

# The Taste for Privacy: An Analysis of College Student Privacy Settings in an Online Social Network

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*The rapid growth of contemporary social network sites (SNSs) has coincided with an increasing concern over personal privacy. College students and adolescents routinely provide personal information on profiles that can be viewed by large numbers of unknown people and potentially used in harmful ways. SNSs like Facebook and MySpace allow users to control the privacy level of their profile, thus limiting access to this information. In this paper, we take the preference for privacy itself as our unit of analysis, and analyze the factors that are predictive of a student having a private versus public profile. Drawing upon a new social network dataset based on Facebook, we argue that privacy behavior is an upshot of both social influences and personal incentives. Students are more likely to have a private profile if their friends and roommates have them; women are more likely to have private profiles than are men; and having a private profile is associated with a higher level of online activity. Finally, students who have private versus public profiles are characterized by a unique set of cultural preferences—of which the “taste for privacy” may be only a small but integral part.*

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## Introduction

University students are often forerunners in the adoption of new communication technologies, and their communication networks tend to be dense and multilayered (Quan-Haase, 2007). Most recently, the popularization of online social networking sites (SNSs) has changed this landscape even further. Unlike previous means of communication, these sites—which “allow individuals to present themselves, articulate their social networks, and establish or maintain connections with others” (Ellison, Steinfield, & Lampe, 2007)—are not simply new ways of connecting with alters. Rather, they also *express* these very relationships, as users are integrated into a live social network consisting of personal profiles and the ties between them. (For an overview and history of SNSs, see boyd & Ellison, 2007.)

Among the many SNSs that have emerged in the past decade, MySpace and Facebook have been especially significant. Facebook, in particular, boasts over 70 million active users, almost half of whom log in daily (Facebook, 2008a). In addition to entering “friend” relationships with peers, users can message one another; upload photos, videos, and notes; join a wide variety of groups; add applications; send electronic “gifts”; and compose elaborate personal profiles containing all kinds of information. Through Facebook’s elaborate system of privacy settings, users also have extremely nuanced control over the extent to which friends, peers, and strangers can access different parts of their profile and monitor their online activity.

This issue of privacy has recently been the subject of public attention. The *New York Times* alone has published several articles relating to Facebook’s security measures (Stone, 2007b; Barnard, 2007a; Barnard, 2007b) and to instances in which information posted on a student’s profile prevented that student from getting a job (Finder, 2006), enabled campus police to crash that student’s party (Hass, 2006), and—in the case of Caroline Giuliani—created an embarrassing situation for that student’s father when she publicly supported a rival candidate (Santora, 2007). Meanwhile, the Internet has long been a hot topic for scholars interested in privacy (e.g. Kirsh, Phillips, & McIntyre, 1996; Regan, 2002; Metzger, 2004; Viégas, 2005), and the phenomenon of Facebook is just beginning to capture these researchers’ attention (e.g. Gross & Acquisti, 2005; Acquisti & Gross, 2006).

Given the widespread adoption of SNSs, the increasing public scrutiny of online behavior, and the policy implications surrounding privacy on the Internet more generally, it is surprising that few empirical data have been collected on the privacy practices of today’s SNS users. Moreover, the *choice* of a privacy level can itself be seen as an act of intrinsic interest, expressing a personal taste. Here, we analyze the privacy preferences of a cohort of undergraduate Facebook users. After providing background on the security options available on Facebook, we posit two types of mechanisms by which an individual may adopt a “private” profile and develop four hypotheses to assess these mechanisms. In our first section of results, we test these hypotheses by analyzing behavioral, demographic, and cultural data from a new social network dataset. In our second section of results, we expand upon these findings with a detailed exploration of the specific cultural preferences that tend to be associated with “the taste for privacy.” We conclude by indicating the relevance of this project for the future study of privacy and online behavior.

### **Privacy Settings on Facebook**

Facebook is distinct among many SNSs in two ways pertinent to personal privacy. First, unlike online universes explicitly detached from “real life” (e.g. Second Life) or at least tolerant of such discontinuity, Facebook requires users to identify themselves authentically. According to its Terms of Use, Facebook users may not “impersonate any person or entity, or falsely state or otherwise misrepresent yourself, your age or your affiliation with any person or entity” (Facebook, 2008b). This means that the information users provide on their profiles is particularly sensitive. Gross and

Acquisti (2005) enumerate several risks that users subject themselves to as a result, including embarrassment, blackmailing, stalking, and even identify theft.

Second, and relatedly, Facebook is organized around a system of *networks* that correspond to physical locations and institutions. Facebook maintains countless college, high school, regional, and work networks across the globe. Membership in such networks, while not required, is recommended by Facebook and allows the general location of a great many users to be known. Networks also determine the default level of “public” exposure afforded a new profile.

When a new user registers on Facebook, she is provided with a blank profile template consisting of a number of predetermined response categories. These include “basic” information (e.g. sex, hometown), contact information (e.g. mobile phone number, campus room/residence), and “personal” information (e.g. interests, favorite movies/music/books), among others. New users may also upload a profile picture and join up to five networks as defined above. The default privacy setting for a new user (“ego”) is that the entirety of this information is viewable by anyone in any of ego’s networks. Ego’s profile is also viewable by anyone who is “friends” with ego on Facebook. While anyone who is not connected to ego via network or friendship cannot view ego’s profile, by default they can still locate ego using a global search function as well as view a version of ego’s profile consisting only of their photograph, name, and network affiliation(s).

While Facebook provides a slew of options for managing the precise level of access of particular groups of people to particular sections of one’s profile, two settings are of particular interest. We consider a profile to be *private* if either (a) the student has changed their default settings such that their profile is no longer *accessible in full* by a nonfriend, same-network user (i.e. only a truncated version is available); and/or (b) the student has changed their default settings such that their profile is no longer even *searchable* by a nonfriend, same-network user. In other words, a “private” profile requires that ego has taken positive steps to limit the visibility of her profile to strangers. At most, only a truncated version is available; at minimum, ego cannot be found at all.

