Is Binge Drinking Normal?

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Existing empirical literature suggests fraternity membership is a causal factor of binge drinking for college students. We re-examine this relationship between fraternity membership and binge drinking; contrary to existing literature, we find that after controlling for risk preference, fraternity membership is not a relevant factor in predicting binge drinking. Rather, our results suggest that measures of overall risk preference are relevant predictors of binge drinking, but because of the irrelevance of fraternity membership we are unable to isolate any direction of causality. We do find evidence, however, that students who consume alcohol prior to having sex belong in a separate sample when considering binge drinking. The implication of previous literature is that restricting or eliminating fraternity membership reduces binge drinking and improves campus safety; however, our results cast doubt over the effectiveness of these policies in reducing binge drinking.

INTRODUCTION

Binge drinking is prevalent among fraternity and sorority members. One theme in the empirical literature of college binge drinking is that, on average, fraternity and sorority members binge drink more frequently and more heavily than non-members (Wechsler et al.,1995, Chaloupka and Wechsler, 1996, Cashin et al. 1996). The literature has identified violence, aggressive behavior, and reduced academic performance as several of the negative effects of binge drinking (see DeSimone, 2007 for a brief summary).

Fraternities, however, are not without their benefits[1]. Fraternity membership has positive psychological effects such as improved self-esteem and emotional security (Astin, 1993, Hunt and Rentz, 1994). Members are more likely to participate on campus (De Los Reyes and Rich, 2003) and in charitable events (Grubb, 2006), help other members (Grubb, 2006), make lifelong friends (Sacerdote, 2001), and financially support their alma mater following graduation (Harrison et al., 1995). In addition, the academic performance of fraternity members is not generally different from non-members (Baier and Whipple, 1990), and members are more likely to have declared majors than non-members (Grubb, 2006), graduate on time (Grubb, 2006), and have a high-salary job (Marmaros and Sacerdote, 2002).

There are many factors that might explain heavier drinking among fraternity members. For instance, joining a fraternity could in itself contribute to the amount of binge drinking, *ceteris paribus*, therefore exhibiting a causal effect on drinking (DeSimone, 2007, 2009)). However, students with a preference for alcohol consumption may choose to join fraternities simply because they are predisposed to drinking, in which case, the students would consume the same amount of alcohol regardless of whether or not they are members in a fraternity. Unobserved personal characteristics such as time preference or degree of risk aversion (Rees et al., 2001) may more closely predict all types of risky behavior, including binge drinking and risky sexual behavior. Because there are both positive and negative attributes of fraternities, it is important to understand the differences in drinking behavior for fraternity members and non-members when designing policies aimed at reducing binge drinking. Campus policy-makers must be careful before implementing any policies that may eliminate or restrict fraternity membership, especially if the effect of restricting fraternity membership on binge drinking is ambiguous while restrictions on membership diminish the positive attributes of fraternities.

DeSimone (2007) identifies a (potentially) causal effect of fraternity membership on binge drinking. Using proxy variables to control for unobserved factors through which students likely self-select into fraternities, he finds robust significance of fraternity membership in explaining binge drinking. While his analysis is compelling, our results suggest the probit model used by DeSimone (2007) is misspecified[2]. While commonly used in empirical applications, the probit model requires relatively strong assumptions to be a consistent estimator. Probit models require the specification of both a single-index functional form and a Gaussian distributed conditional probability. Moreover, the single-index form requires the correct specification of the additivity and separability of the regressors[3]. If the conditional probability is misspecified, the estimator is inconsistent and may lead to incorrect inference.

The policy implications of these results are severe: one way colleges and universities can curb binge drinking in order to increase campus safety is to eliminate (or at least restrict) fraternity membership. Despite the abundant evidence that, on average, fraternity members binge drink more than non-members, we question whether or not restrictions on fraternity membership can successfully reduce binge drinking. After all, binge drinking is not just a concern on campuses with fraternities; college students binge drink outside of fraternities with, for example, teammates or roommates. We expect that a student's preference for risk rather than fraternity membership has a causal effect on binge drinking. Students who are more inclined to participate in all types of risky behavior (e.g., binge drinking, risky sexual activity, drug use, etc.) are more likely to binge drink due to their preference for risk, and may also join a fraternity in order to be in an environment in which alcohol (and other risky activities) may be more easily accessible.

