Strangers You May Know: Social Surveillance and Intimacy Online

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Abstract
Online social networks like Facebook and LinkedIn regularly use People You May Know (PYMK) algorithms to encourage connectivity among their users. We argue that these algorithms have the unintended effect of making users' interactions more visible, which can deter them from being intimate online. To test this theory, we analyze data from a large online social network that lets users buy and exchange electronic greeting cards (eCards) with each other over the network. We find that users are more likely to buy eCards when they have more connections, but less likely to buy them when they have formed connections to friends of friends. We attribute the latter effect to the increased visibility that comes with connecting to friends of friends, which PYMK algorithms encourage. We find no effect of users' friends connecting to each other, suggesting that the PYMK effect has to do with promoting surveillance by relative strangers rather than with increasing network density more broadly.
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1 Introduction[1]

Increasingly, algorithms shape what we see and do online. Google uses an algorithm to rank its search results (Brin and Page 1998), Facebook uses an algorithm to decide what to display in the News Feed (Eslami et al. 2015), and e-commerce sites use algorithms to determine what prices to charge (Hannak et al. 2014). While these algorithms are usually invisible to outsiders (Pasquale 2015), they are often designed to optimize certain metrics – like time spent on site, click rates, or purchase incidence. Recent advances in machine learning and collaborative filtering have greatly improved how well these algorithms optimize pre-specified metrics, but we know relatively little about what some of their unintended consequences might be. These unintended consequences are likely unknown even to algorithm designers themselves, and so may affect a company's bottom line in unexpected ways.

The focus of this paper is on a set of algorithms readily deployed by online social networks, like LinkedIn and Facebook, to encourage connectivity among their users. Commonly referred to as People You May Know (PYMK) algorithms, they generate a list of people with whom users might be interested in connecting. This list is then displayed on the platform's site in the hopes that it nudges users to form new connections on the network. Guy et al. (2009) point out that recommendations generated by PYMK algorithms are mainly people with whom users share mutual connections – otherwise known as friends of friends. This is likely because the metric that platforms optimize in this case is the rate that recommendations convert to connection requests, and people are more inclined to request a connection from those that know their other friends.

What could be some unintended consequences of PYMK algorithms? For one, increasing the size of users' networks makes their actions visible to more people. This can heighten privacy concerns and discourage users from sharing information on the platform (Brandtzæg et al. 2010, Raynes-Goldie 2010). We argue that, in addition to making users' actions more visible, PYMK algorithms also tend to make their *interactions* more visible. To understand why, we must keep in mind that PYMK algorithms encourage connections to friends of friends. Moreover, social media platforms readily show users interactions, or correspondences, that occur between two of their friends. Put together, this suggests that PYMK algorithms make interactions between users more visible (see Figure 1).

Increased visibility can discourage people from being intimate online (Gross and Acquisti 2005). Intimacy requires private disclosures of information (Gerstein 1984), which can be difficult to achieve in settings where interactions are largely public. We thus expect that PYMK algorithms have the unintended effect of deterring intimacy between users, for fear that their correspondences are being watched. We test this hypothesis in the context of a large online social network that lets users buy and exchange electronic

[1] Author order is alphabetical. The authors contributed equally to the work.