### Mechanisms and Hypotheses

Having established this definition of “privacy,” what are the possible motivations for making one’s profile private? We suggest two kinds of mechanisms, and develop four hypotheses concerning the patterns we expect to find if these mechanisms are in fact occurring.

#### *Social Influence Mechanisms*

*Network Effects.* Network analysts and social psychologists alike have long studied the ways in which behaviors, norms, and preferences are influenced by peers. Christakis and Fowler (2007), for instance, examined the spread of obesity through friendships in a large social network. Salganik, Dodds, and Watts (2006) found that participants in a “music market” experiment were much more likely to download

a song if they believed the song was popular among other participants. More generally, the strongest sources of social influence tend to be our direct peers. Adolescents coordinate their behavior to maximize congruency between friendship pairs (Kandel, 1978), and psychologists have documented an array of social processes conducive to compliance and conformity (Cialdini & Goldstein, 2004). Consequently, we expect that students will be more likely to adopt a private profile if their friends have already done so.

H1: The more friends with private profiles a student has, the greater will be the student's likelihood of maintaining a private profile herself.

### *Personal Incentive Mechanisms*

*SNS Activity.* There are reasons to expect that one's level of activity on Facebook—i.e. the frequency with which one logs into the site, updates one's profile, and browses other profiles—will have some effect on privacy behavior. First, social influence may be amplified by SNS activity. The more a person browses online, the more she may become aware of the actual prevalence of private profiles among Facebook users at large, preventing “pluralistic ignorance.” Second, more active users may have more elaborate profiles, and thus may have “more to hide.” Finally, users who spend more time browsing Facebook—and thus taking advantage of the accessibility of others' profiles—may become more sensitive to the accessibility of their own profile and upgrade privacy settings accordingly. We thus expect that the strength of a student's privacy settings will (positively) vary with the student's level of online activity.

H2: The more active a student is on Facebook, the greater will be the student's likelihood of maintaining a private profile.

*Safety.* At the epicenter of public furor about online privacy are issues of personal security. MySpace, for instance, drew fire in 2007 when the service purportedly “discovered thousands of known sex offenders using its service, but...failed to act on the information” (Stone, 2007a). Comparable assaults on Facebook were soon to follow (Stone, 2007b). While researchers have documented a discontinuity between behaviors and professed beliefs regarding privacy (Viseu, Clement, & Aspinall, 2004; Acquisti & Gross, 2006), safety concerns almost certainly motivate the decisions of some students to upgrade their privacy settings. Widespread media attention *about* these risks—most often citing the possible abuse of SNSs by sexual predators—could only enhance their motivational potency. If so, we should expect to find a greater proportion of private profiles among demographic groups at greater risk of personal harm as a result of information disclosure. Specifically, we should find that gender is a significant predictor of privacy settings.

H3: Private profiles will be more common among women than among men.

*Presentation of Self.* Much of contemporary social psychology has developed from Goffman's interpretation of life as a series of “performances.” Fundamental to this

perspective is the idea of a division between the “front” and “back” regions of interaction—the latter defined as “a place, relative to a given performance, where the impression fostered by the performance is knowingly contradicted as a matter of course” (Goffman, 1959, p. 112). Impression management requires that the back region be kept hidden from members of the “audience,” lest the performer’s act be discredited. This notion can also be expressed in the language of role theory (Biddle, 1986), where self-presentation coincides with the *role* one plays in any given social situation and the different roles one performs across different situations may be more or less compatible.

While the Internet in general is a fascinating realm for the study of “presentation of self” (e.g. Walker, 2000; Ellison, Heino, & Gibbs, 2006), Facebook adds another dimension to this complexity because a student’s online “role” (i.e. the information presented on her profile) can be so readily contrasted against the role that student plays in other spheres of life. In particular, employers, parents, and teachers are increasingly logging on to Facebook in order to glimpse their son, daughter, student, or potential new hire’s “back region.” In the process, they may encounter a profile that directly contradicts the performance they are accustomed to elsewhere. This confrontation, in turn, may have important symbolic and/or practical consequences for the student as their performance loses legitimacy in the eyes of that audience (e.g. Finder, 2006).

It is difficult to translate this mechanism—that students maintain private profiles in order to better control which audience has access to which performed role—into a concrete hypothesis. Private profiles may reflect a particularly strong discrepancy between online and other “public” performances; a particularly strong sensitivity to *any* such discrepancy; or a general tendency towards role compartmentalization, even if the roles are compatible. Each of these possibilities, however, suggests a particular *cultural disposition*, not unlike Bourdieu’s notion of “habitus” (1984). This underlying disposition may manifest itself in a specific set of other proclivities displayed by the student. In other words, a desire for privacy may simply be another taste, in keeping with the broader menu of cultural preferences that characterizes an individual.

H4: Students with private profiles will exhibit a set of cultural preferences that is distinct from that of students with public profiles.

## Data

Our study population is drawn from the class of 2009 at a private university in the northeastern United States. Data on these students’ Facebook profiles and friendship networks has been collected for the past two years as part of a new social network dataset, detailed below (Lewis, Kaufman, Gonzalez, Wimmer, & Christakis, under review). This university was selected in part due to the extremely high level of Facebook participation among undergraduates: Of the 1,740 students identified with the class of 2009, 1,710 of them (98.3%) have been located on Facebook at some

point or another during the past 2 years. In this paper, we are concerned only with this subset of 1,710 students.<sup>1</sup>

The data we use here were drawn from three points in time. Times one and two were consulted for explanatory variables. Our response variable was gathered during a special data collection effort at time “2.5,” a few months after time two.

