

# Chapter 8

## The Co-evolution of Social Network Ties and Online Privacy Behavior

Kevin Lewis

### 8.1 Introduction

What is the nature of personal privacy in an increasingly digital world? To what extent should we foster greater information exchange among the public at large, versus protect the ability to limit disclosure to the people of one's choosing? And to what extent do people say they care about either? Previous research on online privacy has predominantly been concerned with questions such as these. Noticeably absent, however, has been research examining actual online privacy behavior and its causes. In other words, regardless of whether people *say* they care about online privacy – and regardless of whether they *should* care about online privacy – given the option to disclose more information or less, what factors are predictive of the actual privacy decision that people make?

In this chapter, I use a new longitudinal dataset combined with recent developments in network modeling to examine the co-evolution of college students' friendships and privacy behavior on Facebook. In contrast to past research approaching the subject from theoretical, ethical, or attitudinal perspectives, I take a behavioral approach to the study of online privacy – one grounded in insights from social network analysis. Researchers have long been interested in understanding how friendships evolve among college students (e.g., Newcomb 1961), and increasingly this work has been extended to the online sphere (e.g., Kossinets and Watts 2009; Mayer and Puller 2008; Wimmer and Lewis 2010). At the same time, given the unprecedented global popularity of Facebook on one hand, and media attention regarding its privacy measures on the other, the topic of Facebook and privacy has recently attracted the attention of academic research as well (Debatin et al. 2009). To date, however, no one has examined the interconnectedness of these two topics: How does social network evolution among college students depend on their privacy

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K. Lewis (✉)  
Harvard University, Cambridge, MA, USA  
e-mail: [kmlewis@fas.harvard.edu](mailto:kmlewis@fas.harvard.edu)

behavior; and how does privacy behavior among college students depend on their social networks?

In the following sections, I first briefly review current findings regarding online privacy behavior and its causes. Next, I sketch seven theoretical mechanisms that we can expect to influence changes in students' network ties on one hand, and privacy settings on the other. I then describe the dataset and methodological tool used in this study; present results from statistical models of the co-evolution of network ties and privacy settings; and conclude with an interpretation of findings, a summary of the limitations of these analyses, and suggestions for future research.

## 8.2 Previous Research

In the voluminous literature on online privacy, there have been remarkably few published studies on the topic of online privacy behavior; and what research has been published is almost exclusively based on self-report rather than natural observation. Debatin et al. (2009), for instance, found a general disconnect between users' understanding of privacy issues and their willingness to upload large amounts of personal information. However, respondents also claimed to be more likely to change their privacy settings if they had personally experienced a privacy invasion. Tufekci (2008) similarly found little to no relationship between college students' online privacy concerns and information disclosure, while Youn and Hall (2008) examined the relationship between gender and privacy protection behaviors – both using survey data. Finally, Livingstone (2008) used interviews to explore teenagers' use of social networking sites for intimacy, privacy, and self-expression.

In a previous analysis of the dataset used in this study, Lewis et al. (2008) examined the predictors of college students having a private versus a public profile on Facebook. They found that women were more likely to have a private profile than men; that having a private profile is associated with a greater degree of online activity; and that students who have a private profile are characterized by distinct cultural tastes. They also found that students were more likely to have a private profile if their Facebook friends and, especially, their roommates also had private profiles – but due to the cross-sectional nature of the analyses, conclusions about causality were tentative.

Researchers have identified the importance of approaching privacy from a behavioral perspective – particularly as it follows (or fails to follow) from users' privacy-related beliefs or prior experiences. However, most studies are based on self-report rather than actually observed behavior. Further, what little work exists has been largely concerned with assessing the relationship between privacy behavior and one additional variable, rather than modeling this behavior as the outcome of several possible processes; and the one paper exploring actual privacy behavior in a multivariate framework has been unable to make strict causal inferences about privacy behavior as cause or consequence. This is the gap in the literature that the current chapter aims to address.

### 8.3 Mechanisms of Network and Behavioral Change

In recent years – and corresponding with the development of new longitudinal datasets as well as analytical tools for modeling longitudinal network data – tremendous advances have been made in our understanding of how social networks evolve over time. In an important review article, Rivera et al. (2010) document three types of mechanisms, or causal factors, that can account for the development and persistence of a network tie between two people. Less work has been published on the dependence of behavioral change on one’s network environment, but this is quickly changing. Below, I organize this research into a framework of seven types of mechanisms that can be used to understand the joint evolution of social network ties on one hand, and online privacy behavior on the other.

#### 8.3.1 *Network Dynamics*

##### 8.3.1.1 Relational Mechanisms

The first type of mechanism that Rivera et al. (2010) describe has to do with the impact of current relationships on the formation of new ties. These effects have nothing to do with characteristics of the particular individuals involved – but rather their location in a broader landscape of relations. One of the most widely-documented regularities in social networks is the tendency for friends-of-friends to become friends, or for individuals to “close triangles” in networks. This is because I am much more likely to meet the friends-of-friends than I am to meet other strangers (because, for instance, our shared acquaintance may invite us both to a party), and also because I am much more likely to feel positively towards these people for reasons of structural balance (Davis 1963; Kossinets and Watts 2009). Another regularity is the tendency for people with large networks to accumulate friendships at a faster rate than do people with smaller networks – both because a larger baseline network may be reflective of a more sociable personality, and because “popularity” is attractive to other individuals (cf. Snijders et al. 2010). Finally, every social network is characterized by a particular “density,” or baseline tendency for a tie to be present versus absent. Networks of acquaintances, for instance, will naturally have many more ties than networks of close confidants – and unless one controls for this tendency, it will be impossible to pinpoint the contribution of other causal factors.