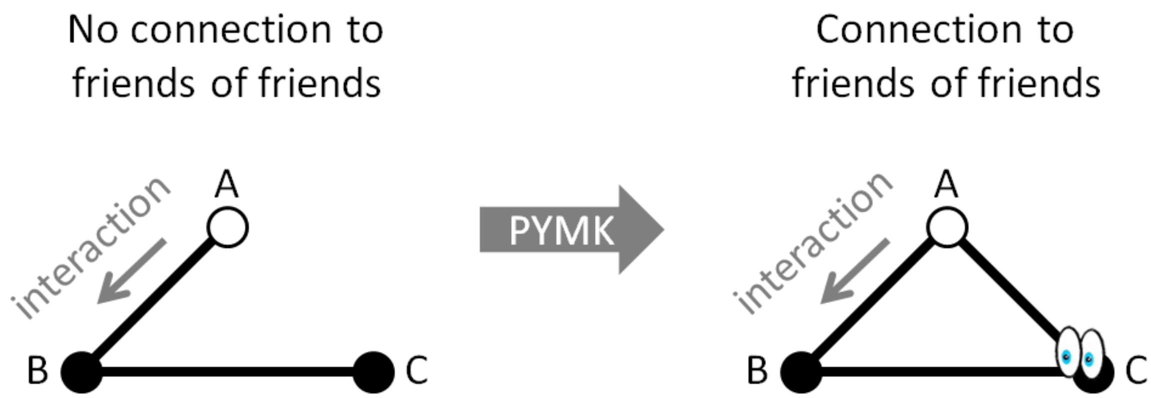

Figure 1. Illustration of how PYMK algorithms increase visibility of interactions

greeting cards (eCards) with one another. We find that users are more likely to buy eCards when they have more connections, but less likely to buy them if they have connected to friends of friends. We use the timing of connection to distinguish the effect of connecting to friends of friends from that of existing friends connecting to each other, and only find evidence for the former. Our study has implications for the success of digital gifting services, and for how intimacy plays out online more broadly. It also calls for a deeper investigation into the unintended consequences of algorithms, both to the companies that design them and to society more broadly.

2 Theoretical Development

The question of how people behave when under surveillance, whether social (like users' friends on Facebook) or institutional (like Facebook the company or the NSA) is garnering considerable scholarly attention. Raynes-Goldie (2010) argues that Facebook users tend to be more concerned about privacy from their connections than from the company or affiliated businesses. Brandtzæg et al. (2010) find that Facebook users with more friends feel greater pressure to conform when posting information to the platform. In fact, Rhue and Sundararajan (2014) show that users of a social shopping website will even alter their buying habits to conform to the comments they receive about previous purchases. Social surveillance thus has the potential to augment user behavior.

Social surveillance can also have implications for how users interact with each other online. Gross and Acquisti (2005) argue that online social networks breed a new kind of intimacy, in which users regularly share personal information widely and with many people. Lambert (2013) calls this new kind of intimacy "group intimacy," and suggests that it is replacing traditional notions of intimacy – which are more interpersonal in nature. Geser (2008) goes as far as saying that intimacy is completely destroyed in online settings, because users are discouraged from revealing information privately and selectively to their various contacts. As Gerstein (1984) points out, it is precisely these private disclosures of information that separate intimate relationships from more casual ones.

We follow Wilson et al. (2014) and take the view that users of online social networks carefully weigh concerns for privacy with those of impression management when disclosing information. Dinev and Hart (2006) call the weighing of costs and benefits in information exchange a "privacy calculus." We apply their insights to the context of gift giving, and show how social network theory helps us separate the costs to privacy from the benefits in impression management that result from digital gift exchange. We believe that gift exchange is a natural setting to study this tension because, as others have pointed out, gift giving itself can have both costs and benefits (Sherry et al. 1993, Wooten 2000) – as we discuss next. Moreover, because gift exchange is a relational act that takes place between people, studying it lets us focus on the effect of social surveillance on interpersonal intimacy in particular, rather than on behavior more generally.