The purpose of this paper is to assess the robustness of the results and policy implications of DeSimone (2007). Simple analysis of the data, specifically sample correlations and unconditional density plots, cast doubt over the finding that fraternity membership has a causal effect on binge drinking. We find fraternity membership is not highly correlated with binge drinking. Rather, binge drinking is more highly correlated with measures of risky behavior and athletic participation.

We relax the functional form assumptions inherent in the probit model by estimating the conditional probability density of binge drinking using nonparametric kernel methods. The advantage of this approach is that we relax the functional form assumptions necessary for probit estimation; the nonparametric estimator remains consistent under more general assumptions. For example, our estimator does not require any distributional assumptions regarding the probability of binge drinking, and allows for nonlinearities and interactions between any of the regressors. Comparison of in-sample prediction accuracy between the probit and nonparametric models suggests that the probit model is misspecified.

Our results suggest that fraternity membership is not a relevant factor in predicting binge drinking. The nonparametric estimator assigns nearly identical weights to both fraternity members and non-members, suggesting information contained in the fraternity membership indicator does not contribute to the prediction of binge drinking. Rather, the nonparametric model divides the sample into two distinct categories based on whether or not the student reported using alcohol prior to the last sexual encounter. Our estimate of the bandwidth for the indicator of whether or not students used alcohol prior to the last sexual encounter suggests there are two separate samples when predicting binge drinking. One sample includes students who use alcohol before having sex and the other includes those who do not. This suggests the binge drinking behavior of students who use alcohol before having sex and those who do not are very different and should be treated so in term of policy actions.

The nonparametric model identifies various measures of risk preference (e.g., drinking and driving, marijuana use) as relevant factors for predicting binge drinking. Because fraternity membership is irrelevant in predicting binge drinking, our results from the nonparametric model do not suggest any particular direction of causality. However, it reveals an intimate relationship between binge drinking and all measures of risk preference, possibly suggesting that observed (and unobserved) preferences for risk may more closely predict all types of risky behavior, including binge drinking and risky sexual activity.

Our model implies that colleges and universities should focus resources on discouraging all types of risky behavior, inside and outside of fraternities, perhaps with an emphasis on curbing risky sexual behavior. Policies aimed at reducing risky activities in general may likely be successful in reducing binge drinking, and do not involve restricting or eliminating membership in social fraternities.

The rest of this paper is outlined as follows. Section 2 discusses the nonparametric conditional density estimator used in our analysis. Section 3 briefly describes the data. Section 4 provides a preliminary analysis of the data. Section 5 presents the empirical results from the nonparametric model. Section 6 addresses the policy implications of our results and Section 7 concludes.

METHODOLOGY

The central focus of our analysis is the conditional probability density function of the binge drinking indicator estimated using nonparametric kernel methods[4]. The use of nonparametric kernel methods to estimate the conditional probability density function allows for a fully flexible functional form, and minimizes the assumptions required for estimation. The probit model requires an assumption of normality which we can relax using nonparametric. The advantage of this approach is a more data driven analysis, and a model more appropriately suited for prediction for the sample of observations.

Nonparametric Conditional Density Estimation

We estimate the nonparametric conditional probability density function as follows. Consider the random variables (X, Y) where X denotes a vector of continuous, ordered and unordered conditioning variables and Y denotes a binary left-hand-side variable. We denote the probability density of Y conditioned on X by $f_{Y|X}(y|x)$. Our conditional density estimator of Y (dropping the random variable subscripts for ease of notation) is

$$\hat{f}(y|x) = \frac{\hat{f}(x,y)}{\hat{f}(x)}, \tag{1}$$

where f(x,y) denotes the joint probability density function of (x,y), f(x) denotes the marginal probability density function of x and f(.) denotes the kernel density estimator. The estimator constructs a smoothed (conditional) histogram of the data by locally weighting observations in the neighborhood[5] of any particular observation. See Li and Racine (2007) for further details.