##### 8.3.1.2 Assortative Mechanisms

A second fundamental determinant of network evolution is the principle of “like attracts like” or “birds of a feather flock together” – often called homophily

(McPherson et al. 2001). Homophily has been studied with respect to a wide variety of attributes, though racial background is typically held to be the most divisive feature of American social networks (but see Wimmer and Lewis 2010). Social networks are also often segregated according to socioeconomic status (Marsden 1988) and gender (Marsden 1987).<sup>1</sup>

### 8.3.1.3 Proximity Mechanisms

The third set of mechanisms involves the focused organization of social interaction, and amounts to the simple fact that people will be more likely to meet and become friends with others who live, work, or otherwise spend time in the same place (Feld 1981). Among college students in particular, propinquity in living arrangements – e.g., sharing the same residence – has been shown to be one of the most powerful determinants of who befriends whom. Sharing an academic major can at times be equally consequential, given that students are more likely to take classes and study with those in their major (Marmaros and Sacerdote 2006; Mayer and Puller 2008; Wimmer and Lewis 2010).

### 8.3.1.4 Privacy Mechanisms

Finally, independent of the above three mechanisms, network evolution can also depend on students' privacy behavior in two basic ways. On one hand, students with a private profile may have a greater or lesser tendency to form ties overall, leading to a larger or smaller overall network size than the average student. Comparable to what others (Goodreau et al. 2009; Wimmer and Lewis 2010) have called a "sociality" effect, students with private profiles – whose personal information is hence blocked by default to all non-friends – may tend to extend or receive a larger number of friend requests precisely because this is the only way others may view their information. An opposite effect could also occur, whereby the activation of privacy settings precedes a general conservatism about extending and accepting friend requests and hence leads to students with private profiles forming fewer ties overall. In both cases, I refer to this as a "main effect" of privacy behavior on tie formation (cf. Snijders et al. 2010).

On the other hand, much like the assortative mechanisms above, students may self-segregate not on the basis of demographic characteristics but on the basis of privacy behavior itself. In other words, alongside the tendency to befriend students of the same racial or socioeconomic background, students may display an affinity with others who share their perspective on information disclosure – students with

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<sup>1</sup>It is also possible that individuals self-segregate based on structural position – people with many ties befriending other people with many ties, and people with few ties befriending other people with few ties (Newman 2002). Such "degree-based" assortative mixing is not considered here.

public profiles seeking out others with public profiles, and students with private profiles seeking out others with private profiles. In both cases, I refer to this as a “similarity effect” of privacy behavior on tie formation (cf. Steglich et al. 2010).

### **8.3.2 Behavior Dynamics**

#### **8.3.2.1 Exogenous Mechanisms**

Of all possible explanations for a shift in a given student’s privacy behavior, perhaps the most plausible has nothing to do with the student at all. In other words, before considering mechanisms that involve the unique situation of particular students, it is important to account for exposure to “external” events or conditions that affect all students equally and may spur a general change in privacy behavior across the population. Such conditions are not hard to imagine: an incident occurs in the college community that increases general awareness about privacy, or perhaps a newspaper article is published to the same effect. Such a change may also be an effect of the website itself – e.g., Facebook alters the ease with which a private profile may be activated – or an “external” effect of time – e.g., students approaching graduation may be more likely to switch to a private profile to avoid the scrutiny of potential employers. In any case, unless one has specific data on such externalities – or particular reason to believe that some students would be more or less susceptible to their effects than others – such effects may be subsumed under a general “baseline tendency” mechanism representing the baseline likelihood of a student adopting a private profile, all else being equal.<sup>2</sup>

#### **8.3.2.2 Associational Mechanisms**

Researchers have long documented the effects of “peer influence” with respect to a wide variety of characteristics and behaviors. Much work, both popular and academic, has addressed the diffusion of ideas, innovations, and trends throughout the population or even the globe (Gladwell 2002; Kaufman and Patterson 2005; Rogers 2003). Other research has focused specifically on interpersonal influence with respect to drug use (Kandel 1978), smoking (Mercken et al. 2010), music tastes (Steglich et al. 2006), and a variety of other (often health-related) outcomes (Smith and Christakis 2008). Each of these findings stems from a fundamental insight of social science: that our behavior depends intimately on the behavior of those with whom we associate. The implication for a longitudinal study of privacy behavior is

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<sup>2</sup>In stochastic actor-based modeling, one typically also controls for potential curvilinearity in this tendency by including a quadratic term. This is unnecessary here because the behavioral variable is dichotomous.

clear. Above and beyond any tendency to adopt a private profile as a result of external factors, students who are friends with other students who have a private profile may become additionally sensitive to privacy concerns themselves; meanwhile, students who are friends with other students who have a public profile may be less likely to be the sole person to deviate from this norm.

