-posterior density from the generalized sample criterion function (e.g., GMM), with the computation following an MCMC procedure.[10]

Since the BBL approach does not involve computing likelihood functions, but instead depends on the $Q(\theta, \beta)$ function defined in equation (10), the LTE is well-suited suited for estimation in conjunction with BBL. One additional advantage of using the LTE is that the standard errors do not need to be estimated separately, a single procedure can be used to obtain both the estimates and the standard error. In the LTE estimation process, we used $R = 10^6$ draws to obtain the quasi-posterior distribution. Following the guidelines suggested by Chernozhukov and Hong [2003], we set the candidate parameter to be a random walk from the current parameter value, with the variance of the random walk selected to ensure that the rejection rate falls in the [0.5, 0.8] range.

Results

We begin our discussion of the results by focusing on the static parameters, determined by the complementary activity, i.e. dyadic communication. Recall that consumers make choices about the amount of dyadic communication, and we observe the aggregate amount of dyadic communication

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[10]Note that LTE is a classical estimator, not Bayesian, although the MCMC procedure for computing is commonly used in Bayesian analysis.

made by consumers in each time period. Thus, the decision on communication does not affect the state variable or the dynamics of the underlying choice behavior for the conspicuous contribution, i.e. the ringback tone.

Static Estimates: Dyadic Communication

The dyadic communication parameters are estimated using the likelihood function defined in equation (6). The parameter estimates are detailed in Table 2.

Table 2: Dyadic Communication (Instrumental Benefit) Estimates

Symbol	Parameter	Estimate	SE
γ_1	Linear Calling Utility	3.89	1.1×10^{-1}
γ_2	Quadratic Calling Utility (scaled by 10^6)	-8.03	1.45
γ_3	Status Interaction	0.88	0.17

We can see that the calling utility is positive in the linear term and negative in the quadratic term indicating decreasing marginal utility for calling time, as we would expect. We also observe that the status interaction term is positive and significant, suggesting higher contribution status enhances value of dyadic voice communication and confirms our intuition that higher contribution status enhances the value of complementary social communication activities.

Dynamic Estimates

The dynamic parameters are estimated in two steps, following the basic idea set forth in Bajari et al. [2007], with a "reduced form" first step, followed by a second step to recover the "structural" parameters of the utility specification detailed in §4.

First Step   In the first step, we flexibly estimate the policy function, i.e. the consumer's contribution decision as a non-parametric regression, specifically a logit model with splines to approximately span the space of real numbers. These estimates must not be structurally interpreted, since they only represent the observed behavior in the data as recovered by the above specification of the reduced-form first stage. We have used both splines and Chebyshev polynomials to provide the non-parametric approximation, and for convenience only report the results of the Chebyshev approximation [Sweeting, 2006, Macieira, 2007]. The results of the first step are in the additional appendix, and are not directly interpretable in terms of economically meaningful constructs. We

Table 3: First Step Model Selection

Number of latent segments	-LL	AIC	BIC
k=1	501	1084	1302
k=2	1025	2217	2659
k=3	472	1193	1860

are not able to find a significant degree of unobserved consumer heterogeneity in the data, and proceed to consider the consumers as belonging to a single segment. We detail the model selection results below, where we evaluate the performance of models based on the number of consumer segments in the model. Table 3 details the AIC and BIC criteria for the multiple models.

Second Step We next use the policy function recovered in the second step to estimate the structural parameters as described in Section 4.3. We describe the effects in the order they appear in the utility function described in (2). We interpret the coefficient of self-state as the altruism effect, with more negative of the coefficient θ_1 indicating a higher utility for relatively newer contributions, i.e. a positive warm-glow effect. We find that this coefficient is positive and significant, implying that consumers are more likely to contribute when their contribution state is lower, i.e. they actually don't place a higher value on making a contribution when they have not contributed for a longer period of time. Older customers value having a lower state, which could be interpreted as a stronger preference for making a contribution due to self-expression. The gender of the individual does not have a statistically significant effect on the utility of self-expression. We find that consumers who are more centrally located in the social network value self-expression less.

Turning to the positional status effect, we find that the coefficient of positional status θ_{21} is positive and significant, implying that consumers really care about their positional status or rank relative to their peers. They value have a higher status, i.e. making more frequent or timely contributions relative to their peers; indeed, the competitive focus driving the dynamic game results from the positional nature of status. Since conspicuous contributions result whenever consumers update their ringback tones, consumers with tones replaced more recently than their peers will have a higher status, if the behavior of their peers is constant. On the other hand, consumers haivng peers who don't regularly update their tones are faced with a smaller competitive effect, even if there is a strong positional incentive to make a contribution.