#### *Response Variable*

In the summer of 2007, we accessed Facebook using an undergraduate account affiliated with this university’s Facebook network. Using an official roster of full names and unique e-mail addresses, we employed Facebook’s search feature to attempt to locate each of these students. Based on search results, students were assigned either a one or zero on a dummy variable indicating their privacy status. Students received a zero (public) if we were able to both locate them on Facebook *and* view their full Facebook profile. Students received a one (private) if we were unable to find and view a full profile for that student.<sup>2</sup>

#### *Explanatory Variables*

Explanatory variables were drawn from the Tastes, Ties, and Time (T3) social network dataset (Lewis et al., under review), a data collection endeavor that began in March 2006 (the spring of the study population’s freshman year). Additional information, and eventually a version of the dataset itself, can be located at <http://dvn.iq.harvard.edu/dvn/dv/t3>. This dataset has a number of important properties. First, in contrast to past studies of Facebook that rely exclusively on survey techniques (e.g. Lampe, Ellison, & Steinfield, 2006; Ellison et al., 2007), these data were extracted directly from Facebook. In other words, the dataset utilizes a *natural research instrument* based on specific online behaviors, rather than on respondents’ reports about these behaviors. Second, in contrast to research focusing exclusively on students’ profile data (e.g. Gross & Acquisti, 2005; Lampe, Ellison, & Steinfield, 2007), this dataset also incorporates *relational* information—allowing us to examine not only individual “attribute” data, but data on friendship and roommate ties as well (the latter were provided by the university). Finally, in contrast to social network datasets that contain exclusively “structural” variables, this dataset also includes *cultural* data in the form of students’ favorite movies, music, and books.

The T3 dataset consists of a large number of individual-level and dyadic variables. We restrict our attention to those variables relevant to the above four hypotheses. Specified in parentheses is the wave at which the given variables were collected. Wave 1 data were downloaded in March 2006; data for wave 2 were downloaded in March 2007. Descriptive statistics on all variables (including our response variable) are provided in Table 1.

*Network Effects (wave 2).* For each student (ego), we measured the number of Facebook “friends” and (separately) the number of roommates of ego who have private profiles. We also recorded the total number of friends and roommates for

**Table 1** Descriptive statistics on all variables

Variable	Mean	Minimum	Maximum	Valid N
Private profile	.33	0	1	1564
# Facebook friends	144.63	0	631	1435
# Facebook friends (private)	46.74	0	216	1435
# Roommates	2.06	0	6	1556
# Roommates (private)	.69	0	4	1556
Days since last update	15.33	0	208	1393
Female	.51	0	1	1583
Black	.09	0	1	1568
Asian	.21	0	1	1568
Mixed	.03	0	1	1568
Latino	.06	0	1	1568
Mean popularity (favorite movies)	37.26	1	144	1056
Mean popularity (favorite music)	40.15	1	249	1076
Mean popularity (favorite books)	50.03	1	289	1046
SD popularity (favorite movies)	32.37	0	75.66	1056
SD popularity (favorite music)	39.49	0	157.68	1076
SD popularity (favorite books)	50.93	0	198.70	1046
Liking classical music	.27	0	1	1076

each student to use as control variables. Network data at wave 2 were used in all cases in order to approach most closely the time at which privacy data were collected.

*SNS Activity (wave 1).* Facebook profiles do not indicate the amount of time that a user spends online. Originally, however, each profile included an automatically generated element indicating the date on which that profile was last updated by its creator. While this feature was discontinued by the time of wave 2, “last updated” data were available for most students at wave 1. We were thus able to construct a continuous measure of the number of days that had passed since a student last updated her profile at the time of the wave 1 download, and—following Lampe et al. (2007)—we interpret this as “a very rough measure of account activity.”

*Demographics (constant).* Almost all students indicated a gender on their profiles, and we could easily infer the gender of those who did not using first names and official school photographs. Students in the T3 dataset were also coded with respect to race/ethnicity. The appropriate ethno-racial category for each student was determined using their full name (as provided by the official student roster), their appearance (as determined by the myriad photographs accessible via most students’ profiles), and their membership in any of the many ethno-racial organizations on campus or groups on Facebook (as indicated on student profiles). Further details are available on the dataset’s website.

*Cultural Tastes (wave 1).* Responses for students’ “favorites” are completely open-ended, and as such are difficult to integrate into standard quantitative

analysis. Students do, however, almost universally present their tastes in list form. Drawing on prior literature, we developed three sets of variables to summarize these preferences.

First, we constructed for each student a measure of the *mean popularity* of their tastes in each of the categories of movies, music, and books. The popularity of each taste was determined endogenously as the quantity of students in our study population who listed that taste among their favorites. Every student was thus located along a continuous spectrum of very “popular” tastes on one end and highly idiosyncratic or “specialized” tastes on the other (Carroll, 1985)—a longstanding dichotomy in the sociology of culture that contemporary social network analysts have drawn upon, as well (Erickson, 1996; Lizardo, 2006; see also Liu, 2007, p. 262).

