Social Visibility and the Gifting of Digital Goods

Jameson K. M. Watts
Atkinson Graduate School of Management
Willamette University
jwatts@willamette.edu

Yotam Shmargad
School of Information
University of Arizona
yotam@email.arizona.edu

ABSTRACT

One of the defining features of online social networks is that users' actions are visible to other users. In this paper, we argue that such social visibility has a detrimental effect on users' willingness to gift digital goods. The gift giving process often generates substantial anxiety, and social visibility exacerbates this anxiety to the point that it can deter gifting altogether. To study the effect of social visibility on the decision to gift, we analyze a unique dataset from a large online social network that offers users the option of buying a digital gifting service. We find that purchase rates of the service increased with the number of social ties that users kept on the network, but decreased with the extent to which those ties were tied to each other. We argue that the latter effect is due to the fact that, when a user's ties are tied themselves, any gift sent between the user and one tie is visible to their mutual contacts. This argument is bolstered by a stronger negative effect of social visibility for users with larger, less intimate, and categorically diverse networks.

Categories and Subject Descriptors

K.4.1 [**Computing Milieux**]: Computers and Society—*Privacy*; K.6.0 [**Computing Milieux**]: Management of Computing and Information Systems—*economics*

Keywords

Privacy, Social Networks, Social Risk, Digital Gifts

1. INTRODUCTION

In August 2014, Facebook shut down a service called Gifts, which allowed users to send digital gift cards to one another over its online social network. The move surprised Wall Street investors and online commentators alike, who only two years earlier had heralded the service as a potential threat to the dominance of the popular online retailer Amazon.[1] Because the gift cards that Facebook sold were digital, not physical, users did not need to know a gift receiver's home address to send a gift. Moreover, since the production and distribution of digital goods take little money or time [17], Facebook's service was ideal for last minute gifting. So why was it unsuccessful?

One of the defining features of online social networks is that users' actions are visible to other users [41, 36]. Rhue and Sundararajan [27] show that such social visibility can alter users' purchasing decisions and, in particular, makes users conform to others' expectations. Of course, gifts are inherently socially visible to the extent that receivers see their gifts. However, in an online social network there is an additional layer of social visibility not often present in the offline world — gifts sent between two users are visible to any mutual contacts they share. The degree to which a gift conforms to the expectations of these observers constitutes what Yadav et al. [41] refer to as "social risk." Given that there is already substantial anxiety surrounding the gifting process [33, 40], we argue that such "third-party" social visibility increases social risk, which can the exacerbate anxiety and deter users from gifting through online social networks altogether.

If the presence of third-parties can deter gift exchange, then services like Facebook Gifts will be less successful in networks where users' friends are friends with each other. When users' friends are friends themselves, gifts sent to one friend will be visible to other friends. On the other hand, in networks where users' friends are not friends, gifts are only visible to their intended recipients, and gifting services should be more successful. In fact, in 2008, Facebook introduced a feature called People You May Know, which encouraged users to form connections with friends of their existing friends.[2] While the feature may have increased the number of connections users had on Facebook, it likely also increased the tendency for users' connections to be connected to each other. The feature may thus have had the unintended effect of increasing third-party social visibility on Facebook, rendering the gifting service unappealing from the moment it launched.

To study how social visibility affects the gifting of digital goods, we analyze data from a large online social network that sells a service which lets users send electronic greeting cards (eCards) to one another. We find that purchase rates of the service increased with the number and strength

[1] Facebook is Shutting Down Gifts to Focus on its Buy Button and Commerce Platform, TechCrunch, July 2014
[2] People You May Know, Facebook, May 2008

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of ties users kept on the network, but decreased with the extent to which those ties were connected to each other. Moreover, this negative effect of third-party social visibility was stronger for users with larger, less intimate, and categorically diverse social networks.

2. THEORETICAL DEVELOPMENT

The behavior of individuals under surveillance, whether social (like users' friends on Facebook) or institutional (like Facebook the company or the NSA) is gaining in popularity as a topic for scholarly attention. For instance, Raynes-Goldie [25] argues that Facebook users are more concerned about privacy from their connections than from Facebook itself or affiliated businesses. Brandtzæg et al. [3] find that Facebook users with many friends feel more pressure to conform when posting information on the platform. Indeed, Rhue and Sundararajan [27] show that users of a social shopping website sometimes alter their buying habits in order to conform to comments received on previous purchases.

Social visibility can also have implications for how users interact with each other online. Gross and Acquisti [11] argue that online social networks engender new kinds of intimacy. This is evidenced by the fact that users regularly share personal information broadly and with many people. Lambert [16] refers to this new kind of intimacy as "group intimacy," and suggests that it may be replacing traditional versions of intimacy—those which are more interpersonal in nature. Geser [9] goes further and suggests that intimacy is completely destroyed in most online settings because individuals are discouraged from revealing information privately to their close social ties. As Gerstein [8] suggests, it is precisely these private disclosures of information that separate intimate relationships from those of a more casual nature.