### 8.3.2.3 Structural Mechanisms

Finally, there are reasons to expect that one's structural position in a social network – irrespective of the specific people to whom one is connected – will have an independent effect on the likelihood of adopting a private versus public profile. One measure commonly emphasized in the networks literature is degree centrality. Sometimes called “neighborhood size,” degree centrality refers to one's total quantity of direct network connections (Freeman 1978). While peer influence has to do with the specific people one associates with, then, “degree” effects stem only from having a larger versus smaller friend network. In the context of privacy behavior, students with larger social networks may be particularly informed about public concern regarding online safety. Students with a large social network may also feel as though the costs of a private profile in terms of information sharing are relatively low (because relatively more people will still be able to see their information anyway); although students with a small overall network may be closer, in turn, with each of these friends, and therefore more content to share information only with them and no one else.

### 8.3.3 Summary

What are the determinants of online privacy behavior among college students? In particular, what is the relationship between college students' online privacy behavior and college students' social network ties? Above, I outlined four general categories of factors that may influence students' friendship choices – relational mechanisms, assortative mechanisms, proximity mechanisms, and privacy mechanisms – and three categories of factors that may simultaneously influence students' privacy behavior – exogenous mechanisms, associational mechanisms, and structural mechanisms. In order to pinpoint the contribution of each of these categories of factors to observed network and behavioral change, it is analytically necessary to control for all of them: Firstly, because two very different mechanisms may produce effects that are otherwise indistinguishable; and secondly, because otherwise it is impossible to disentangle the direction of causality. In particular, if students with private profiles are found to have larger or smaller networks, is this a “main effect” of privacy behavior on network activity, or a “degree effect” of network position on privacy behavior? And if students are found to cluster together according to privacy setting, is this because these students seek each other out (“similarity effect”) or because privacy behavior “spreads” among peers

(“peer influence”)? It is therefore only with appropriately sophisticated modeling tools – combined with fine-grained, longitudinal data on students’ networks and privacy behavior – that such questions can be answered.

## 8.4 Data and Methods

### 8.4.1 *The “Tastes, Ties, and Time” Dataset*

Data for these analyses are drawn from the “Tastes, ties, and time” social network dataset (Lewis et al. 2008). Together with colleagues – and with permission from both Facebook and the college in question – I downloaded longitudinal profile and friendship data for the class of 2009 at an American private college ( $N = 1640$  at wave 1). Students were located on Facebook using an official class roster with all students’ names and e-mail addresses, though the data were immediately stripped of all identifiers. Data draws took place once a year for 4 years, in March of 2006, 2007, 2008, and 2009 – such that we could view the evolution of students’ social networks and profile data over the 4 years of college. For the purpose of the following analyses, I restrict attention to those 876 students who (1) were members of the study cohort for all 4 years (i.e., they did not transfer in or out) and (2) had publicly available data on Facebook friendships for all 4 years (i.e., they did not set their Facebook friend data to “private”).<sup>3</sup> While procedures for dealing with missing data in longitudinal network studies are available (Huisman and Steglich 2008), given that the central question of this study relates to the interrelatedness between network ties and privacy behavior – and further, that stable model estimation generally relies on having no more than about 20% missing data (Snijders et al. 2008), but 27% of students have missing network data in wave 4 alone – I chose instead to only include students with public Facebook friendship data for all 4 years. While practically motivated, this decision has the unfortunate consequence that those students who arguably disclosed the least – i.e., who hid both profile and network data from non-friends – are not considered.<sup>4</sup>

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<sup>3</sup>Because it is not possible to distinguish between a student who is not on Facebook and a student who is on Facebook but has hidden herself from searches, I first restricted attention to only those students who could be located on Facebook for all 4 years. Of the 1,421 students who remained in the study cohort for all 4 years, 1,272 (89.5%) met this criterion. The remaining 396 students who were dropped from my analyses were active on Facebook for all 4 years, but did not have available network data for at least one year. Comparing these 396 students with the final population of 876, dropped students were significantly more likely to have a private profile in every wave – creating some risk of selection bias – and significantly more likely to be Asian. Otherwise, however, the two samples were statistically indistinguishable with respect to gender, race, and socioeconomic status.

<sup>4</sup>An alternative approach would have been to simply maximize the available data for each transition period separately (see below). However, this would have the undesirable consequence

In the analyses that follow, the central network variable is the presence or absence of a Facebook friendship between two students, and the central behavioral variable is whether each student maintained a public or a private profile at the time of the data draw.<sup>5</sup> Data on housing assignments and academic majors were provided by the college. Gender was coded based on self-report; racial background was coded based on online photos and any listed affiliations with Facebook groups or college organizations signaling race/ethnicity; and socioeconomic status was coded using the median household income of each student’s “hometown” ZIP Code Tabulation Area based on the 2000 Census (coded as missing data in the event of a private profile for all 4 years).

### 8.4.2 Stochastic Actor-Based Modeling

Stochastic actor-based models were designed to overcome prior limitations in the joint analysis of networks and behavior, and in particular disentangling social selection versus peer influence. In short, these models respect the network dependence of actors; account for alternative possible mechanisms of network and behavioral change; and model the co-evolution of social networks and individual behaviors in continuous time (Steglich et al. 2010).