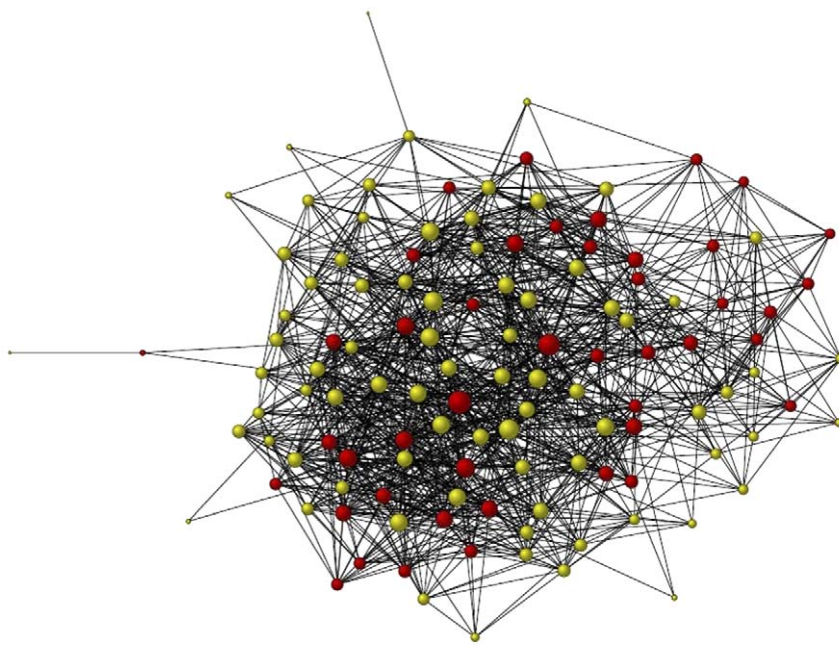
Second, we measured the *standard deviation* of the popularity of each student’s tastes in each of the three categories. Parallel to recent research on cultural “omnivorousness” (Peterson, 1992; Peterson & Kern, 1996; Warde, Wright, & Gayo-Cal, 2007), this variable enabled us to complement our measure of the general popularity of each student’s tastes with a measure of the *breadth* of these tastes as well. In other words, a student’s tastes may be fairly common or fairly specialized on average; but among either, higher standard deviation popularity is indicative of greater familiarity with (and appreciation for) both ends of this spectrum. While crude, these variables are easily interpretable even though students may vary greatly in the number of tastes listed per category.

Finally, “cultural capital” has been shown to be associated with a number of important life outcomes in the United States (e.g. DiMaggio & Mohr, 1985; Kaufman & Gabler, 2004), and is arguably the most socially significant component of “cultural disposition” in Bourdieu’s social theory. While Facebook provides no straightforward means of assessing cultural capital, we constructed a dichotomous indicator for all students based on whether or not they listed any *classical* preferences among their “favorite music”—thus demonstrating the presence or absence of one quintessentially “elite” or “highbrow” genre of taste.

Though data on network ties and privacy settings were collected in 2007, taste data were available for many fewer students at wave 2 than wave 1. Hence, the above taste measures were all determined using wave 1 data. Additionally, if a student did not list any tastes in an overall category, such as listing no tastes in the category of “music,” or if their tastes were not accessible, these data were interpreted as missing.

## Results

Of the 1,710 students in our population, 568 (33.2%) had private profiles in the summer of 2007 (at wave “2.5”). Of these, 39 (6.9%) had profiles that were searchable but could not be viewed in full, and 529 (93.1%) were not searchable at all. A subset of our population—those students living in a single undergraduate dorm—and the Facebook friendships connecting them are displayed in Figure 1.



**Figure 1** Facebook friendship network in a single undergraduate dorm. Red nodes represent students with private profiles; yellow nodes represent students with public profiles. Node size is proportionate to degree centrality.

#### *Results I: Predictors of Privacy Settings*

Table 2 presents the logistic regression coefficients for six models of profile privacy. Robust Huber-White standard errors were calculated for all regressions (see Stata Corporation, 1999, p. 556–560). This technique relaxes the assumption of independence among observations, a clear necessity for our (densely networked) population.<sup>3</sup> The first four models in Table 2 correspond to our four hypotheses. Model 1—the “network effects” model—shows that students with more private profile friends ( $p < .01$ ) and more private profile roommates ( $p < .001$ ) are in fact more likely to maintain a private profile themselves, controlling for total number of friends and roommates. These results confirm Hypothesis 1, and provide support for our “social influence” mechanism.<sup>4</sup>

In Model 2, we test our second hypothesis: that privacy settings will (positively) vary with online activity (and therefore *negatively* vary with days since last update). The coefficient is negative and significant ( $p < .001$ ), indicating that the more frequently a user manipulates their profile, the more likely the user is to adopt a private profile in the future.

In Model 3, we incorporate indicator variables for female students (male = reference category), black students, Asian students, Latino students, and students of “mixed” racial background (white = reference category). As predicted by

**Table 2** Logistic regression coefficients for regressions of profile privacy on network effects, SNS activity, demographics, and cultural tastes

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
<b>A. Network effects</b>						
# Facebook friends	-.004 (.003)				-.007* (.003)	-.001 (.004)
# Facebook friends (private)	.022** (.008)				.028** (.009)	.010 (.012)
# Roommates	-.098 (.058)				-.097 (.067)	-.110 (.089)
# Roommates (private)	.370*** (.083)				.346*** (.094)	.318** (.124)
<b>B. SNS activity</b>						
Days since last update		-.009*** (.003)			-.006 (.003)	-.005 (.005)
<b>C. Demographics<sup>a</sup></b>						
Female			.289** (.110)		.268* (.136)	.275 (.181)
Black			.355 (.187)		.038 (.242)	-.002 (.307)
Asian			.103 (.136)		-.008 (.174)	.008 (.234)
Mixed			-.122 (.341)		.032 (.373)	.473 (.458)
Latino			-.069 (.245)		-.253 (.334)	-.015 (.381)
<b>D. Cultural tastes</b>						
Mean popularity (movies)				.001 (.005)		-.002 (.006)
Mean popularity (music)				.008* (.004)		.012** (.004)
Mean popularity (books)				.000 (.003)		-.002 (.003)
SD popularity (movies)				-.002 (.006)		.001 (.007)
SD popularity (music)				-.009* (.004)		-.012** (.005)
SD popularity (books)				-.002 (.003)		-.002 (.003)
Liking classical music				-.412* (.191)		-.312 (.214)
N	1414	1393	1554	870	1270	809

Note: Numbers in parentheses are Huber-White standard errors. Constants are suppressed.

<sup>a</sup> Dummy-coded variables, with “male” and “white” as reference categories, respectively.

\* p < .05. \*\* p < .01. \*\*\* p ≤ .001.

Hypothesis 3, women are significantly more likely to have private profiles than are men ( $p < .01$ ). We observe no significant association between privacy settings and ethno-racial category.