The coefficient of the positional tie in contribution status on the utility of consumers is also

positive and significant. It is also higher in magnitude than the coefficient of non-tied positional status. This confirms our conjecture that consumers also positively value being tied with their peers and that they value being tied with their peers differently compared with have a higher contribution. Relative to average consumers, older and male consumers place more value on positional ties. More interestingly, higher centrality consumers place a larger value on ties, and we expect that this may be because more central consumers have a larger number of connected peers, and competing intensely in situations with positional ties might be more costly for them.

The coefficient of experience utility measures the marginal utility that consumers receive from contributions made by their peers, i.e. whenever their peers replace their ringback tones with a new one. As we might expect, consumers obtain a positive consumption utility from the contribution made by their peers. Consumption benefit is higher for older consumers, which is consistent with the observation that older consumers may contribute to induce contributions from peers, rather than to compete for positional status. In addition, more centrally located consumers in the network value consumption more. The cost parameter characterizes a fixed cost of contribution rather than the price paid by the consumer, and must be interpreted with care since it is a measure of the fixed contribution cost incurred whenever the consumer makes a contribution. We find this coefficient to be negative, as expected, with older and male consumers having more negative values, and highly central consumers having less negative values of this cost effect.

Table 4: Structural Estimates of Dynamic Model

Parameter	Symbol	Estimate	Low CI	High CI
Self-state	θ_1	0.017	0.012	0.023
	Age	-0.023	-0.027	-0.018
	Gender	0.001	-0.001	0.004
	Centrality	0.075	0.052	0.089
Positional Status	θ_{21}	0.791	0.410	0.963
	Age	-0.884	-0.975	-0.772
	Gender	0.081	0.044	0.154
	Centrality	1.146	1.116	1.302
Positional Ties	θ_{22}	1.230	1.062	1.293
	Age	-0.051	-0.098	-0.032
	Gender	1.201	1.103	1.614
	Centrality	1.044	0.979	1.136
Consumption	θ_3	0.931	0.706	0.989
	Age	1.082	1.015	1.209
	Gender	1.075	1.028	1.129
	Centrality	0.852	0.801	1.007
Cost	θ_4	-2.139	-2.064	-2.191
	Age	-2.064	-2.177	-1.998
	Gender	-0.270	-0.327	-0.214
	Centrality	1.411	1.092	1.848

Counterfactuals

We conduct counterfactuals simulations to determine how the nature of interdependence between consumer decisions affects the overall social network. Modeling the micro-foundations allows us to perform simulations to determine the answers to "what-if" counterfactual type questions, so long as the consumer preferences as outlined in the model are invariant to the changes. We begin with the parameter estimates recovered in the results, and examine the effects of differences in the social network environment for the same set of consumers.

Our focus here is to determine two primary changes that can happen within the network. First, a consumer can receive a promotional song, which would still be considered a connected good contribution, and we explore the implications of this for the network. Second, we vary the network structure of the consumers, in essence changing the connections between consumers. Both these

changes are merely changes to the state variable, and do not reflect any changes to the underlying consumer preference. Thus, we examine the implications of starting with different states of the network, and varying the network structure of connections between consumers. For instance, we set a zero state for a focal consumer by providing a promotional ringback tone for free, and examine whether this change might induce further purchases by peers connected to the focal consumers, and then progress through the social network in a dynamic manner. This method allows us to characterize the resulting dynamic effects that affect the mobile service provider.

Characterizing the Networked Value of a Consumer

Each consumer contributes to the social network, and thus creates value for peers in the network, but only captures part of the value. Since the product is an information good, the non-rivalrous property allows a single contribution by a consumer to result in multiple peers receiving experience utility. We seek to answer the question regarding the degree of externality: how much of the value created by a contribution is captured by the user? This is not as straightforward as it may initially seem: the contribution creates utility for peers, which in turn leads to them contributing more, resulting in higher experience utility for the contributing consumer. Our dynamic model permits the careful delineation of the degree of internalization of value by consumers in contributing to connected goods.