Nonparametric Bandwidth Selection

In any type of nonparametric kernel estimation, the key is correctly estimating the bandwidths. In applied research, data-driven bandwidth selection methods provide the most convenient and reliable means for selecting the bandwidths[6]. We estimate the bandwidths via likelihood cross-validation which selects the bandwidths by minimizing the expected Kullback-Leibler loss (see Li and Racine, 2007 for details).

While the bandwidths are essential for correctly estimating the conditional pdf, a direct analysis of the bandwidths reveal which variables are relevant in terms of predicting the left-hand-side variable. Hall, Racine and Li (2004) show that if the cross-validation procedure selects a 'large' bandwidth for any variable, then the variable is automatically removed during estimation, rendering the variable statistically irrelevant in prediction. Intuitively, when the bandwidth is 'large', all values for that variable are assigned the same weight, thereby failing to provide any additional information to help predict the left-hand-side variable. The size of the bandwidth is determined by comparing the bandwidth to a predetermined upper bound. If the bandwidth is below the upper bound, then the variable is not removed during estimation and the variable is relevant for prediction. If the bandwidth hits the upper bound, then the variable is irrelevant. In the continuous variable case, the theoretical upper bound is infinity, however, Hall, Li and Racine (2007) show that irrelevant covariates are effectively smoothed out if the bandwidth exceeds several standard deviations of the data. The upper bound for unordered discrete variables is $(r_j-1)/r_j$, where r_j is the number of categories the variable can take and the upper bound for ordered discrete variables is unity.

One additional possibility is that the estimated bandwidth is (approximately) zero. In this case, the kernel function for that variable is reduced to an indicator function that takes the value unity for any observations with the same value and zero otherwise. Intuitively, this means that observations in each distinct category in the variable belong in separate samples when estimating the conditional probability density function. Consider, for example, a binary variable whose estimated bandwidth is approximately zero. For any observation whose value is equal to zero, only other observations with a value of zero are assigned any positive weight. All observations with a value of unity are given zero weight, and are excluded from the sample before estimation. Hence, the sample is split prior to estimating the conditional density.

Model Selection

After estimating the nonparametric model and comparing the results to those from the parametric specification, we must decide whether to accept the nonparametric results or reject the nonparametric model in favor of the parametric alternative. Li and Racine (2007) suggest comparing the predictive abilities of the nonparametric estimator with a feasible parametric estimator. If the nonparametric estimator is better able to predict the true value of the left-hand-side variable[7], it is unlikely that the parametric model is correctly specified. Indeed, the finite sample simulations conducted by Hall, Racine and Li (2004) show a correctly specified parametric model has better predictive power than the nonparametric conditional probability density estimator. However, they show that when the parametric model is misspecified, the nonparametric estimator has superior predictive ability.

To determine which estimator has superior predictive ability, we compare the accuracy of in-sample predictions from each estimator via the correct classification ratio (CCR). The CCR is the ratio of the number of correctly predicted observations to the total number of observations in the sample. For the parametric model, we predict the binary left-hand-side variable as follows: if the fitted value (i.e., probability) from the estimated probit model is greater than or equal to 0.5, we classify the prediction as unity. Otherwise, we classify the prediction as zero. Intuitively, if the estimated probability is greater than 0.5 then we expect that there is a greater chance that this respondent will binge drink, while if the estimated probability of binge drinking is less than 0.5, there is a greater chance that the respondent will not binge drink. We also use threshold values of 0.25 and 0.75, to ensure that the predictive accuracy was not sensitive to the chosen threshold level. Prediction accuracy is highest using the 0.5 threshold level; the prediction accuracy using the alternative threshold levels is within 5 percentage points of the prediction accuracy obtained using the 0.5 threshold. In the nonparametric case, we predict the binary left-hand-side variable by estimating the conditional mode for each observation in the sample (see Li and Racine, 2007 or Racine, 2008). We then compare our predictions to the actual values and calculate the CCR. The estimator with the highest CCR provides the most accurate predictions of the left-hand-side variable, and is therefore our preferred estimator.