2.1 Gift Giving in Social Networks

The decision to give a gift can put givers in an awkward place. On the one hand, giving a gift can make a giver look favorably in the eyes of the receiver. Mauss (1954) argues that gift exchange even puts the giver in a position of power over the receiver until the gift is reciprocated. On the other hand, gift selection and delivery can also generate substantial anxiety for the giver (Sherry et al. 1993, Wooten 2000). The source of anxiety can be around selecting the right gift, or breaking some norm around gift giving. For example, people may worry that by giving a gift to one person they are ignoring others that are equally deserving. People must thus weigh a variety of costs and benefits when deciding to participate in gift exchange. Since knowing more people provides more opportunities for the benefits of gift exchange to outweigh the costs, we propose the following hypothesis:

H1: People with larger social networks will be more likely to participate in gift exchange

The anxiety associated with gift giving may be exacerbated in settings where exchanges are visible to others. In such settings, more people may be present to witness a poor gifting decision, and there are more opportunities for comparisons of who did and did not receive a gift. The extent to which interactions between people are visible to others can be linked to structural properties of social networks. In particular, dense social networks – wherein people's friends are friends with each other – limit the extent to which interactions are private (Boissevain 1974, Portes 1998). Thus, we expect that people who form connections to friends of friends will be less likely to participate in gift exchange, for fear that their exchanges will be visible to third parties that are not directly involved in the exchange.

H2: People that have connected to friends of friends will be less likely to participate in gift exchange

From an individual's perspective, dense social networks can arise either because the individual connected to friends of friends, or because their friends connected to each other. We argue that only the former should affect gift exchange for two reasons. First, actively connecting to friends of friends makes the density of an individual's network more salient, and should more directly influence their perceptions of privacy. In fact, a user may never find out that two of their friends connected to each other. Second, in our setting, and in online social networks more broadly, a friend of a friend connection is often prompted by an algorithm, and may not exist in the absence of the algorithm. These connections are thus likely to be weaker, on average, and their surveillance is likely to be more disconcerting.

H3: Having friends connect to each other will not affect the likelihood of participating in gift exchange

Next, we test these hypotheses in the context of an online social network that lets users buy and exchange electronic greeting cards with each other.

3 Empirical Setting

The company in our study launched its online 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. To stimulate connections on the network, the company displayed a list of recommended contacts in a widget on the main page of the site with the heading "People you may know" (see Figure 2). When a user clicked on one of these recommendations, she received a prompt that allowed her to request a connection from the recommended contact. If she chose to request the connection, the contact received an email notification alerting him of the connection request and allowing him to accept the request – which would form a connection between the two users. The widget then refreshed to replace the requested contact with a new recommendation.

The company used an algorithm to generate a personalized list of recommendations for each user. This algorithm relied on two key pieces of data about users: 1) connections of their existing connections (i.e. friends of friends), and 2) people in their email address books. If a user had already formed connections, then the list of recommended contacts would largely consist of connections of those connections – ranked by the number of connections the user and the potential recommendation shared. However, the company also encouraged users to upload their email address books when signing up for the service. Users that uploaded their address books were prompted to send connection requests to their contacts during the sign-up process. Sometimes, these contacts would also appear in the recommendation widget.

A unique feature of this online social network is that users could send electronic greeting cards (eCards) to each other over the network. While a small sample of these eCards were provided free of charge, the company also offered users the option of buying an annual subscription to premium eCards for $12.95. The company even had an artist on staff who was responsible for designing these eCards.

Links to the company's eCard collection were found on various places on the site, and users who wished to send an eCard to one of their connections could simply click on any one of these links. After selecting an eCard,

Figure 2. The online social network with "People you may know" widget

users had the option of adding a personal message to the card before sending it off. Once sent, the eCard was displayed on the receiver's profile page.

Figure 3 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 receiver's 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. Next, we model the diffusion of the premium eCard service to relate eCard purchase to properties of users' social networks.

3.1 Modeling the Diffusion of eCards

To examine how properties of users' networks influenced their decisions to pay for premium eCards, we construct a discrete hazard model using a complementary log-log link function (Prentice and Gloeckler 1978, Bell and Song 2007, Katona et al. 2011). There are a number of advantages to using this model. First, estimates from it are also estimates from a continuous time proportional hazards model (Prentice and Gloeckler 1978). Second, the model is ideal for including time-varying covariates (Bell and Song 2007), which allows us to include several network measures that varied across time. Finally, Katona et al. (2011) also use this model to study the effects of network characteristics on diffusion, lending further support for its application in our setting.