Model 4 includes terms for the mean and standard deviation popularity of students' tastes in movies, music, and books, as well as an indicator variable for liking classical music. The coefficient for mean music popularity is positive and significant ( $p < .05$ ), and the coefficient for SD music popularity is negative and significant ( $p < .05$ ). Additionally, we find that students who like classical music are significantly less likely to have a private profile than students who do not. We thus find support for Hypothesis 4: The cultural preferences of students with private profiles are significantly different from those of students with public profiles. In particular, students with private profiles tend to have more "popular" tastes in music on average; they more often prefer music concentrated at a particular section of the popularity spectrum (i.e. lower SD, or less "omnivorous"); and they less frequently display "cultural capital" in the form of a preference for classical music.

Our final two "combined" models (Models 5 and 6) test the robustness of these findings. While we employed taste data from wave 1 in order to maximize the number of observations available, the overall number of students who provided such data at wave 1 is still relatively small (hence, the large drop in N between Models 1–3 and Model 4).<sup>5</sup> Consequently, we include two combined models: one without tastes, and one with them. Even controlling for SNS activity and demographics, we observe significant network effects operating through both friendship ties and especially—as evinced by significant coefficients in Models 5 and 6—through roommate ties. Our activity variable is of borderline significance in Model 5, at  $p = .057$ . The coefficient for females continues to be significant through Model 5 ( $p < .05$ ), and while no longer significant by Model 6, its point estimate does not change much. Finally, we find the most robust associations between privacy settings and two of our taste variables. Even controlling for network effects, SNS activity, demographics, and other measures of tastes, (high) mean music popularity and (low) SD music popularity are significant predictors of a taste for privacy at  $p < .01$ .

### *Results II: A Closer Look at Tastes*

This finding—that music preferences are significantly associated with privacy settings—warrants closer examination. Taste popularity is important for music in a way that it is not for movies and books, but important differences may be obscured by only considering summary statistics of all three kinds of "favorites." Even if the tastes of students with public versus private profiles did not overlap at all, this difference would be masked if each set of tastes still shared the same popularity distribution. Here, we account for this possibility by examining the *specific* cultural preferences that are most associated with each kind of profile (public vs. private), as well as the relationship of these tastes to each other—an effort parallel to other recent work documenting the structure of online cultural fields (Paolillo & Wright, 2005; Liu, 2007).

Students collectively displayed a vast array of cultural preferences: We observed a total of 1,962 unique listings for “favorite movies,” 3,532 unique listings for “favorite music,” and 1,629 unique listings for “favorite books” at wave 1. In order to determine which of these tastes are most associated with privacy, we calculated the quantity of “private” students that we would *expect* to have each of the 7,123 possible tastes under conditions of independence. In other words, for every taste X, we multiplied the proportion of students who listed that taste by the proportion of students with a private profile, and multiplied this product by the total number of students ( $N=1,239$ ; all students with no taste data at wave 1 were omitted). We then subtracted this quantity from the total number of private profile students who *actually* listed that taste. The resulting difference indicated how many more or fewer private students listed that taste than we would expect if privacy preferences are completely independent of other cultural preferences.

Table 3 lists the 38 tastes most associated with privacy, i.e. those tastes whose “actual minus expected” value fell at least 5 standard deviations from the mean (approximately 0.5% of all possible tastes). For example, 8.9 more students with private profiles list Dan Brown among their favorite books than we would expect from chance alone, setting him apart as the top “private” taste. Meanwhile, The Beatles are listed 16.7 *fewer* times among private profile students than chance alone would predict, setting them apart as the most “public” taste.

Perhaps most striking about these lists is their *diversity*: Each contains multiple tastes from all three types of media (movies, music, books), and a variety of different genres are represented on each side of the dividing line (including those who explicitly state a preference for classical music, which is again found to be associated with having a public profile). Public students prefer movies from *Team America* to *Casablanca*, music from 50 Cent to Billy Joel, and authors from Kurt Vonnegut to C.S. Lewis; private students’ tastes are no less variegated.

Additionally, highlighted in yellow are all tastes that appeared among the five most popular movies, music, and books in our dataset overall. Coinciding with our previous findings—though not limited to just music—four of the nine top private tastes are among the most popular in our dataset, while only 3 of the 29 most public tastes have the same status. Beyond this, however, are there any other themes that unify the cultural preferences in each list? In other words, what is the relationship of each of these tastes to *each other*; and to what extent do the preferences displayed by students with private profiles form a distinct “cultural disposition”?