DATA

Our data come from DeSimone (2007), which is based on the 1995 National College Health Risk Behavior Survey (NCHRBS) conducted by the Centers for Disease Control (CDC). The 1995 NCHRBS survey was designed to assess risky behavior in a nationwide sample of college students. The raw data along with supplemental materials (i.e., survey description and codebook) is available from the website of the CDC. Details regarding the survey sampling methods used by the CDC can be found in CDC (1997).vvAll information contained in the NCHRBS 1995 survey was self-reported by respondents.

The sample in this paper is restricted to full time students, aged 18-24, that are enrolled in a 4-year college or university, and that have an academic class standing of senior or below. Any observations with missing values for any of the variables used in the estimation of the models were dropped, leaving a sample of 1401 observations. All variables were either taken directly from or constructed from the NCHRBS (1995) survey.

The left-hand-side variable is an indicator of whether or not the respondent reported binge drinking in the past 30 days. The explanatory variable of particular interest is an indicator of whether or not the respondent is a member of a fraternity.

In an effort to control for spurious correlations between fraternity membership, binge drinking, and self-selection of risky individuals into fraternities, DeSimone (2007) constructs variables that fall into three categories: exogenous drinking determinants, alcohol use measures, and heterogeneity controls. Exogenous drinking determinants include indicators for sex, age, class standing, ethnicity, marital status, and parental education levels. There are five alcohol use measures: the number of days that alcohol was consumed in the past 30 days, the number of times in the past 30 days alcohol was used before driving, the number of times in the last 30 days alcohol was used in combination with illegal drugs, whether or not alcohol was used before the last sexual encounter, and the number of years since alcohol was first consumed. Specific details regarding data construction are available in DeSimone (2007). The heterogeneity control variables include location of residence (i.e., fraternity house, dormitory, parent's house, etc.), hours of paid work per week, participation in athletic teams, the student's height and weight, whether or not the student wears a seatbelt when riding in the car, the number of cigarettes smoked in the past 30 days, and the number of times marijuana was used in the last 30 days.

The five alcohol use measures were included by DeSimone (2007) to control for drinking preferences in order to control for endogenous selection into fraternities and help isolate a potentially causal relationship between fraternity membership and binge drinking. We argue that one might also interpret these measures as additional indicators of risk preference. Other measures of risk include: whether or not the student wears a seatbelt while riding in the car, the number of cigarettes smoked in the past 30 days, and the number of times marijuana was used in the past 30 days.

The data used for the nonparametric analysis is identical to the data used by DeSimone (2007) except for the case of non-binary categorical discrete covariates (e.g., age, ethnicity, class-standing, parental education, etc.). In the parametric specification, non-binary categorical discrete covariates are represented via (r_{j-1}) binary indicator variables, where r_j is the number of categories the variable can take. In the nonparametric models, we construct a single categorical variable from the r_j categories by assigning a separate integer value to each category. This, in turn, reduces the number of covariates in the model. See Racine and Li (2004) for details.

Finally, we note that DeSimone (2007) uses survey sampling weights for most regressions. To allow for a direct comparison between the parametric specification and the nonparametric conditional probability density model we omit the survey sampling weights from all estimations. We stress that comparisons between overall significance levels, individual covariate significance levels and in-sample prediction rates show qualitatively and quantitatively similar results between the weighted and unweighted probit specifications (Table 6 in DeSimone 2007). Omission of the probability sampling weights do not alter the results of DeSimone (2007) and are omitted from this analysis.

DATA ANALYSIS

Before presenting our nonparametric conditional density results, we look at the correlations and unconditional densities of the data to obtain a fresh insight into the relationship between binge drinking behavior, fraternity membership, and additional control variables. An unconditional analysis of the data cannot confirm or refute causality between fraternity membership and binge drinking; however, it can in part provide a better understanding of the relationship between the variables in the sample.