We model the probability that user i buys a premium eCard subscription in period t, given that they have purchased a subscription at an earlier point in time, as

$$\mathrm{Prob}(\mathrm{P_i} = \mathrm{t} \mid \mathrm{P_i} \geq \mathrm{t}\,) = 1 - \exp\big(-\exp\big(\alpha + \beta \mathrm{X_i}(\mathrm{t})\big)\big)$$

$\mathrm{P_i}$ denotes the period that user i first purchases a premium eCard subscription. The right-hand side of the equation is the complementary log-log link function of the covariate vector $\mathrm{X_i}(\mathrm{t})$. This vector contained time-varying network measures as well as several control variables. Next, we discuss these network measures and controls in more detail.

3.2 Network Measures and Controls

Our first measure is the size of users' networks, which is simply the number of connections they had formed. The second and third measures capture the density of users' networks from connecting to friends of friends and having friends connect to each other, respectively. To construct these measures, we calculate

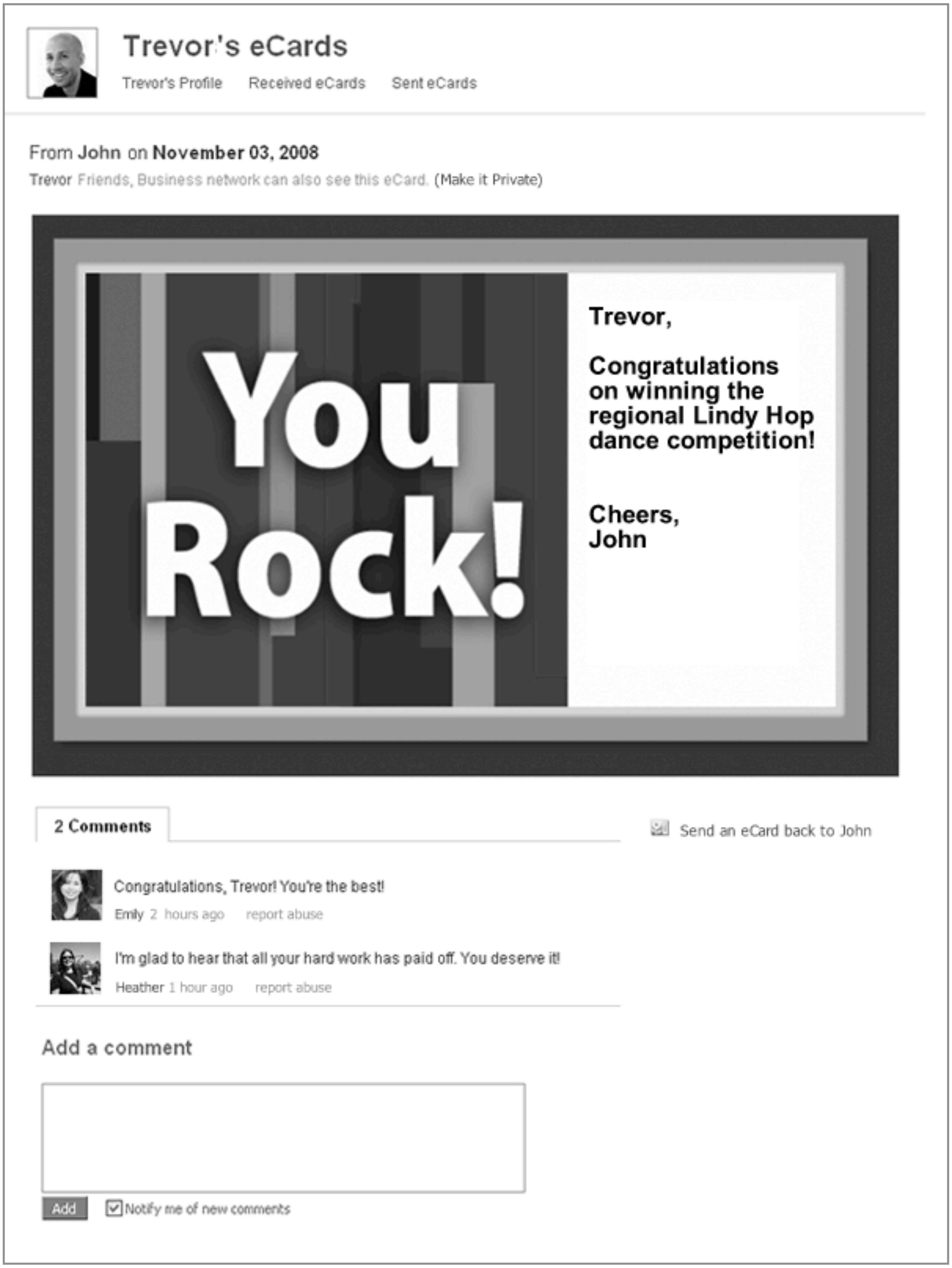

Figure 3. An eCard with third party comments

the clustering coefficient, which is the number of connections between one's contacts divided by the number of possible connections between them (Watts and Strogatz 1998). Like Jiang and Chen (2014), we use the timing of connection to break down the clustering coefficient into two separate measures. When users connected to friends of friends, then the last connection formed in the triad will be to one of their friends. On the other hand, when users' friends connected to each other, the last connection formed will be the connection between their friends (see Figure 4).

To estimate the effects of these measures on eCard purchase, we fix the network of connections at twelve points in time – every two months between November 1, 2007 and September 1, 2009. We use the measures on those days to predict eCard purchases in the following two months. In each period, we only consider the decisions of users that had at least two connections. This requirement ensures that our density measures are well-defined. We also only study the decisions of the 53,823 users that eventually purchased a premium eCard subscription, for two reasons. First, by restricting our analysis to those who eventually purchased, we study users for whom a subscription was actually a consideration. Second, there were nearly 7 million users of the network in total. It would be computationally taxing to calculate network measures and estimate our models for all of these users in all twelve periods.