An accessible introduction to stochastic actor-based models is available in Snijders et al. (2010). Here, it is sufficient to note that the heart of these models consists of two “objective functions” – one for changes in dyadic network ties, and one for changes in individual behavior – that represent the short term “objectives” that each actor will probabilistically pursue. The function  $f_i^X(\beta, x, z) = \sum_k \beta_k^X s_{ki}^X(x, z)$  represents the network component of this function for actor  $i$  given  $x$  state of the network, where effects  $s_{ki}^X(x, z)$  correspond to the various mechanisms for network dynamics described above and weights  $\beta_k^X$  are effect strengths. Similarly, the function  $f_i^Z(\beta, x, z) = \sum_k \beta_k^Z s_{ki}^Z(x, z)$  represents the behavioral component of this function, where effects  $s_{ki}^Z(x, z)$  represent the different mechanisms for behavioral dynamics described above and  $\beta_k^Z$  are effect strengths. In short, the

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that results could no longer be compared over time, because each model would be estimated over a slightly different subset of students.

<sup>5</sup>It is important to note that this dataset was not compiled with the intention of studying privacy behavior, and hence some distortion in the central behavioral dependent variable was introduced insofar as research assistants were recruited from the college of study. Consequently, an unknown minority of students in the study population may have falsely appeared to have “public” profiles if they happened to be Facebook friends with the specific research assistant assigned to download their profiles. However, because research assistant assignments were random, this scenario would only be more likely to have occurred the more Facebook friends the given student had; and therefore the “degree effect” of Facebook friendships on privacy behavior can be expected to capture (and control for) much of this variation.

strength of these models is that they are able to pinpoint the precise contribution of a number of distinct mechanisms to both network and behavioral change, each while controlling for all of the others.

Previous applications of stochastic actor-based models have primarily focused on adolescent substance use (Mercken et al. 2010; Steglich et al. 2010) as well as visible versus non-visible attributes (de Klepper et al. 2010). These models have yet to be applied to the topic of online social network ties and online behavior of any sort.

### ***8.4.3 Model Specification and Interpretation***

At the end of their freshman year, each student at the college was randomly assigned to one of 12 upper-class residences where the student would live during her sophomore through senior years. These residences fall naturally into four “neighborhoods,” each containing three residences in relatively close proximity – though the size, individual character, and physical arrangement of each neighborhood varies (neighborhood 1, for instance, is slightly smaller and more geographically isolated from the main campus than the other three). In order to consider possible variation of model parameters across these sub-populations, all results are presented separately for each neighborhood. In order to capture variation in the importance of the various mechanisms over time, results are also presented separately for each “transition period” that was observed: wave 1 to wave 2 (period 1), wave 2 to wave 3 (period 2), and wave 3 to wave 4 (period 3).<sup>6</sup>

Each model contains two distinct components: a set of terms related to network dynamics, and a set of terms related to behavior dynamics. Table 8.1 presents a summary of the mechanisms described above as well as the specific model terms that correspond to each mechanism. Also included are two “rate parameters” that refer, respectively, to the average number of opportunities each student receives to change a network tie and change privacy settings in the given transition period. Interpretation of parameters varies depending on the specific term in question; but in general, a positive and significant “network dynamics” coefficient means that the given mechanism plays a significant role in the evolution of network ties while a positive and significant “behavior dynamics” coefficient means that the given mechanism plays a significant role in the evolution of privacy settings. Negative and significant coefficients indicate that the mechanism is consequential but in the opposite direction.

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<sup>6</sup>The average within-neighborhood density at wave 1 is 0.076, compared to an average across-neighborhood density of 0.059. At wave 2, these numbers are 0.124 and 0.080 respectively; at wave 3, 0.150 and 0.091; and at wave 4, 0.166 and 0.100.

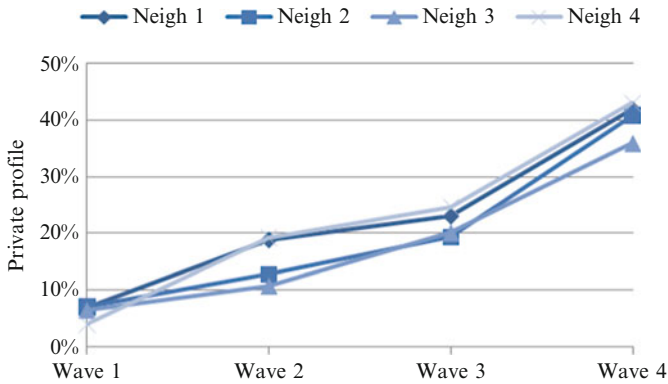
**Table 8.1** Summary of mechanisms and corresponding model terms

<b>Network dynamics</b>	
1. Rate parameter	Rate at which students receive the opportunity to change a network tie
<i>Relational mechanisms</i>	
2. Density	Overall tendency for ties to be present
3. Triadic closure	Tendency for A and B to become friends if A and B are both friends with C
4. Degree accumulation	Tendency for popular students to become more popular <sup>a</sup>
<i>Assortative mechanisms</i>	
5. Gender homophily	Tendency for males to befriend males and females to befriend females
6. Racial homophily	Tendency for students from the same racial background to become friends
7. Socioeconomic homophily	Tendency for students with similar SES to become friends
<i>Proximity mechanisms</i>	
8. Shared residence	Tendency for students who live in the same residence to become friends
9. Shared major	Tendency for students who share the same major to become friends
<i>Privacy mechanisms</i>	
10. Privacy main effect	Tendency for students with a private profile to form more friendships overall <sup>a</sup>
11. Privacy similarity effect	Tendency for students with the same privacy setting to become friends
<b>Behavior dynamics</b>	
12. Rate parameter	Rate at which students receive the opportunity to change privacy settings
<i>Exogenous mechanism</i>	
13. Baseline tendency	Baseline tendency to adopt a private profile
<i>Associational mechanism</i>	
14. Peer influence	Tendency to adopt the privacy behavior of one's friends
<i>Structural mechanism</i>	
15. Degree	Tendency for popular students to have a private profile