We follow Wilson et al. [39] and others by taking the view that users of online social networks typically consider the privacy of an interaction when choosing to disclose information. Dinev and Hart [7] refer to this consideration in information exchange as a "privacy calculus." We use their framework in the context of gift giving, and show how social network theory helps to quantify the potential threats to privacy that result from digital gift exchange. We believe that gift exchange is a natural setting to study privacy concerns because, as others have pointed out, gift giving is often the subject of social scrutiny [32, 40].

We present our conceptual model in Figure 1. In this model, we look at the effects of social visibility on the adoption timing of a service that lets members of an online social network send eCards to one another. Social visibility constitutes the potential that an interaction between two individuals (i.e. an eCard) is observed by a third-party. Adoption is defined as a new purchase of the eCard service. The primary focus of our model is on social visibility. However the effect of social visibility on eCard adoption depends on an individual's perception of social risk [41, 40]. The magnitude of this social risk may depend on characteristics of those observing the interaction. Thus, we explore the moderating effects of audience size, type, and diversity. Finally, we control for a number of alternate explanations such as the influence of prior adopters as well as various user demographics.

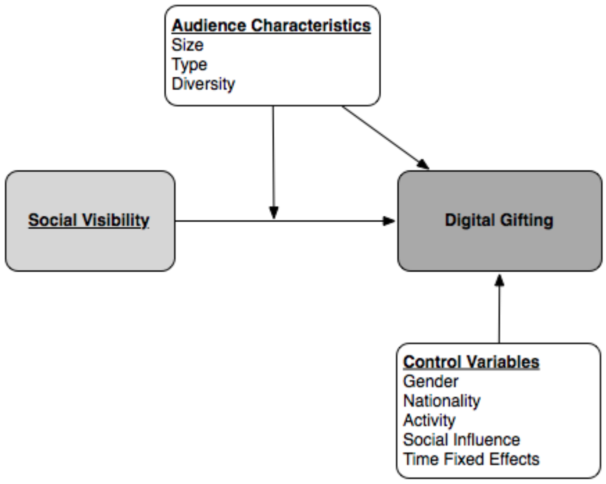

Figure 1: Conceptual model.

2.1 Gift Giving Under Surveillance

The anticipation that a gift will be ill-received can generate substantial anxiety for the giver [20, 33, 40]. Researchers have identified two primary sources for this anxiety. The first relates to the uncertainty that a giver may have with regards to the recipient's preferences. When givers are unsure of these preferences, they tend to experience higher levels of anxiety in the gift selection process [21]. The second source of anxiety is more social in nature. Individuals view gifts as tools to manage impression, and givers get anxious when they are concerned about how they will be evaluated by others who observe their gifting behavior [33, 40]. It is from this latter source of anxiety—that which stems from an individual's social context—that we construct our hypotheses.

One of the defining features of online social networks is that users' actions are visible to other users. As a result, users are attuned to the potential for social surveillance—the monitoring of one's behaviors by other users [3]. For example, Rhue and Sundararajan [27] show that users alter their online purchasing behaviors in response to feedback from other users. Thus, we suggest that the anxiety surrounding online gift exchange will increase when one's gifting behaviors are socially visible to other users.

To capture the extent to which a user's gifting behavior will be visible to other users, we borrow a concept from the social networks literature known as clustering. Clustering measures the extent to which an individual's social ties are themselves also tied. In practice, the concept is sometimes referred to as redundancy by cohesion [5] or the clustering coefficient [37]. When a user's social ties are themselves tied, then any gifts that the user sends to one tie will be visible to their mutual contacts. On the other hand, when a user's ties do not know each other, then gifts will only be visible to their intended recipient. Clustering thus captures the potential for third-party social visibility. For this reason, we hypothesize:

Hypothesis 1. *The time to adoption of a digital gifting service increases with the level of clustering in an individual's online social network.*

2.2 Audience Characteristics

2.2.1 Diversity

The degree to which social visibility poses a social risk is often a function of observer characteristics (Rogers 2002). This is especially true if a potential interaction contains content that is either controversial or has the potential for misinterpretation (Chen and Berger 2013). Often the intent of an interaction must be understood within the context of prior interactions or shared cultural understandings. A third-party observer can misinterpret the meaning of an interaction if that observer is not privy to the context—a communication issue that Fleming et al. (1990) term the 'multiple-audience problem'.