We should note that, while we only study the purchase decisions of users who eventually purchased a premium eCard subscription, we include all of these users' connections when calculating the network measures. Table 1 shows summary statistics of the network measures by date. The average number of connections per user increased over time. Interestingly, both density measures also generally increased over time. This may seem somewhat surprising, since density might be expected to decrease as networks get larger. However, in our setting, one of the main drivers of connectivity was an algorithm that encouraged users to connect to friends of friends. We interpret the joint increases in network size and density as additional evidence for the algorithm.

In addition to our network measures, we also include several control variables when estimating our models. Table 2 provides a summary of these variables. We include an indicator for the user's gender, how many contacts they had in their email address book, and how many of those contacts were also users of the network. We also include indicators for each of the time periods in our study, which we interpret as baseline hazards in the absence of other covariates (Bell and Song 2007). We also include indicators for the period that users joined the network to account for differences between early and late adopters. Finally, we include indicators for the 175 countries that are represented in our dataset. Table 3 shows the most popular countries in our dataset, along with the number of users originating from each of these countries. Next, we discuss the results of estimating our model.

4 Results

We estimate five specifications of the complementary log-log model, which vary in the set of network measures we include. Table 4 displays parameter estimates from these different specifications. Across all of these models, females are more likely to buy a premium eCard subscription than males. When network measures are not included in Model 1, there is a significant negative effect of address book size but a positive effect of address book contacts who are themselves users of the social network. We find consistent support for the positive effect of social network connections across Models 2-4, lending support for our first hypothesis. When number of connections is included in the model, the effect of address book size is no longer significant and address book contacts who are also users have a negative effect.