Sample Correlations

We first look at a basic correlation matrix between the covariates in the sample and our binary binge drinking indicator variable. If we are to identify a potentially causal relationship between fraternity membership and binge drinking, we expect to find a (strong) correlation between fraternity membership and binge drinking. The sample correlations are reported in Table 1. It should be noted that the correlations for unordered categorical variables (ethnicity, type of residence, marital status, and class standing) are not necessarily directly comparable to the other correlations because the covariance is not immune to any rescaling of the data. However, we can directly compare the correlations between the

TABLE 1
SAMPLE CORRELATIONS BETWEEN COVARIATES AND BINGE DRINKING

Variable	Binge Drinking Indicator
Binge drinking indicator	1.0000
Days binge drank in past 30 days	0.6313
Days drank in past 30 days	0.6239
Times drank and drive in past 30 days	0.4017
Used alcohol last time had sex	0.3679
Years since first alcoholic drink	0.2879
Sports teams played for this year	0.2460
Times used marijuana in past 30 days	0.2239
Height in inches	0.2232
Times used alcohol with drugs in past 30 days	0.2178
Ethnicity	-0.2091
Cigarettes smoked in past 30 days	0.2034
Fraternity membership	**0.1905**
Female	0.1562
Mother's education	0.1358
Always wears seatbelt when riding in a car	-0.1260
Father's education	0.1176
Weight in pounds	0.1103
Type of residence	-0.0947
Marital status	-0.0888
Age	-0.0401
Hours per week works for pay	-0.0363
School indicator	0.0233
Class standing	0.0028

other covariates and binge drinking; we find that fraternity membership has a relatively low correlation with binge drinking using the Pearson, Spearman, and Kendall's (tau) methods of calculating the correlation coefficient. The variables are listed in descending order based on the absolute value of the correlation.

Table 1 reveals binge drinking is most highly correlated with the number of days the respondent drank alcohol in the past 30 days, followed by several measures of alcohol and risk preferences (drinking and driving, sexual activity under the influence of alcohol, years since first consuming alcohol, alcohol use combined with illegal drug abuse, cigarette and marijuana use), height, and sports participation. The correlation between binge drinking and fraternity membership is 0.19 which suggests relatively weak correlation between binge drinking and fraternity membership. This strong correlation with number of days the respondent drank alcohol with fraternity membership leads us to question the causality. It is possible that fraternity membership causes days of drinking, as well as, binge drinking which could lead to unobserved heterogeneity issues. We find that binge drinking is most highly correlated with measures of risk preference, the height of the respondent and sports participation.

Unconditional Density Plots

We next analyze unconditional density plots of the number of days in which the respondent binge drank in the past 30 days for fraternity members and non-members and for respondents who reported consuming alcohol prior to the last sexual encounter and those that did not. Here we use the number of days in the past 30 days in which the respondent reported binge drinking instead of the binary binge drinking indicator since it provides a deeper insight into the binge drinking preferences for each of the samples used throughout this section. By comparing the number of binge drinking days, instead of using the binary binge drinking indicator, we can compare the extent to which different subsamples of the data choose to binge drink. The results are displayed in Figure 1. To estimate the unconditional densities shown in Figures 1 and 2, we estimate a nonparametric (unconditional) density for each subsample using a normal reference (1.06) bandwidth.

It is clear from the figure that fraternity members binge drink more frequently than non-members, with the majority of non-members binge drinking fewer than 5 times in the past 30 days. It is also apparent that those who reported consuming alcohol prior to the last sexual encounter binge drink more frequently than those who did not. Moreover, the lower right panel of Figure 1 displays a mass of respondents around both 7 and 15 days that do not appear in the upper right panel and contains fewer respondents who report binge drinking fewer than five days in the last 30 days. This suggests that those who reported consuming alcohol prior to the last sexual encounter are more likely to binge drink and binge drink more frequently than a sample of respondents who reported membership in a fraternity. Of the 259 fraternity members in the sample, only 74 reported consuming alcohol prior to the last sexual encounter (of which there are 254 observations). Therefore, the similarities in the densities for fraternity members and non-members and those who reported consuming alcohol prior to the last sexual encounter and those who did not are not because of identical samples of respondents. There is a significant group of respondents in the sample who report both binge drinking heavily and consuming alcohol prior to the last sexual encounter that are not fraternity members.