In the present context, some users have online social networks that are fairly homogenous, while others have networks comprised of individuals with varying characteristics. In a broad sense, we expect that individuals who share certain demographic characteristics, are more likely to interpret the meaning of an eCard in the same way. In contrast, a diverse set of individuals may interpret the meaning of an eCard in very different ways. Thus, users with the same level of social visibility, will experience more social risk if their online social network is diverse on some characteristic. We test this argument by calculating the diversity of a user's online social network according to gender, culture and tie type and hypothesize that:

Hypothesis 2. *The effect of clustering on time to adoption of a digital gifting service increases with the level of a) gender b) cultural and c) tie type diversity in an individual's online social network.*

2.2.2 Size

For a given level of clustering, social visibility should be more salient to users with larger networks than smaller ones. This is due to the fact that large networks contain more individuals that can potentially monitor one's gifting behavior. With a large social network, individuals are unlikely to have close relationships with all of their social ties and may find it more difficult to predict the response of every observer of an interaction. Moreover, large social networks make it more likely that audience members differ across a variety of characteristics. Thus, audience size may also be capturing a level of unobservable diversity. Thus we predict that the negative effect of clustering will be greater for individuals that keep larger networks.

Hypothesis 3. *The effect of clustering on time to adoption of a digital gifting service increases with the size of an individual's online social network.*

2.2.3 Intimacy

Individuals often maintain several distinct social groups. For example, social ties in a business setting may have little overlap with ties in a family or friendship setting. Thus, the effect of clustering on the value of a digital gifting service could vary across these distinct groups. Wooten [40] proposes a mechanism driving social anxiety based on the lack of parameters established prior to gift exchange. For social groups that consist of more personal (or intimate) ties, these parameters (rules) may be tacitly agreed upon or even openly discussed. For social groups that consist of less intimate ties, the parameters of gift exchange may be less obvious. Indeed, Sherry et al. [33] provide some empirical evidence that individuals are more anxious about exchanging gifts with relative strangers than they are giving gifts

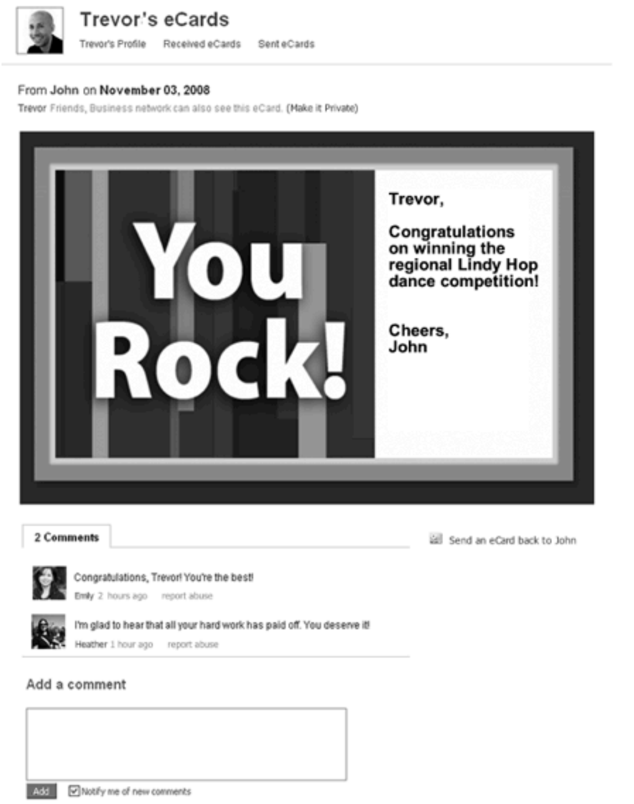

Figure 2: An example of an eCard displayed on a recipient's profile page. Senders and recipients had the option of making these cards private, though the default was to make them public.

to closer friends and family. While we expect that additional social ties will decrease the time to adoption in general (because there are more individuals with whom one can exchange eCards), we expect the effect to be greater with increases in more intimate connections. We test this argument by looking at the number of family, friend and business ties in an individuals online social network and hypothesize that:

Hypothesis 4. *Family and friendship ties decrease the time to adoption of a digital gifting service more than business ties.*

If individuals are less comfortable giving gifts to relative strangers, they are likely to also feel less comfortable exchanging gifts in the *presence* of strangers. We test this argument by looking at the effect of clustering in distinct networks comprised of only family, friend or business ties and hypothesize that:

Hypothesis 5. *The time to adoption of a digital gifting service increases more with the level of clustering in an individual's business network than with the level of clustering in an individual's family or friend network.*

3. EMPIRICAL SETTING

3.1 Overview

The dataset that we analyze in this paper originates from a California-based company that launched an email address book management service in 2002. Users of the service could update their contact information, and these updates were then automatically pushed to their contacts' email address books. However, when online social networks like Facebook and LinkedIn started gaining popularity a few years later, the company decided to launch an online social network of its own.