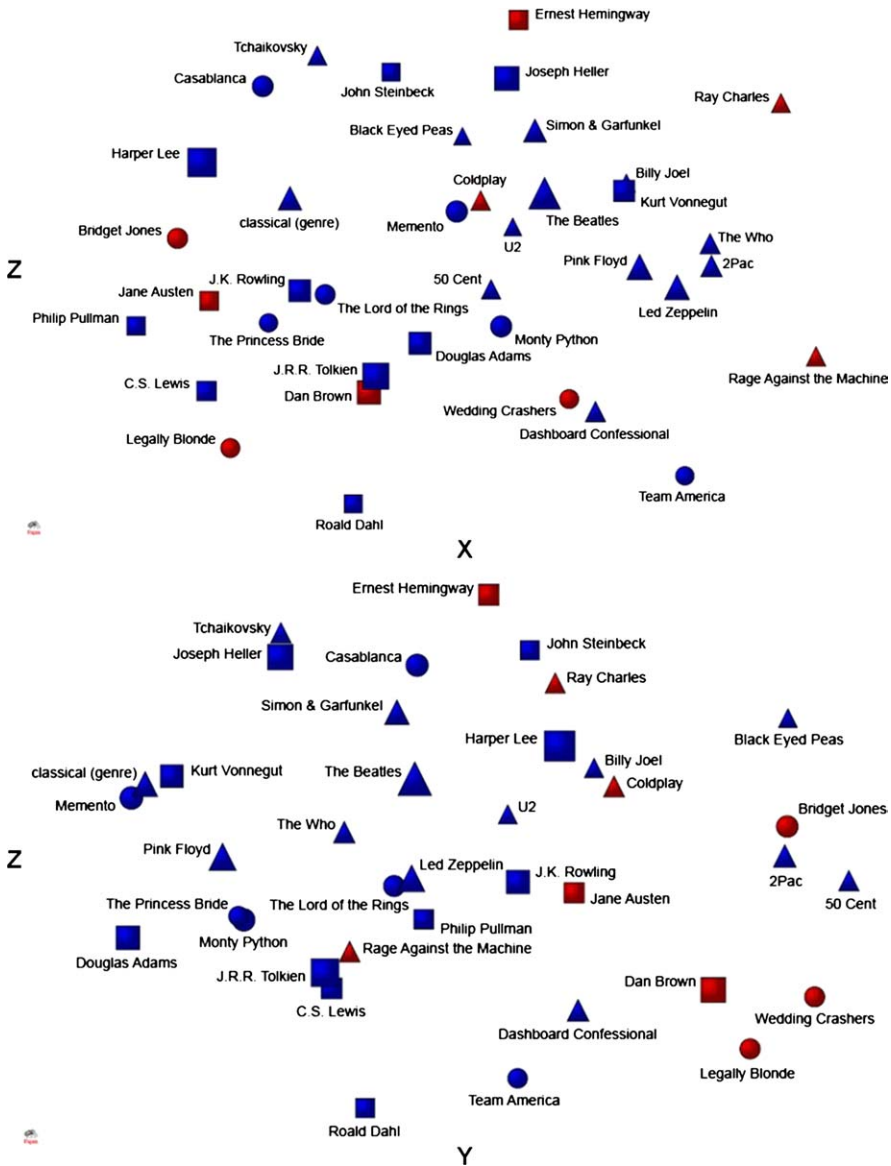
To answer this question, we extended our analysis one step further. Based on the overall popularity of each taste, we calculated the expected number of times that every possible pair of tastes should occur together if each were randomly distributed in the population, and compared this to the actual figure. We thus created a  $38 \times 38$  matrix of “similarity scores,” where the similarity between tastes was defined *endogenously* based on observed minus expected rates of co-occurrence (as opposed to “exogenous” criteria such as genres which may or may not be meaningful to students in selecting their favorites).

**Table 3** Tastes most associated with privacy (difference > 5 standard deviations from mean)

Private tastes			Public tastes		
Taste	Category	Diff <sup>a</sup>	Taste	Category	Diff <sup>a</sup>
Dan Brown	Book	8.88	The Beatles	Music	-16.73
Bridget Jones	Movie	6.76	Harper Lee	Book	-13.67
Coldplay	Music	6.31	J.R.R. Tolkien	Book	-11.43
Rage Against the Machine	Music	6.10	Pink Floyd	Music	-11.01
Ernest Hemingway	Book	6.02	Led Zeppelin	Music	-10.43
Legally Blonde	Movie	5.89	Joseph Heller	Book	-9.81
Wedding Crashers	Movie	5.84	classical (genre)	Music	-9.19
Ray Charles	Music	5.82	Simon & Garfunkel	Music	-8.98
Jane Austen	Book	5.80	Douglas Adams	Book	-8.29
			J.K. Rowling	Book	-8.05
			2Pac	Music	-7.77
			Memento	Movie	-7.73
			Kurt Vonnegut	Book	-7.60
			Monty Python	Movie	-7.57
			Casablanca	Movie	-7.46
			The Who	Music	-7.01
			Dashboard Confessional	Music	-6.91
			The Lord of the Rings	Movie	-6.75
			C.S. Lewis	Book	-6.46
			50 Cent	Music	-6.25
			Tchaikovsky	Music	-6.21
			Team America	Movie	-5.80
			The Princess Bride	Movie	-5.73
			Philip Pullman	Book	-5.73
			Billy Joel	Music	-5.60
			Roald Dahl	Book	-5.56
			U2	Music	-5.47
			John Steinbeck	Book	-5.46
			Black Eyed Peas	Music	-5.32

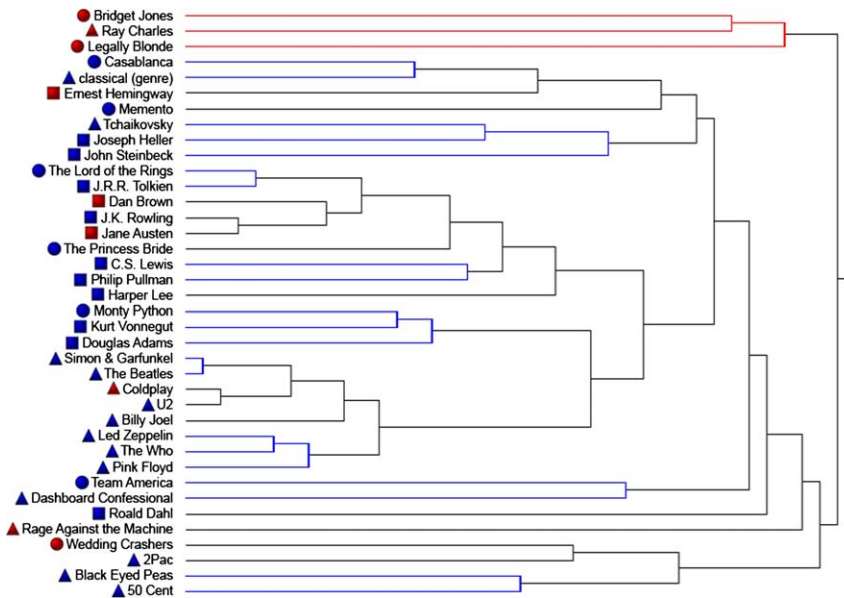
<sup>a</sup> Difference = (# private students observed with taste X) - (# private students expected to have taste X).