Another key issue to examine involves the value of a consumer to the network. How is a consumer's local network affected when the consumer is removed from the network? This simulation will inform us of the value of each consumer, specifically it enables us to determine which consumers the network would suffer most from losing. We evaluate this factor by altering the network structure (relationship matrix), so as to remove all the social ties belonging to the focal consumer. We then study the effect on peers in the social network, paying specific attention to the utility effects and resulting contributions. As an illustrative example, consider removing consumer 18 from the network. In our setting, consumer 18 is connected to 7 other peers. It is not immediately clear whether 18's peers will lose utility in consumer 18's absence. They certainly lose experience utility because they do not have access to the contributions made by consumer 18. However, 18's absence may improve the status of the remaining peers, especially if 18 usually made frequent contributions, and therefore had a low state and high status. Thus, the effects of the status and experience utility

are in opposite directions, and it's not obvious a priori which effect dominates. Notice that in a densely connected network where consumers have a several connected peers, the absence of a consumer may not impact status competition to a significant degree. However, in a setting where consumers have few peers, the absence of a single consumer will significantly impact the status competition.

The simulation details are as follows: we begin the network with the same endogenous state for the original full network and the altered network with one consumer's social ties removed. In both cases, we simulate the system $N_{SIM} = 1000$ times, with each simulation proceeding for T_{MAX} periods, chosen so that the degree of discounting is less than 1%. We compute the current value of the expected discounted stream of utilities in all cases. We aggregate over the utilities of peers to obtain the overall utility in the presence and absence of a specific consumer.

We simulate the model to determine the effects due to the absence of a consumer on peers by modifying the exogenous state. We obtain the difference in utilities for consumers who are arranged in order of their centrality scores. The horizontal axis represents consumers after ordering them based on eigenvector centrality, with the least central consumers on the left and with consumers becoming more central as we move rightward along the x-axis. The vertical axis in panel (c) captures the fractional change in peer utilities when the consumer is removed from the network, i.e. when consumer X is removed, what is the percentage change in the utilities of X's peers?

Much of the literature in social network analysis posits that centrality is key to identifying important players in the network. This proposition has intuitive appeal, i.e. more well connected consumers can be hubs of information dissemination and adoption etc. To determine whether this finding holds in our setting, we measure how much the absence of a consumer affects connected peers.

First, we observe that not all consumers have a negative effect on their peers when removed, i.e. their peers benefit when they are not present. From the factors discussed above, i.e. contribution status and consumption utility, we know that when a consumer is absent, the *loss* of consumption utility experienced by peers is always positive. We expect that when certain consumers leave, they diminish the high intensity of status-based competition, so that their absence leads to less intense competitive pressures, and the peers benefit from this effect. We find that approximately half the consumers have a positive effect, so that their absence results in a loss of utility to their connected

peers. Third, we find that more central consumers have a higer negative impact, implying that their absence might result in a higher utility for their peers.

Consumers with low or high levels of centrality have a lower effect on their peers, as compared to consumers with middling levels of centrality. We first observe that consumers who are central to the network are also likely to be connected to *other* central consumers. Our results suggest that low centrality consumers value consumption less and are therefore less likely to be influenced by making a contribution. Hence, the absence of such a consumer is not likely to lead to much loss due to lower contributions and the impact of absence may be small. For highly central consumers, we expect that the marginal value added due to higher contributions to peers to induce consumption may not have a large marginal impact, since the impact of any one consumer on the status of peers will likely be small.

Suppose we choose the top 10% as indicated by the eigenvector centrality measure and evaluate whether these consumers are the most valuable to the network. We find that only one of these consumers would rank in the top 10 % as chosen by the actual contribution difference due to the absence of that consumer. Further details on all counterfactuals are provided in the additional appendix.

Discussion, Limitations and Conclusion

Consumers visit network platforms primarily because they value the experience of new content contributed by their peers, as well as the act of making their own contributions. In social networks, we find a variety of shared consumer generated or created content that we characterize as connected goods. These connected goods are contributed by consumers with the experiencers being network peers of the contributor.

We therefore seek to understand the drivers of the social networking phenomenon through the following questions: what drives consumers to contribute to connected goods, adding content to the social network even though they do not obtain immediate experience utility? Why do some consumers contribute a lot and others little? How does leadership in network contribution relate to the value of a consumer? What are the substantive implications of understanding the drivers of contributions?