The company launched its social network in 2007. The network allowed users to maintain an online profile, connect with other users, and share messages, photos, videos, and other content with their connections. A unique feature of the network is that it required users to specify the types of connections they had with other users. Connections could be specified as family, friend, business, or any combination of these types, and only the types that were mutually agreed upon by both users were associated with a connection on the network. This feature made it easier for users to share content with each group separately.

We analyze the purchases of a digital gifting service provided by this online social network, which let users send electronic greeting cards (eCards) to their connections. The service cost users $12.95 for a one-year subscription, and the price did not change during the period under investigation. While the service was occasionally promoted to all users of the platform, it was not targeted towards any specific group.

Figure 2 shows an eCard exchange between two users of the online social network. In general, users could choose to make eCards private, which meant that only the sender and receiver were able to see them. However, eCards where public by default, and few users opted to make them private. In addition to being displayed on the receiverâĂŹs profile page, eCards were also visible in the content streams of users who had connections to both the sender and receiver. Thus, users that were not directly involved in an exchange could see and even comment on the eCard.

3.2 Data

Social networks are usually bounded artificially. As researchers, we tend to define what constitues ties between individuals and largely ignore the set of interactions that occur outside of our chosen context. This is often a matter of practical necessity. For example, Nitzan and Libai [22] study a social network based on the occurrence of millions of phone calls between individuals. In their context, it is not feasible to document the set of face to face interactions that may have occurred in concert with the phone communication. In our study, we avoid this concern by focusing on a digital gifting service that requires both givers and recipients to be users of the online social network. As such, the value of the service can be directly linked to the existence of social ties in the online social network, and not to ties by some other definition.

To estimate the effects of users' social network characteristics on purchase of the company's eCard service, we construct a set of network measures for each user by analyzing her ties on the online social network. Our data start in 2007, when the company's social network launched, and ends in September of 2009. We sample the network of connections in this dataset at 12 points in time (i.e. every two months), and only consider users that, at every time point, had at least two ties. This requirement ensures that users' clustering measures are well-defined throughout the timespan of our study.

The network was growing rapidly during the period of our study, and by the end of the two-year window there were 3,702,474 users that met our criteria for inclusion and a total 38,891,294 ties. To calculate network measures, we analyzed all available 6,711,964 users and 39,116,763 ties. In the first time period, approximately 2.25% of all users had a subscription to the eCard service. That number dropped to approximately 1% by the final time period. Table 1 breaks down the number of users, ties, and subscriptions by time period.

Table 1: Usage by time period

Time Period	Users	Ties	Subscribers
11/2007	67,915	432,721	1,454
01/2008	540,850	4,108,562	6,734
03/2008	866,771	6,923,045	9,600
05/2008	1,194,273	9,702,064	11,985
07/2008	1,569,877	12,537,632	15,752
09/2008	2,180,914	19,005,294	21,184
11/2008	2,664,137	24,868,597	25,541
01/2009	2,937,110	28,791,961	29,027
03/2009	3,203,440	32,377,461	31,515
05/2009	3,442,508	35,475,822	33,389
07/2009	3,588,735	37,319,627	33,460
09/2009	3,702,474	38,891,294	32,250

Due to the size of our dataset, it was not feasible to estimate the parameters using the entire population of users. We therefore employed a sampling technique, in which we selected approximately 100,000 – 300,000 users at random and only included their records in our estimations. We used at total of 10 such samples to estimate our models, and results were qualitatively similar across these samples.

4. METHODOLOGY

Scholars regularly use hazard models to examine the duration prior to some event [18, 22, 28]. In our context, the event of interest is the purchase of the company's eCard service. The hazard specification has several advantages over standard regression methods like ordinary least squares and logistic regression. For one, it can handle data that are right-censored, which allows us to include users who do not adopt by the end of our sampling window. Another advantage is that hazard models can capture both time-varying and time-constant independent variables. This allows us to include social network measures that changed from period to period, as well as demographic variables (e.g. gender and nationality), which did not. We address left-censoring by using the date a user joined the social network to define the point at which they become at risk of adoption.

Following Risselada et al. [28], Polo et al. [23] and others, we specify the baseline hazard function using the complementary log-log parametric form. This approach approximates an underlying continuous-time process given data that are grouped into discrete time intervals (e.g. every two months). In this approach, the hazard of user i with individual characteristics x_{it} of purchasing an eCard subscription at time t can be expressed as:

$$h_i(t) = 1 - exp[-exp(\beta_0 + \beta^{'} x_{it})], \tag{1}$$

where $\beta^{'}$ captures the effects of the variables in the vector x_{it} on the hazard rate.