Figure 4. Distinguishing connections to friends of friends from friends connecting

Date	Number of Users	Number of Connections		Density: Friend of a Friend		Density: Friends Connecting	
		Mean	Std. Dev.	Mean	Std. Dev	Mean	Std. Dev
1. Nov 1, 2007	2,742	9.7	19.1	.07	.22	.07	.21
2. Jan 1, 2008	13,652	13.9	31.4	.06	.16	.05	.15
3. Mar 1, 2008	20,415	15.8	33.7	.06	.16	.05	.14
4. May 1, 2008	25,845	16.9	34.8	.06	.16	.05	.14
5. July 1, 2008	32,211	18.2	35.4	.07	.17	.06	.15
6. Sep 1, 2008	40,257	23.2	42.0	.08	.17	.07	.15
7. Nov 1, 2008	45,153	27.4	50.0	.09	.17	.07	.14
8. Jan 1, 2009	48,141	30.6	58.2	.10	.17	.07	.13
9. Mar 1, 2009	50,434	33.4	65.0	.10	.17	.07	.13
10. May 1, 2009	52,199	35.5	69.1	.10	.16	.07	.12
11. July 1, 2009	53,186	36.8	71.8	.10	.16	.07	.12
12. Sep 1, 2009	53,823	38.0	74.4	.10	.16	.07	.12

Table 1. Summary Statistics of Key Variables by Date

Variable	Description
Gender Indicator	Indicator equal to 1 for females users
Email Contacts	Number of contacts in user's email address book
Email Users	Number of other users in user's email address book
Period Indicators	Indicators for period of study
Joined Indicators	Indicators for period user joined the network
Country Indicators	Indicators for country of origin

Table 2. Descriptions of Control Variables

Country	Number of Users	Country	Number of Users
United States	39,725	Denmark	638
United Kingdom	1,961	Brazil	573
Canada	1,300	South Africa	519
Netherlands	1,273	Norway	423
Australia	870	Germany	421
Belgium	680	France	414

Table 3. Most Popular Countries in the Dataset

In Model 3, we find a significant negative effect of density due to connecting to friends of friends, which supports our second hypothesis. Moreover, both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion point to this as the best model. In Model 4, we include the density due to users' friends connecting, which does not have a significant effect as our final hypothesis predicts. When all three network measures are included in Model 5, the direction and significance of their effects do not change. In the next section, we discuss a model that controls for unobserved heterogeneity by adding user-level random effects to our regression.

4.1 Models with Frailty

To control for unobserved heterogeneity, we model the probability that user i buys a premium eCard subscription in period t, given that she has not purchased one at an earlier point in time, as

$$\mathrm{Prob}(\mathrm{P_i} = \mathrm{t} | \mathrm{P_i} \geq \mathrm{t}\,) = 1 - \exp(-\exp(\alpha + \beta \mathrm{X_i}(\mathrm{t}) + \mathrm{u_i}))$$

where we assume that $\mathrm{u_i}$ ~ N(0, σ^2). These random effects vary by individual, and are sometime referred to as "frailty" in the context of hazard models (Jenkins 1995). We estimated our models from the previous section with the added frailty term, and we find similar results as before. Connections have a positive effect, while the effect of density from connecting to friends of friends is negative. We still find no support for an effect of density due to users' friends connecting to each other. While we do not report the estimates of this alternative specification here, they are available from the authors upon request.