We find that consumers contribute to connected goods for the following inter-related reasons: (a) consumers obtain a utility from having a higher relative positional status in relation to their peers, (b) consumers obtain (future) experience utility from the connected goods provided by their peers, (c) consumers do not significantly value warm-glow altruism, and (d) consumers may obtain an interaction benefit from status and complementary activities. The combination of these factors imply that consumer contribution decisions are dynamically inter-related in the sense that it can induce peers to contribute due to the change of positional status. We formulate consumers' decisions on whether to actively contribute content to the social network as a dynamic game in the tradition of Ericson and Pakes [1995], and focus on Markov Perfect Equilibrium as the solution concept. In this game, forward-looking consumers strategically manage their network positional status in order to maximize long-term utility.

Based on a panel with purchase history of ringback tones of consumers as well as phone calls between pairs of consumers, we construct the social network and estimate the parameters of our model using the two-step estimation approach that obtains from combining Bajari et al. [2007] and Arcidiacono and Miller [2011]. We demonstrate that positional contribution status plays a significant role in explaining consumer contribution decisions in a social network setting. This can encourage an "arms race" among consumers, who make strategic contributions to ensure they are "keeping up with the Joneses." We conduct policy simulations to investigate the influence of consumers in the network and evaluate the evolution of network contribution decisions when a fraction of consumers are recruited as seeds to encourage their peers to contribute.

In summary, we establish the microfoundations explaining why consumers choose to contribute to connected goods. This study is among the first to apply the empirical analysis of dynamic games, originally developed to study the industrial organization of firms in a market, in the context of investigating interdependence in the decisions of consumers connected by a social network. Our results suggest several directions for managers who face challenges in attracting more voluntary contributions of user generated content when designing an online social network platform. Since competing for status and experience benefit from contribution made by peers are strong drivers of contribution, designers can leverage their platform design to take advantage of these factors. More specifically, our results suggest the following guidelines:

1. Social network platforms can be designed to better encourage competition among peers by

frequently announcing recent contributions made by each consumer and by providing a clear ranking order of contributions. For example, companies can explicitly display the ranking or positional status of each individual relative to peers. Such a message might say "Alex is the #1 contributor of videos in January. Her total views are 232." Such an explicit ordering would likely lead consumers to implicitly compete and strengthen the status effect.

2. It might be useful to incorporate a complementary benefit, like a prize for some of the higher contributors, especially when the network has a lower level of activity. This will make the implicit competition more explicit, and has the potential to enhance the positional status competition effect, thorough increased complementary utility.

3. When selecting seeding consumers, the firm should carefully differentiate consumers with high centrality and high influence. Even though central consumers have many more connections, the impact of their high ranking status may be diluted and thus less influential in encouraging peers to contribute. It is more effective for firms to target consumers considering the impact of the present overall state of the network.

We acknowledge that our research is subject to explicit and implicit assumptions and limitations. Since the present study is among the first to empirically demonstrate competitive and conspicous consumption, we view relaxing the assumptions and incorporating richer settings as open avenues for further exploration. First, future research can relax the assumption that social ties between individuals are exogenous. An approach that explicitly models how and why consumers form social relationships with specific peers, and how such relationships evolve would be very helpful [Jackson, 2008]. Second, for computational feasibility, we assume individuals perfectly observe the state of each of their friends in every period. It would be interesting to consider web network platforms, where there is a large amount of message and multimedia traffic among consumers, where it might be difficult to form an accurate impression of the state of each peer. As the number of connected peers increases, and consumers have hundreds of friends, we can instead allow them to have an imperfect perception of the contributions made by their peers. Third, a particularly promising direction would be to consider different types of contributions, extending the one-dimensional nature of connected goods in our setup. When consumers in the platform have access to different media, consumers face trade-offs between contributing multiple types of connected goods, each with different measure of status. It will be instructive to study consumer choice of contribution types. Fourth, another

avenue would be to investigate how consumers may be interdependent in their responses to marketing activities by firms, especially in the context of mobile and web social networks. Finally, the overall framework with positional status competition in the dynamic competitive setting developed in this paper can be extended to other settings that move beyond the consumer. One such context is the contributions of developers to open source software, where developers make contributions to publicly available open source to signal their ability and attain status in the project team [Lerner and Tirole, 2002]. Another setting where status-based competition may prove particularly useful is in designing salesforce compensation schemes including sales contests.

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Appendix A: Computational Details

Figure 7: Overview of Estimation Procedure

First Step
Data ➜   Optimal Policy

Second Step
(1) Policy ➜   Value Function
(2) Perturb Optimal Policy
(3) Check Violation of Equilibrium

BBL Estimate minimizes violations

Laplace Type Estimator

Use MCMC to estimate parameters without
likelihood (Quasi-Bayesian approach)