In the standard hazard specification, one assumes that all users will, eventually, experience the event of interest. In our context, actual purchase rates are quite low, which highlights the possibility that many users are never actually 'at risk' of adoption [23, 31]. Digital gifting represents an additional layer of technological complexity above and beyond routine use of the online social network, and for technologically complex products, there is often a significant group of consumers who will resist adoption [24].

To account for the possibility that some users will never purchase the eCard service (i.e. have zero probability of adoption), we estimate both the adoption probability and adoption timing simultaneously. This approach is often referred to as a 'split-population' hazard model [30, 13], because it weighs the likelihood of each observation by the probability of belonging to the 'at risk' population to begin with. In this way the survival analysis is applied only to the users who are predicted to adopt in the future.

Following the notation of Jenkins [13], we define an indicator A of whether a user eventually adopts or not, where $A = 1$ means eventual adoption, and $A = 0$ means never adopt (i.e. the event of interest never occurs). Using this indicator, we can say that $prob(A = 1) = 1-c$ (the eventual adopter probability) and $prob(A = 0) = c$ (the never adopter probability). For those with an adoption observed during a given time interval, the contribution to the likelihood is $(1-c)\times$ (probability of no adoption to end of the previous time interval) $\times$ (probability of the event in the given interval). Censored observations consist of those where $A = 0$ plus those still at risk but not yet observed to adopt. Thus, the contribution to the likelihood from a censored survival time is $c + (1-c)\times$ (probability of survival to end of the given time interval).

Taken together, we can express the (log)likelihood contribution for person i with a survival time of t periods as:

$$\begin{aligned} ln(L_i) = d_i \times ln[(1-c) \times (h_{it}) \times (S_{it-1})] \\ +(1-d_i) \times ln[c + (1-c) \times S_{it}], \end{aligned}$$

where S_{it} is the discrete-time survivor function and d_i is a censoring indicator that equals 1 if adoption is observed in the current time period and 0 otherwise. Parameters for the hazard portion are estimated along with a value for c using the maximum likelihood methods available in Stata.

4.1 Variables

We extend the notation in Shmargad [34], which accommodates social networks with multiple relation types and multiple time periods. We denote a social network of type $r \in \{Family, Friend, Business\}$ at time $t \in \{1, ..., 12\}$ by $G_t^r(V_t, E_t^r)$. Here, V_t is the set of active users and E_t^r is the set of type r relations among them at time t. We define the set of user i's type r ties at time t as $N_{it}^r = \{j | j \in V_t \text{ and } (i,j) \in E_t^r\}$. We then define $N_{it} = N_{it}^{Family} \cup N_{it}^{Friend} \cup N_{it}^{Business}$ and $E_t = E_t^{Family} \cup E_t^{Friend} \cup E_t^{Business}$, which capture the set of user i's ties and all of the ties in the network, respectively, at time t. To construct variables based on a user's social ties, we also define the following indicator for any two users $i, j \in V_t$,

$$e_{ijt} = \begin{cases} 1 & \text{if}(i,j) \in E_t \\ 0 & \text{otherwise.} \end{cases}$$

4.1.1 *Network size*

In the social networks literature, degree is simply a count of the number of direct ties, or *neighbors*, an individual keeps. In most naturally occurring social networks, the number of ties individuals keep is distributed according to a power law [see e.g. 2, 38]. To adjust for this skew, we take the natural log of each user's degree. Formally, we define the size of a user's network as $CON_{it} = ln(\|N_{it}\|)$. We also generate variables that capture the size of each type of network (i.e. family, friend, or business), and denote them by CON_{it}^{FA}, CON_{it}^{FR}, and CON_{it}^{BU}, respectively.

4.1.2 *Clustering*

We operationalize the extent of social visibility in a user's network by calculating their clustering coefficient, which is the number of ties between a user's neighbors divided by the number of possible ties [37]. The clustering coefficient for user i at time t is thus defined as

$$CLS_{it} = \sum_{i \neq j \in N_{it}} e_{ijt} / \sum_{i \neq j \in N_{it}} 1.$$

We also generate this measure for each relation type (i.e. family, friend, or business) and denote these variables by CLS_{it}^{FA}, CLS_{it}^{FR}, and CLS_{it}^{BU}, respectively.