	Model 1	Model 2	Model 3	Model 4	Model 5
Number of Connections		.0015***	.0015***	.0015***	.0015***
		(.0001)	(.0001)	(.0001)	(.0001)
Density: Friends of Friends			-.11***		-.11***
			(.03)		(.03)
Density: Friends Connecting				-.01	-.01
				(.04)	(.04)
Gender	.022**	.026**	.028**	.026**	.028**
	(.01)	(.01)	(.01)	(.01)	(.01)
Email Contacts	-.00001***	4.8×10^{-6}	4.0×10^{-6}	4.8×10^{-6}	3.9×10^{-6}
	(5×10^{-6})	(5×10^{-6})	(5×10^{-6})	(5×10^{-6})	(5×10^{-6})
Email Contact Users	.0002***	-.0002***	-.0002***	-.0002***	-.0002***
	(.00004)	(.00006)	(.00006)	(.00006)	(.00006)
Period Indicators	Included	Included	Included	Included	Included
Joined Indicators	Included	Included	Included	Included	Included

Country Indicators	Included	Included	Included	Included	Included
Observations	155,329	155,329	155,329	155,329	155,329
χ^2	8604.82	8727.06	8741.56	8727.16	8741.70
AIC	161,087	160,967	160,954	160,968	160,956
BIC	162,858	162,748	162,746	162,760	162,757

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are in parentheses.

Table 4. Complementary Log-Log Models

5 Conclusion

In this study, we demonstrate that social visibility deters users from sending digital greeting cards to each other over an online social network. Moreover, we argue that the algorithms which social media companies readily use to encourage connectivity can make users' interactions more visible to third parties – often to people with whom users would not necessarily connect in the absence of an algorithm. We use the timing of connections to separate the effects of density from users connecting to friends of friends and density from users' friends connecting to each other, and only find evidence for the former. These findings have implications for the success of digital gifting services, and for how algorithms shape our online interactions more broadly.

Facebook, the most popular online social network, has twice tried and failed to launch a service that lets its users send digital gifts to each other.[2] Our findings suggest that Facebook's People You May Know (PYMK) algorithm could have contributed to these failures. However, we also find that increasing the size of users' networks increases their propensity to buy gifts. Thus, it is not encouraging connectivity in general that can be harmful, but encouraging connections to friends of friends in particular. One implication of our findings is that companies need to be more strategic about the types of connections they recommend. Another implication is that companies should be wary of showing interactions between users to third parties. Facebook may already know this, as its News Feed algorithm now regularly hides interactions between users' friends (Eslami et al. 2015).

Our study has a number of limitations that are worth discussing. First, we constrain our analysis to users who eventually purchased a premium eCard subscription. Our results are thus best interpreted as reflecting the timing of purchase rather than the decision to purchase. For example, we find that users with more connections purchased an eCard subscription earlier than those with fewer connections, and that users that connected to friends of friends purchased an eCard subscription later than those who did not. An equally interesting question is what distinguishes users that chose to buy a subscription from those that did not, and we leave this question for future research. Second, we do not have data about the actual exchange of eCards, but only about purchases of an eCard subscription. Thus, what we measure is the intention to send gifts. An important consideration is the extent to which intentions to give gifts translate into actual gift exchange. This, too, we leave for future research.

Algorithms will continue to shape our lives for the foreseeable future. At times, they will enrich them, like by pointing us to books and movies that we love and would never know about otherwise. At other times, they will frustrate and even offend us, like by telling us that our names are not real names.[3] In either case, as researchers we have an obligation to reveal the effects that these hidden processes have on people's lives (Pasquale 2015). For some good (and possibly some bad) reasons, companies will likely continue to err on the side of keeping their algorithms secret. However, our study makes the case that there can be unintended consequences of algorithms that are unknown even to the very companies that design them. Moreover, these unintended consequences can hurt these companies, as we suggest was the case with Facebook's failed gifting services. Companies could benefit from providing greater

[2] See http://techcrunch.com/2014/07/29/an-obituary-for-facebook-gifts/, viewed January 31, 2016
[3] In 2015, Facebook suspended Native Americans, drag queens, and domestic abuse survivors from their accounts for not providing their "real name." See http://www.theguardian.com/technology/2015/feb/19/native-american-activist-facebook-lawsuit-real-name, viewed January 31, 2016

transparency into these processes, especially to the academic community. In any case, society would surely benefit.

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