<sup>a</sup>Because Facebook friendships are undirected, it is impossible to determine whether this is because popular students/students with a private profile initiate more friendship requests or receive more friendship requests

## 8.5 Results

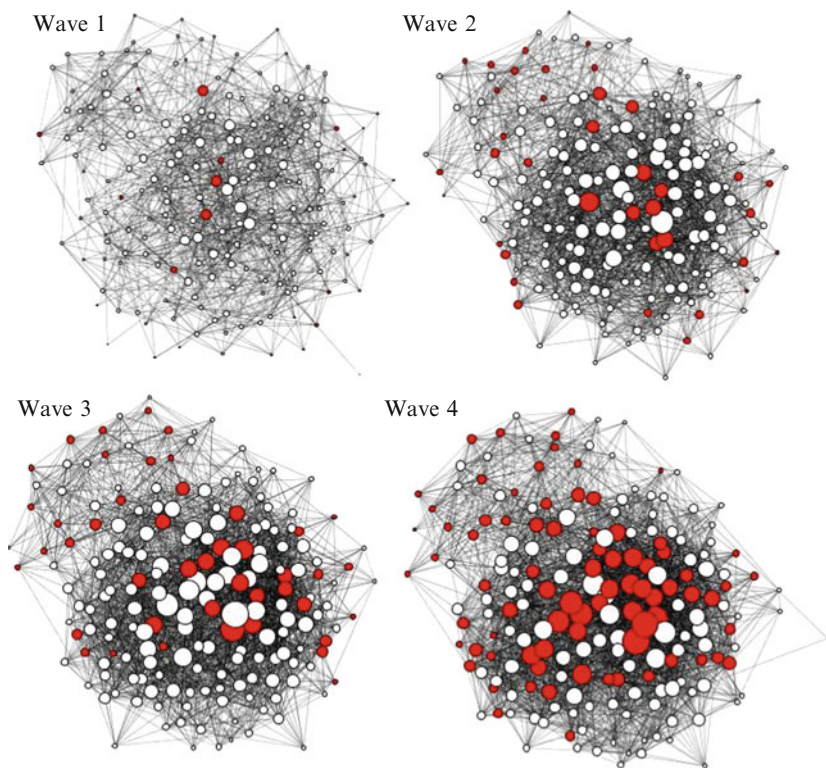
From March 2006 through March 2009, and in each of the four neighborhoods, we see a pronounced trend towards more students adopting a private profile over time (Fig. 8.1). At wave 1, a mere 53 students (6.1% of the study population) had a private profile. This number increases to 133 students (15.2%) at wave 2, 190 students (21.7%) at wave 3, and 353 students (40.3%) at wave 4. While a minority of students in each transition period shifted their privacy settings from “private” back to “public,” the vast majority of change was in the opposite direction (Table 8.2). These trends were roughly consistent in all four neighborhoods, though



**Fig. 8.1** Percentage of students with a private profile in each of four residential neighborhoods

**Table 8.2** Descriptive statistics of changes in network structure and privacy behavior

	Network structure							
	Wave 1	Period 1	Wave 2	Period 2	Wave 3	Period 3	Wave 4	
<i>Network density</i>								
Neigh 1	0.073		0.132		0.162		0.177	
Neigh 2	0.070		0.118		0.142		0.161	
Neigh 3	0.075		0.116		0.137		0.151	
Neigh 4	0.086		0.130		0.157		0.173	
<i>Ties created</i>								
Neigh 1		1088		552		324		
Neigh 2		1280		644		516		
Neigh 3		1159		560		414		
Neigh 4		1155		689		451		
<i>Ties dissolved</i>								
Neigh 1		25		9		44		
Neigh 2		31		37		21		
Neigh 3		36		13		27		
Neigh 4		71		26		62		
	Privacy behavior							
	Wave 1	Period 1	Wave 2	Period 2	Wave 3	Period 3	Wave 4	
<i>Proportion private</i>								
Neigh 1	0.068		0.188		0.230		0.419	
Neigh 2	0.070		0.127		0.193		0.408	
Neigh 3	0.064		0.107		0.201		0.359	
Neigh 4	0.040		0.193		0.247		0.430	
<i>Public to private</i>								
Neigh 1		25		21		39		
Neigh 2		19		25		51		
Neigh 3		19		28		41		
Neigh 4		36		27		45		
<i>Private to public</i>								
Neigh 1		2		13		3		
Neigh 2		6		10		2		
Neigh 3		9		6		4		
Neigh 4		2		15		4		



**Fig. 8.2** Evolution of Facebook friendships and privacy settings in a single residential neighborhood (Neigh 1,  $N = 191$ ). Nodes represent *students*, and lines represent *Facebook friendships*. Shaded nodes correspond to students with private profiles; node size is proportionate to degree centrality (i.e., larger nodes have more friends). Visualizations were generated using SoNIA (<http://sonia.stanford.edu>)

students in neighborhoods 1 and 4 (the smallest neighborhoods) displayed a slightly greater overall tendency to adopt a private profile than did students in neighborhoods 2 and 3.