Using this matrix, we created a multidimensional scaling (MDS) solution to visualize the similarities and differences between tastes (Figure 2). This procedure seeks an optimal arrangement such that more similar tastes are closer together and less similar tastes further apart—here, in 3-dimensional space. For further clarity, we also employed a hierarchical clustering algorithm to identify *groups* of very similar tastes. A dendrogram of this procedure is reproduced in Figure 3, where very similar tastes are clustered together first and less similar tastes slowly added as groups increase in size and decrease in cohesiveness. The computer program UCINET (Borgatti, Everett, & Freeman, 2002) was used for both analyses.



**Figure 2** 3-dimensional MDS solution of private and public tastes (stress = 0.2). Colors correspond to privacy level (red = private, blue = public); shapes correspond to taste categories (circles = movies, triangles = music, squares = books); shape sizes are proportionate to the SD of each “observed minus expected” value from the mean.

Immediately evident from both the MDS and clustering diagrams is that the subset of private tastes do *not* form a cohesive whole. While tastes are somewhat divided by privacy status along the Y-axis, both public and private tastes are scattered across the two other dimensions of variation and there is no single cluster secluding



**Figure 3** Results of hierarchical clustering algorithm. Blue clusters consist exclusively of public tastes; red clusters consist exclusively of private tastes; black clusters include tastes from each category.

all private tastes from the others. In fact, some private tastes (e.g. Coldplay and Jane Austen) are *very* similar to selected public tastes (U2 and J.K. Rowling, respectively); and the one cluster composed exclusively of private tastes (Bridget Jones, Ray Charles, and *Legally Blonde*) is relatively internally dissimilar: These tastes are clustered together only after *all* other tastes have been grouped with more similar others.

Nonetheless, two important trends are visible. First, while the collection of private tastes clearly does not form a single coherent “disposition,” the landscape of *public* tastes is divided into *multiple* such dispositions—each inclined towards public display but also characterized by its own unique identity. Students who love *Monty Python* movies also enjoy reading books by Kurt Vonnegut and Douglas Adams, and are more likely to have a public profile than a private one. Meanwhile, there is another group of students who listen to Led Zeppelin, The Who, and Pink Floyd—three tastes that form their own distinct cluster, but are also strongly associated with publicity. Other highly coherent “public” clusters include *Lord of the Rings* lovers (both the books and the movies), on one hand, and students who listen to both Simon & Garfunkel and The Beatles, on the other. Less cohesive “public” clusters are present as well (e.g. 50 Cent and Black Eyed Peas; *Team America* and Dashboard Confessional).

Second, private tastes tend to be relatively *marginalized* vis-à-vis others—they are dissimilar not only from other private tastes, but from the bulk of public tastes as well. In other words, except for Coldplay (which is located square in the center of

a cluster with 10 public tastes) private tastes tend to fall along the outskirts of the three-dimensional space in Figure 2 and the dendrogram in Figure 3. The “taste for privacy,” then, is a cultural mixed bag: Those preferences most associated with privacy are also least associated with each other, and tend not to be preferred alongside extremely public tastes either.

While we have documented a number of discrete tastes associated with privacy and sets of tastes associated with publicity, the particular *content* of these cultural profiles is not always easy to interpret. What does Tchaikovsky, for instance, have in common with Joseph Heller or *Bridget Jones* with Ray Charles? Moreover, why are the former associated with public profiles and the latter with private ones? With IRB approval, interview data could be collected from these respondents in subsequent waves to help clear such ambiguities; and a detailed analysis of *all* tastes, not just those most associated with privacy, could shed light on the principal components of variation among students’ preferences more generally (cf. Paolillo & Wright, 2005; Liu, 2007). For now, however, some general observations are noteworthy:

We have pointed out that classical tastes, in particular, may serve (qua “cultural capital”) as markers of social distinction. Consequently, students with these tastes may want them to be especially *visible*. It is not unreasonable to suppose, also—particularly in a society that prizes individuality and increasingly also “omnivorousness” (Peterson & Kern, 1996)—that specialized or idiosyncratic tastes (i.e. low mean popularity) or tastes that are drawn from diverse parts of the popularity spectrum (i.e. high SD popularity) would tend to be more culturally valued and hence prominently displayed. If this is true, the particular mappings of “public” versus “private” tastes that we have described may provide helpful insight into the local culture of this cohort of college students—a culture that privileges (and stigmatizes) not one single cultural profile but several, and displays (and hides) these tastes accordingly. In other words, if the *content* of what is displayed is entwined with the *propensity to display* itself, online privacy is not just about those who keep Goffman’s stage curtain tightly drawn. It is also about those who throw it wide open—where a performance tells as much about the performer as about what she wants the audience to see. Future studies should examine the connection between stated cultural preferences and attitudes toward privacy and display, and how both are related to the particular social contexts in which they develop.

## Discussion

### *Mechanisms of Privacy Mobilization*

Corresponding to our hypotheses, we found four important predictors of privacy settings. A student is significantly more likely to have a private profile if (1) the student’s friends, and especially roommates, have private profiles; (2) the student is more active on Facebook; (3) the student is female; and (4) the student generally prefers music that is relatively popular (high mean) and *only* music that is relatively

popular (low SD). We also documented a number of *distinct* cultural preferences associated with the taste for privacy. We speculate that these tastes—which co-occur relatively infrequently with each other as well as with highly publicized tastes—are particularly undervalued in the local social context, and are kept hidden for this very reason. Meanwhile, clusters of very “public” tastes may represent cultural profiles particularly privileged by this cohort of students.

We proposed two general mechanisms by which a student may adopt a private profile. These correspond to reasons why a student might *independently* have a private profile (SNS activity, safety, and presentation of self), and reasons why privacy behavior might *spread* to other students (network effects). While our hypotheses were tailored to assess these mechanisms, our results cannot be conclusive. Each mechanism refers to a very specific motivation for a very specific behavior, to which the limited data students provide on their profiles can speak only imperfectly. Further, our data were collected from a single college cohort over a particular span of time. Our hypotheses may be tested in other settings and/or times, but the specific groups of “public” and “private” tastes we describe, in particular, are potentially unique to these students and are open to other interpretations than the “local cultural capital” argument we offer here.