4.1.3 *Diversity*

We operationalize three diversity measures based on the composition of an individual's network by gender, nationality and tie type. Gender is a self-reported measure that takes on a value of 0 for male and 1 for female. Nationality indicators were created from an individual's self-reported country of origin; however, only the top 10 countries by absolute membership were used in the diversity score. All other countries were lumped together. Tie types were family, friend or business as described above. Our measure uses the Herfindahl index [12, 10], defined as

$$H = 1 - \sum_{j=1}^{d} p_j^2,$$

which is maximized when the probability of randomly selecting two items of the same type at random is minimized. For example, an individual would have a high tie-type diversity score if their network consisted of an equal number of family, friend and business ties. A low diversity score would occur if that individual's network consisted of only business ties.

4.1.4 *Control variables*

To account for the possibility of social influence in the adoption process [e.g. 28], we include a count of the number of individuals in N_{it} that have already adopted an eCard subscription. Because users send eCards to one another, the existence of prior adopters in a user's social network could indicate additional exposure to the product or a social influence effect. A user's level of activity on the social network could also affect their purchase likelihood. We control for this by including a variable that measures the amount of time since the user last created a tie on the network. Users that have not formed connections in a long time may have lost interest in the online social network altogether.

In addition to these exposure and activity effects, purchase could also depend on demographic and cultural characteristics. For example, females are generally expected to play a larger role in gift exchange [1]. To account for this possibility, we include a dummy variable indicating the user's gender, along with variables that capture a user's age and country of origin. We found no major differences with the inclusion of dummy variables for each of the 229 countries in our sample, and instead use a dummy variable to indicate whether or not users reside in the US.

Finally, we include time period fixed-effects (i.e. monthly dummy variables) to capture factors that affected all users, like mass-media advertising by the firm or its competitors and the popularity of this type of service in the market. Table 2 summarizes our variables and their operationalizations.

Table 2: Summary of Variables

Variable	Description	Formula
$t_2, ..., t_{12}$	Dummy variables indicating the month of the observation period	
CON_{it}	Natural log of count of user's social ties	$ln(\sum_{i \neq j \in N_{it}} e_{ij})$
CLS_{it}	% of actual ties out of all possible between neighbors	$\frac{\sum_{i \neq j \in N_{it}} e_{ij}}{\sum_{i \neq j \in N_{it}} 1}$
DIV_{it}	Diversity score by gender, tie type and nationality for a user's ego network	$H = 1 - \sum_{j=1}^{d} p_j^2$
EXP_{it}	# of neighbors who are subscribers at time t	
ACT_{it}	Negative of time in days since last tie was formed (less negative = more active)	
AGE_{it}	Age in years	
SEX_i	Sex of user (0=male, 1=female)	
US_i	Country (1=USA, 0=other)	

5. RESULTS

5.1 Main effects

From the nearly seven million users in our dataset, we constructed a random sample of 300,000 to estimate the parameters in our hazard model. Of these, 168,801 users had at least two ties, which was required in order to calculate the clustering coefficient. Those with fewer than two connections were dropped from the sample, and were likely users of the company's address book service but not the online social network. There were no other missing variables. Across our two year time window, these users constituted 1,007,915 observations and 1,593 purchases of the eCard service.

Table 3 presents the estimation results for Model 1 (control variables only), Model 2 (main effects) and Model 3 (interaction of network size and clustering). The direction of the estimates from Model 1 are as expected. The hazard of adoption increased with exposure to prior adopters and higher activity levels, and was higher for females and residents of the US. We see that each adopting neighbor is associated with an increase of 41.8% in the focal user's hazard of adoption; however this is attenuated to 19.3% once total network size is accounted for. This value is inline with social influence effects reported in other studies of adoption or defection [see e.g. 22].

Table 3: Hazard of eCard Subscription

	(1) Controls	(2) Main Effects	(3) CON x CLS
CON		1.530***	1.663***
		(0.0616)	(0.0774)
CLS		0.331***	0.798
		(0.0529)	(0.223)
$CONxCLS$			0.629***
			(0.0808)
EXP	1.418***	1.193***	1.172***
	(0.0337)	(0.0330)	(0.0330)
ACT	1.006***	1.004***	1.004***
	(0.000366)	(0.000392)	(0.000394)
AGE	1.005***	1.011***	1.011***
	(0.000922)	(0.00105)	(0.00106)
SEX	1.248***	1.404***	1.408***
	(0.0694)	(0.0832)	(0.0837)
US	1.968***	2.054***	2.049***
	(0.121)	(0.133)	(0.133)
Observations	1007915	1007915	1007915
AIC	22732.1	22451.5	22440.7
BIC	22933.1	22676.1	22677.2

Exp. coefficients; Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Model 2, we also added the measures of network size and clustering. This increased the fit of our model substantially, according to both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Moreover, the parameter estimate of our clustering variable indicates that social visibility hads a significant and negative effect on eCard purchase. This provides support for hypothesis 1.