The evolution of privacy behavior can also be visualized a second way, which provides greater insight into the possible interdependence between students' friendship decisions and privacy behavior. Figure 8.2 presents "snapshots" of students' social ties and privacy settings in neighborhood 1 at each of the four waves of observation. In general, we see both a gradual increase in network density (the quantity of ties present) over time, and also a gradual change in privacy behavior as more and more students adopt a private profile. There is also some evidence of clustering according to privacy settings, and a possible tendency – particularly visible at wave 4 – for students with many friends to have a private profile. Statistical models are required to identify the significance of these effects, and also to effectively disentangle the direction of causality between networks and behavior.

### 8.5.1 Network Dynamics

Results for stochastic actor-based models of Facebook friendships and privacy behavior are presented in Table 8.3. All models were estimated using Siena version 3.18 (Snijders et al. 2008). Given that results are distributed across 12 distinct models (three transition periods for each of four neighborhoods) – each with 15 terms – it is helpful to focus on patterns rather than individual coefficients, and to discuss the network and behavior components of the models separately.<sup>7</sup>

Most consistently, I find robust effects of triadic closure and shared residence for every neighborhood in every transition period. In other words, the two most dominant forces shaping the evolution of students' Facebook friendships is the tendency to become (and remain) friends with one's friends' friends, and to become (and remain) friends with other students who share the same dorm – what could be thought of as social and physical propinquity respectively (cf. Kossinets and Watts 2009).<sup>8</sup> There is also a tendency for Facebook friendships to be relatively sparse overall (i.e., less than half of possible ties are actually present), and for students to befriend others who share the same academic major, given that the “density” (negative) and “shared major” (positive) terms are significant in all but two models. Interestingly, students with relatively many Facebook friendships during period 1 are actually *less* likely to acquire additional friendships (negative, significant “degree accumulation” term for all neighborhoods); and the importance of racial homophily varies according to both neighborhood and period (always significant for neighborhood 3, significant for nearly all neighborhoods in period 3, two neighborhoods in period 1, and only one neighborhood in period 2). Gender homophily does not appear to play a positive role in the evolution of Facebook friendships, although this term is negative and significant for two neighborhoods in period two, suggesting that men and women become friends at a particularly high rate. Finally, socioeconomic homophily is positive and significant only for neighborhood 1 in periods 1 and 2.

With respect to the focal privacy-related mechanisms of this chapter, I find that – even after controlling for all of the effects described above – students' privacy

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<sup>7</sup>All models were estimated using Siena's unconditional moment estimation and the “initiative/confirmation” model type for undirected networks (Snijders et al. 2008; see also van de Bunt and Groenewegen 2007). This model type essentially simulates the process whereby Facebook friendships are actually created and dissolved: a tie is created if and only if one student “requests” a friendship and the other student then “accepts,” while a friendship can be terminated by either student. All models were run using five phase two subphases and 1,000 phase three iterations. Model convergence was in all cases excellent: the t-ratios for all parameters were less than 0.1 in absolute value.

<sup>8</sup>Technically, positive “network dynamics” coefficients refer to both the tendency for new ties to form *and* the tendency for old ties to be maintained; while negative coefficients refer to both the tendency for new ties *not* to form and the tendency for old ties to be *deleted*. Because friendship deletion is very rare in this network, however (Table 8.2), I focus only on the case of new tie formation for the remainder of my interpretation of results.