Despite these limitations, our results have important implications for the study of SNS privacy and for our understanding of privacy on the Internet more generally. First, researchers interested in SNS privacy must be especially careful in data interpretation due to the unique nature of their object of study. When the unit of observation is, in a sense, the absence of observation itself, private data and missing data can easily be confounded. We used an official student roster of the “eligible” population, as well as longitudinal data, to surmount this obstacle—an approach we recommend to others. Second, in their 2005 study of Carnegie Mellon University students, Gross and Acquisti (2005) concluded that “only a vanishingly small number of users change the (permissive) default privacy preferences” on Facebook. In contrast, an entire *third* of the 1,710 students in our population made use of these settings in 2007. While this difference in findings may also be attributable to differences in the two study populations (as well as, to a limited extent, conflation of nonexistent students and students who have completely hidden themselves from searches; A. Acquisti, personal communication, November 11, 2007), the existence of so many “private” users in our dataset suggests that the so-called privacy “movement” (Viseu et al., 2004, p. 106) may, 3 years later, finally be taking hold.

#### *Negotiating Privacy: A Theory of Internal Regulation*

Finally, our data are relevant to understanding online privacy more generally—especially within fledgling communication technologies like SNSs. In *Ruling the Waves: Cycles of Discovery, Chaos, and Wealth From the Compass to the Internet*, Debora Spar (2001) argues that new technologies tend to undergo a predictable pattern of transitions. At first, they are concentrated only among a small group of “innovators.” This phase is characterized by excitement, freedom, and creativity.

Next, the technology becomes “commercialized,” as the lay public rushes en masse to adopt it. Eventually, however, this rapid growth outstrips the spirit of the innovative period. Problems of coordination and competition foster “creative anarchy” and the search for freedom is replaced by a demand for property rights. Finally, government enters the scene, restoring order at the behest of the very pioneers who once sought to escape it.

While not identical in form, the negotiation of privacy in online settings may be characterized by a similar pattern. When a new technology such as Facebook is released, there is a high degree of *ambiguity* over appropriate norms of conduct—the very definition of this space as public or private is contested. College students, professors, parents, employers, and Facebook itself each have different and potentially conflicting interests in the way the technology is used. Students are surely aware that the information they post is “public”—but the full extent and possible consequences of this display may not be recognized by all. Slowly but inevitably, excitement outstrips precaution. The technology diffuses throughout the population, and users provide ever more data on their profiles—all the while maintaining the (rather permissive) default privacy settings, not yet having reason to do otherwise (see Mackay, 1991).

Eventually, however, this behavior becomes *consequential*. The boundary between public and private is suddenly and unequivocally asserted by virtue of being overstepped. Users venture too far into public space with private details, and the consequence is a crashed party, a lost job opportunity, or—at an extreme—sexual assault or identity theft. *Awareness* is suddenly raised for a certain type of user: those users concerned with safety, or with maintaining a division between their public “face” and their online profile, or whose own high level of online activity gives them a better perception of their surroundings; this awareness *spreads*, most directly through the social ties represented by Facebook friendships and cohabitation. Communication about the importance of noncommunication takes place. The upshot of this process is that a normative boundary emerges where before none existed. Facebook is increasingly recognized as a space within which some precaution must be exercised, and users respond by retreating behind a virtual line of privacy—in proportion to the extent to which their awareness has been raised by a concern that applies to them personally.

Here, we have considered such a progression from excitement and ambiguity to (self-) regulation. However, rather than regulation being at once explicit, legal, and externally imposed (by government), the public/private boundary on Facebook is implicit, normative, and *internally* negotiated. We may thus see new online spaces as “self-regulating systems” where awareness is the impetus for change and equilibrium the final product—both proceeding along a pattern of predictable regularities. In the meantime, researchers of SNSs will watch their study populations wax and wane, and the sites themselves may become less open and more exclusive. Whether users will still “Facebook” in the future to share ideas and social ties, or whether the form and/or site of these interactions will change, remains to be seen.

## Notes

- 1 This study population of 1,710 includes anyone who was listed on the class of 2009 roster in *either* the 2005/2006 academic year *or* the 2006/2007 academic year. For all logistic regressions, however, we drop from consideration all students who were not present on *both* years' rosters (reducing our baseline population to 1,564 students).
- 2 It is impossible to distinguish between a student who is not on Facebook and a student who is on Facebook but has hidden themselves from searches. For this reason, we limit our focus to only those students who had previously been located on Facebook at some point or another. This means that even if they could not be located during the summer of 2007, they had at one time *been* registered and visible on Facebook and have since terminated this public accessibility (whether through increased privacy settings or through cancelling their account altogether).
- 3 Other, more traditional network methods—such as exponential random graph, or  $p^*$  modeling—could also be used. While appropriate for the study of social influence (Robins, Pattison, & Elliott, 2001),  $p^*$  models are less helpful for analyzing individual behavior as the joint product of multiple social and social-psychological mechanisms. Consequently, we prefer the approach of standard logistic regression for this paper.
- 4 This pattern could also be explained by homophily—the principle that “birds of a feather flock together”—among students with private profiles. Longitudinal data on privacy settings are needed to fully understand the respective importance of these two mechanisms (social selection vs. social influence).
- 5 Even in Models 1–3, we note that our N has dropped considerably from the original eligible population of 1,710. This is due primarily to our exclusion of the 146 students who transferred in or out of the college between waves (see note 1), though results were no different when these students were included. The N for Model 1 declines further because even by wave 2 students had begun hiding themselves (and their network data) from searches. Model 2 loses observations because “last update” data were not available for students who blocked access to their profiles at wave 1. Finally, a handful of students could not confidently be assigned to an ethno-racial category, resulting in an imperfect N for Model 3.

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