In Model 3, we introduce an interaction between network size and clustering, which is statistically significant and in the direction predicted. This means that marginal increases in clustering have a stronger negative effect on eCard purchase for users with larger networks, which provides support for hypothesis 3. We depict this relationship graphically in Figure 3. This result also rules out an important alternative explanation for our results—that the negative effect of clustering on eCard subscriptions is driven by new users joining, who are both unaware of the eCard service and whose networks are small and thus highly clustered.

Table 4 Model 1 shows parameter estimates for the effects of the sizes of users' family, friend, and business networks. For example, the estimate of the coefficient for the variable CON^{FA} represents the effect of increases in the size of a user's family network. From the estimated values, it is clear that the hazard of eCard subscription increased most with the size of a users' family and friend networks, and little with increases in the size of users' business networks. If we assume that, in general, family and friend ties are more intimate than business ties, then these results provide support for hypothesis 4.

Table 4 Model 2 shows parameter estimates for interactions of clustering with our three diversity measures. While

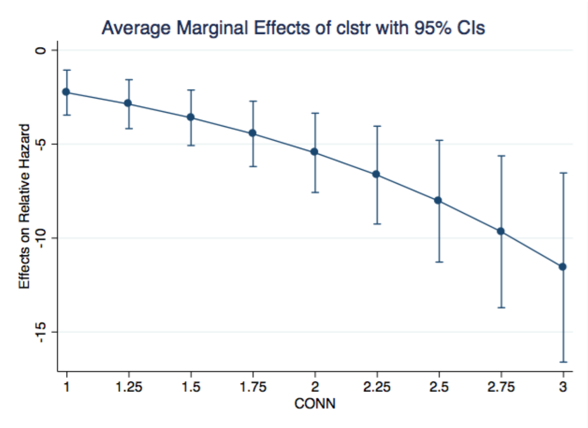

Figure 3: Marginal effects of clustering at different levels of connectivity

Table 4: Scaled Clustering Variables

	(1) $CLSTR^{FA}$	(2) $CLSTR^{FR}$	(3) $CLSTR^{BU}$
CON^{FA}	2.135***		
	(0.381)		
CON^{FR}		2.021***	
		(0.104)	
CON^{BU}			1.338***
			(0.0588)
CLS^{FA}	1.170		
	(0.532)		
CLS^{FR}		1.061	
		(0.443)	
CLS^{BU}			1.373
			(0.557)
$CON^{FA}xCLS^{FA}$	0.611		
	(0.201)		
$CON^{FA}xCLS^{FR}$		0.503**	
		(0.123)	
$CON^{FA}xCLS^{BU}$			0.419***
			(0.0824)
EXP	1.311***	1.236***	1.277***
	(0.0479)	(0.0325)	(0.0362)
ACT	1.006***	1.005***	1.006***
	(0.000652)	(0.000437)	(0.000482)
AGE	1.005**	1.010***	1.009***
	(0.00167)	(0.00110)	(0.00118)
SEX	1.160	1.317***	1.420***
	(0.112)	(0.0838)	(0.0942)
US	1.846***	1.770***	1.998***
	(0.219)	(0.123)	(0.141)
Observations	212486	721712	737247
AIC	7266.2	18898.3	17632.9
BIC	7471.5	19128.1	17863.1

Exp. coefficients; Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the interaction is statistically significant for both gender diversity and tie type diversity, it is not significant for the diversity measure calculated using nationality. This provides support for hypothesis 2a and 2c.

As we noted above, Table 3 Model 3 confirms that the effect of clustering depends on network size. This presents a challenge when trying to compare parameter estimates for clustering within the different network types, which we know differ in size. For example, users in our sample have, on average, just one family tie, but over thirteen business ties. Thus, a more negative effect of clustering in the business network could be due to the fact that business ties are impersonal, or that business networks are generally larger. To address this, we compare the *rates* at which the negative effect of clustering increases as these networks grow, rather than simply the negative effect of the clustering coefficients themselves. In practice, this means that we compare the interactions between network size and clustering for each network type. Table 4 reports the results of this analysis.

While the parameter estimate for the interaction in the family network is not statistically significant (Model 1), it is close ($z = -1.3$) and is strongly significant when we use a larger sample. However, the important feature is that the negative effect of clustering increases as we move from the family to the friendship network, and from the friendship to the business network (i.e. as ties become less personal). As we discussed above, this effect of clustering is independent of network size, and thus provides support for hypothesis 5.

5.2 Robustness

To account for potential unobserved heterogeneity that we could not capture with the demographic variables, we estimate a parametric hazard model with an additional random intercept (or frailty term) to account for the potential effects of omitted variables [28, 35]. Table 5 shows the results of this estimation. Model 1 confirms that all of the hypothesized main effects still hold. In fact, the negative effect of clustering is stronger and the effect of increased connectivity is weaker once we account for unobserved heterogeneity. Model 2 shows that the interaction we predicted in hypothesis 5 also holds under this specification. Though not shown here, we also ran all other models using the new specification, and find that the results are qualitatively the same.