**Table 8.3** Model results for co-evolution of Facebook friendships and privacy behavior

	Period 1				Period 2				Period 3			
	Neigh 1	Neigh 2	Neigh 3	Neigh 4	Neigh 1	Neigh 2	Neigh 3	Neigh 4	Neigh 1	Neigh 2	Neigh 3	Neigh 4
	<i>Network dynamics</i>											
Rate	8.346	8.268	7.825	9.164	3.741	4.545	3.249	4.508	3.019	3.225	2.798	3.686
Density	<b>-0.633*</b>	<b>-0.716*</b>	<b>-0.714*</b>	-0.754	-0.521	<b>-0.720*</b>	<b>-0.790*</b>	<b>-0.396*</b>	<b>-0.857*</b>	<b>-0.791*</b>	<b>-0.948*</b>	<b>-0.920*</b>
Triadic closure	<b>0.354*</b>	<b>0.367*</b>	<b>0.280*</b>	<b>0.244*</b>	<b>0.256*</b>	<b>0.201*</b>	<b>0.225*</b>	<b>0.204*</b>	<b>0.209*</b>	<b>0.194*</b>	<b>0.178*</b>	<b>0.136*</b>
Degree accumulation	<b>-0.006*</b>	<b>-0.005*</b>	<b>-0.002*</b>	<b>-0.004*</b>	<b>-0.003*</b>	<b>-0.001*</b>	0.001	<b>-0.007*</b>	<b>-0.012*</b>	-0.001	-0.001	-0.002
Gender homophily	0.017	0.057	0.008	0.042	<b>-0.205*</b>	0.044	0.033	<b>-0.229*</b>	0.087	-0.110	-0.093	-0.002
Racial homophily	0.063	<b>0.201*</b>	<b>0.277*</b>	0.003	0.096	-0.058	<b>0.314*</b>	0.190	<b>0.193*</b>	<b>0.229*</b>	<b>0.344*</b>	-0.068
Socioeconomic homophily	<b>0.911*</b>	0.204	-0.046	0.351	<b>0.971*</b>	-0.119	<b>-0.654*</b>	0.611	0.371	0.102	-0.084	0.418
Shared residence	<b>1.054*</b>	<b>0.909*</b>	<b>0.806*</b>	<b>0.648*</b>	<b>0.964*</b>	<b>0.808*</b>	<b>0.894*</b>	<b>0.817*</b>	<b>0.528*</b>	<b>1.004*</b>	<b>0.787*</b>	<b>0.756*</b>
Shared major	<b>0.575*</b>	<b>0.825*</b>	<b>0.602*</b>	<b>0.448*</b>	<b>0.660*</b>	<b>0.806*</b>	<b>1.019*</b>	<b>0.557*</b>	0.224	<b>0.581*</b>	0.340	<b>0.485*</b>
Privacy main effect	-0.099	<b>0.770*</b>	0.026	<b>0.822*</b>	0.001	-0.766	0.125	-0.146	0.311	<b>-0.652*</b>	-0.128	-0.140
Privacy similarity effect	-0.270	<b>0.683*</b>	0.158	0.163	0.113	-0.029	0.408	-0.038	-0.173	0.211	0.075	0.185
<i>Behavior dynamics</i>												
Rate	0.356	0.689	1.174	0.502	0.727	0.646	0.471	0.726	0.376	0.396	0.348	0.466
Baseline tendency	<b>5.222*</b>	-1.351	-0.021	1.073	-0.038	-0.438	2.150	0.919	<b>-10.740*</b>	0.460	-0.095	1.019
Peer influence	<b>5.245*</b>	2.037	2.875	1.953	2.634	1.617	1.085	<b>4.153*</b>	-7.094	0.281	0.968	<b>4.406*</b>
Degree	<b>-0.078*</b>	<b>0.060*</b>	<b>0.017*</b>	0.003	0.016	0.015	<b>-0.072*</b>	0.012	0.500 <sup>a</sup>	0.043	0.052	0.045

Note: Significant coefficients in bold.  $N = 191$  for Neigh 1,  $N = 228$  for Neigh 2,  $N = 234$  for Neigh 3, and  $N = 223$  for Neigh 4. To test that the rate parameters are not zero is meaningless, because if the rate parameters were zero we would observe no network or behavioral change between waves

<sup>a</sup>“Degree” parameter (Neigh 1, Period 3) fixed at this value in order to obtain model convergence

\*  $p < .05$

behavior plays an independent causal role in the evolution of their social network ties. Firstly, in period 1 and for two out of the four neighborhoods (neighborhoods 2 and 4), students with private profiles are actually more likely to create and maintain friendships than are their peers with public profiles (positive and significant “privacy main effect”). Between their freshman and sophomore years, then, these students either initiate a significantly greater number of new friendships or receive more friendship requests, on average, than do students with public profiles. This pattern actually reverses itself for students in neighborhood 2, however, in the time between their junior and senior years: during this time period, students with private profiles are less likely to initiate (or receive) new ties (negative and significant “privacy main effect”). Finally, to the extent to which students who are friends tend to share the same privacy behavior, there is only scant evidence that this results from a process of social selection whereby students with similar privacy settings seek one another out to become friends: the effect of “privacy similarity” on network dynamics is significant only for neighborhood 2, and only in period 1.

### **8.5.2 Behavior Dynamics**

In the behavioral dynamics section of the model, we see that each of the mechanisms of behavioral change contributes in some way to the evolution of privacy behavior in this population – though effects again vary depending on neighborhood and transition period. In neighborhood 4, the sole significant determinant of privacy dynamics is peer influence: students in this neighborhood are significantly likely to assimilate to the privacy behavior of their peers during the second and third transition periods. In other words, students tend to adopt and maintain the average privacy setting (public or private) held among their Facebook friends – but only following their sophomore year.

Meanwhile, a number of distinct behavioral effects are present for neighborhood 1 (the smallest and most isolated neighborhood, and the neighborhood presented in the visualization above). Between wave 1 and wave 2 (i.e., period 1), model results confirm that students do in fact cluster according to privacy settings – but that this results solely from a process of peer influence rather than similarity-based social selection. Additionally, students in neighborhood 1 in the first transition period have a strong baseline likelihood of adopting a private profile (positive, significant “baseline tendency” effect); but students who have relatively large networks of Facebook friends are less likely to adopt a private profile (negative, significant “degree” effect). No significant behavioral effects are present for this neighborhood in period 2. In period 3, however, the model would not converge after repeated runs. This sometimes happens when a very strong effect is present for a single parameter – i.e., the precise value of the coefficient does not matter, only that the coefficient is very large or very small, and so the model will have trouble converging on a stable estimate. In this case, the problematic parameter was the “degree” effect, which tended towards very high values in estimation attempts. Therefore, I fixed the

model parameter at a stable, high value (0.5), and the model had no trouble converging. Conditional on this fixed parameter – indicative of a particularly strong tendency for students with large networks of Facebook friends to adopt a private profile (the visual evidence of which is many large, shaded nodes in wave 4 of Fig. 8.2) – students in that neighborhood actually display a significant baseline tendency *away* from having a private profile, most likely to counterbalance the strength of the degree effect.