Finally, given that we ran our models on a random sample of users, and not on the entire population, it is possible that our results could be caused by biases introduced by our sampling method. For example, the number of users increased rapidly during the two years in our study. Thus, a purely random sample of users will draw more heavily from users that joined later. To account for this potential bias, we resampled the data by choosing twelve 10,000 user random samples that were stratified on when users joined the network. The results of our model with this sample are also displayed in Table 5. Model 3 confirms that the hypothesized effects are in the predicted directions.

6. DISCUSSION

In this paper, we test how the presence of social visibility influences the decision to gift through online social networks. We analyze a novel dataset from a large online social network that offers users the option of buying a service that lets them send electronic greeting cards (eCards) to other users.

Table 5: Robustness

	(1) Main Frailty	(2) Inter. Frailty	(3) Stratified
CON	1.433***	1.591***	1.719***
	(0.0869)	(0.108)	(0.0874)
CLS	0.114***	0.430+	0.291***
	(0.0323)	(0.204)	(0.0834)
CON x CLS		0.503**	
		(0.106)	
EXP	1.096***	1.084**	1.002
	(0.0266)	(0.0269)	(0.0167)
ACT	1.006***	1.006***	1.004***
	(0.000506)	(0.000509)	(0.000757)
AGE	1.036***	1.036***	1.004**
	(0.00189)	(0.00189)	(0.00158)
SEX	2.025***	2.037***	1.504***
	(0.210)	(0.211)	(0.125)
US	3.993***	3.937***	1.771***
	(0.456)	(0.449)	(0.161)
Observations	1007915	1007915	360956
AIC	18757.0	18748.6	13181.2
BIC	18993.4	18996.9	13364.7

Exp. coefficients; Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We find that purchase rates of the service increased with the number and strength of the ties that users kept, but decreased with clusteringExp.-the extent to which users' ties were tied themselves. We argue that social visibility is more prominent in networks that are highly clustered, because gifts sent from a user to one tie can be monitored by any mutual contact they share. Given the well-documented anxieties surrounding the gifting process, such social monitoring can discourage users from gifting digital goods altogether.

The negative effect of clustering we uncover is relatively strong compared to the effects of other variables. After controlling for a variety of individual and environmental factors, we find that the hazard of adoption increases by 53% for every 1 point increase in network size. Since we operationalized network size as the natural log of the number of ties in a user's network, a one point increase here is actually equivalent to a 270% increase in the number of ties. Thus, a 10% increase in the size of an individual's network only increases the hazard of subscription by 1.9% on average. In contrast, the hazard rate *decreases* by 6.7% for every additional 10% of clustering in a user's network and the number is higher for individuals with relatively large social networks.

A key question facing managers of large online social networks is what types of social ties to promote. Companies like Facebook and OkCupid regularly make feature changes that affect the ways in which their users interact with one another [14, 29]. For example, Facebook introduced their PYMK feature in 2008. Since that time, Facebook has twice tried and failed to implement a revenue-generating gifting service for its users [6]. To be successful, managers of products and services that rely on large social networks will have to think more strategically about how they recommend users to connect to each other. Importantly, companies could also benefit from giving users better control over whether or not their online activity is visible to other users. For example, the company in our study allowed users to send eCards in private, but this was not the default option. By making private gifting the default option, the company may have been able to mitigate some of the concerns around social monitoring.

Often, product managers are provided with incentives to increase the number of connections users have in order to encourage more engagement with online social networks. For many of these companies, greater engagement means higher revenue from advertising dollars. However, there can be hidden costs that depend on the *type* of connectivity that drives engagement. For example, in our context, increases in clustering had a large negative impact on eCard adoption when the increases were in users' business networks, but not in their friendship networks. This is because there is more anxiety associated with giving gifts to impersonal social ties, and likely also with giving gifts *in the presence* of these ties. The implication of this finding is that product managers should encourage connections to friends of friends, but not to business ties of business ties.

More generally, our findings relate to the broader issue of practicing intimacy in an increasingly public, online world. Social psychologists have long argued that individuals require private disclosures of information in order to build meaningful relationships with those around them [26, 19]. The public nature of interactions on Facebook could be on of the reasons why the platform is increasingly associated with loneliness and decreases in well-being [4, 15]. This has also created a void which is quickly being filled by competitors like Snapchat and Sup, which give users more privacy in their interactions. If large online social networks and the services that rely on them are to succeed over the long term, managers need to be more strategic about the types of interactions they promote.

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