Finally, students in neighborhood 2 as well as students in neighborhood 3 (the two largest neighborhoods) display a positive and significant degree effect in the first transition period – an effect which reverses itself in the second transition period for neighborhood 3. In other words, between their freshman and sophomore years, students who have particularly many Facebook friends are particularly likely to adopt a private profile (perhaps to insulate themselves from additional requests); but between their sophomore and junior years, it is students with relatively few Facebook friends who are more likely to adopt a private profile (at least in neighborhood 3).

## 8.6 Discussion

These findings present the first available insight into the dynamic unfolding of online network and privacy behavior. Despite the very different nature of these ties – friendships documented online – compared to traditional network measures, results for the network dynamics section of the models largely uphold what has been found elsewhere: in particular, the crucial role of both social distance (triadic closure) and spatial distance (co-residence and shared academic major) in determining the shape of social networks. Interestingly, the role of “assortative mechanisms” is less consistent than prior research might lead us to expect: We see no self-segregation among students according to gender; minimal self-segregation by socioeconomic status; and significant racial homophily for only about half of all models. There is also evidence that students with particularly small networks at the end of their freshman year do some “catching up” during the following year only.

Past research on selection and influence has also found that – across a wide variety of attributes that might “spread” through social ties as well as influence their creation – social selection almost always plays a stronger role than does peer influence. In other words, to the extent to which friends in social networks tend to resemble one another, this is largely because they seek one another out rather than become more similar over time (de Klepper et al. 2010). Privacy behavior, therefore, appears to constitute a rare exception to this trend: I find little evidence that privacy behavior impacts the evolution of students’ networks; and to the extent to which it does, this almost always has to do with variation in students’ “sociality” according to privacy setting rather than students with similar privacy settings becoming friends. Meanwhile, peer influence indeed plays a significant role in the evolution of students’ privacy behavior – but one that also varies considerably

across time and context. On one hand, students in neighborhood 1 display a strong tendency to assimilate to the privacy settings of their peers early in college (period 1) but not later. On the other hand, students in neighborhood 4 are influenced by their peers' privacy behavior late in college (periods 2 and 3) but not earlier. Finally, privacy behavior is not only influenced by the specific people with whom one associates, but also by one's structural position: I find multiple significant degree effects on students' privacy behavior, though primarily positive (i.e., students with larger networks are more likely to have a private profile) rather than negative, and primarily early in college (i.e., period 1) rather than later (though students with large networks in neighborhood 1 are particularly likely to adopt a private profile in period 3 – an effect so strong it effectively destabilized the model).

These analyses are limited in a number of ways. Most importantly, they are restricted to students in a particular college setting – a college in which Facebook use was particularly widespread, even in 2006 – which may or may not be generalizable. Without detailed qualitative descriptions of the four neighborhoods, which are here omitted in order to preserve the anonymity of the college, I have only pointed out a few patterns in findings based on the size of the neighborhood(s) in question. Due to practical limitations regarding missing data as well as ambiguities regarding how to interpret students who could not be found on Facebook, I only considered students who could be located on Facebook for all 4 years and who had publicly available friendship data. Finally, while stochastic actor-based modeling represents the most sophisticated available method for modeling the joint evolution of social networks and behavior, there are also nontrivial limitations of applying this method to the study of privacy behavior. Even in the final wave of observation (when private profiles are most widespread), only a minority of students had a private profile; and almost all changes in privacy settings over all three transition periods were due to students moving from “public” to “private” rather than the opposite. Consequently, while all models converged to a satisfactory degree, I was not able to consider additional mechanisms of behavioral change (such as the impact of demographic background on privacy behavior) due to insufficient bidirectional variation in the behavioral variable. Future research should not only replicate these findings in other settings and using other measures of online privacy behavior, but also consider additional mechanisms of network and behavioral change that were not examined here.

This research provides preliminary insight into a topic of clear importance to academics and policymakers alike – yet one that has been strikingly absent from previous work on online privacy. These findings are also noteworthy for future research on network and behavioral evolution more generally. In particular, they demonstrate that mechanisms of change must be sensitive not only to actors' social (i.e., relational) environments, but also to the *time* and *setting* at which this change takes place. Some mechanisms are relevant in certain contexts – here, college residential “neighborhoods” – but not in others; while other mechanisms vary in significance depending on the particular time in the life course (or transition through college) in question. Future research should go beyond simply demonstrating *that* such variation exists, and explore in greater detail how such

variation may be systematically related to certain key properties of the local sociohistorical context (cf. Pattison and Robins 2002; van Duijn et al. 2003). While these possibilities are rarely explored, recent advances in available data and methods provide the opportunity for much progress; and as online information disclosure plays an increasingly important role in the conduct of day-to-day life, so we should be increasingly concerned with understanding who is actually disclosing what information, and why.

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