FIGURE 1
UNCONDITIONAL DENSITIES OF BINGE DRINKING DAYS

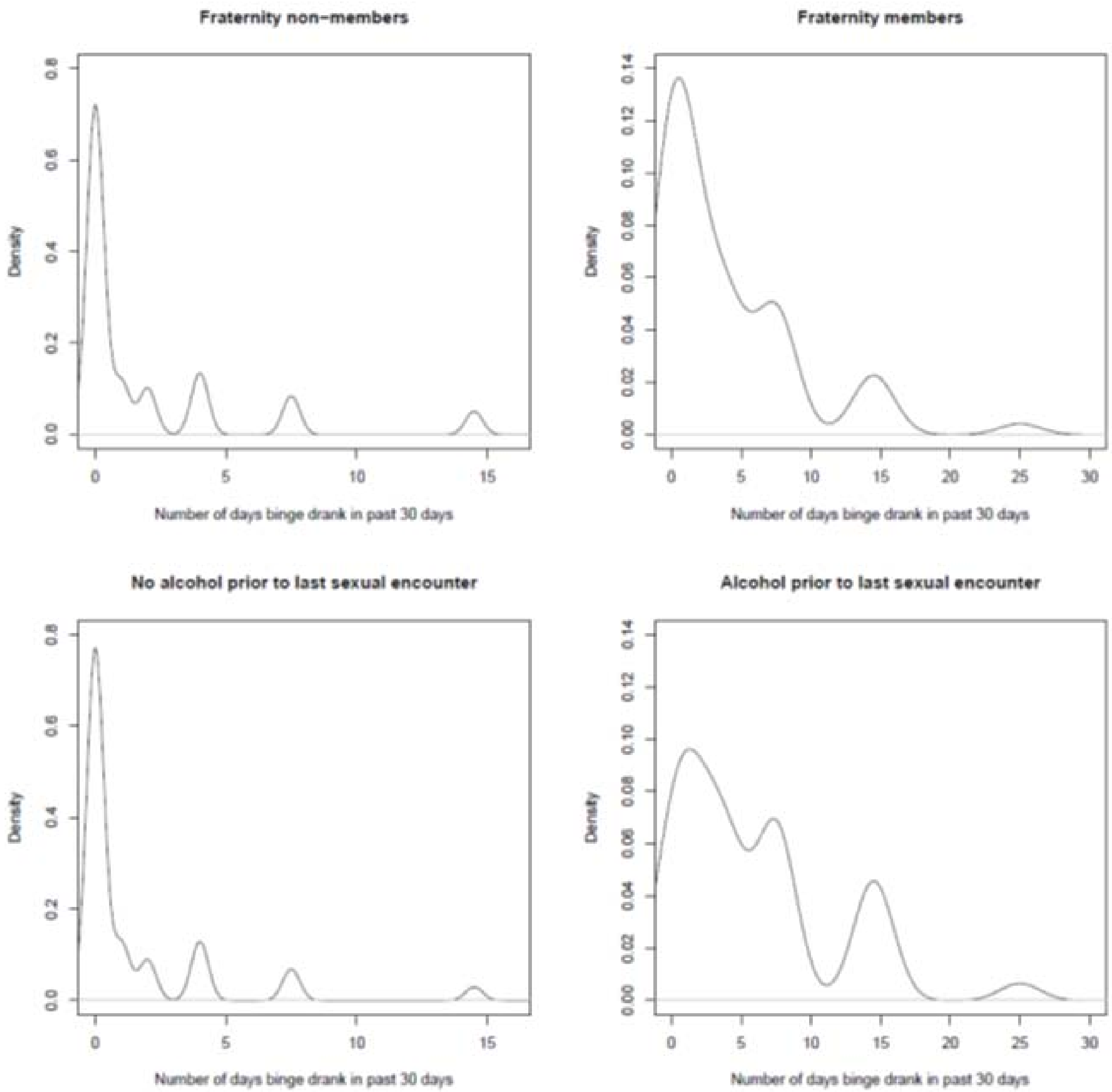
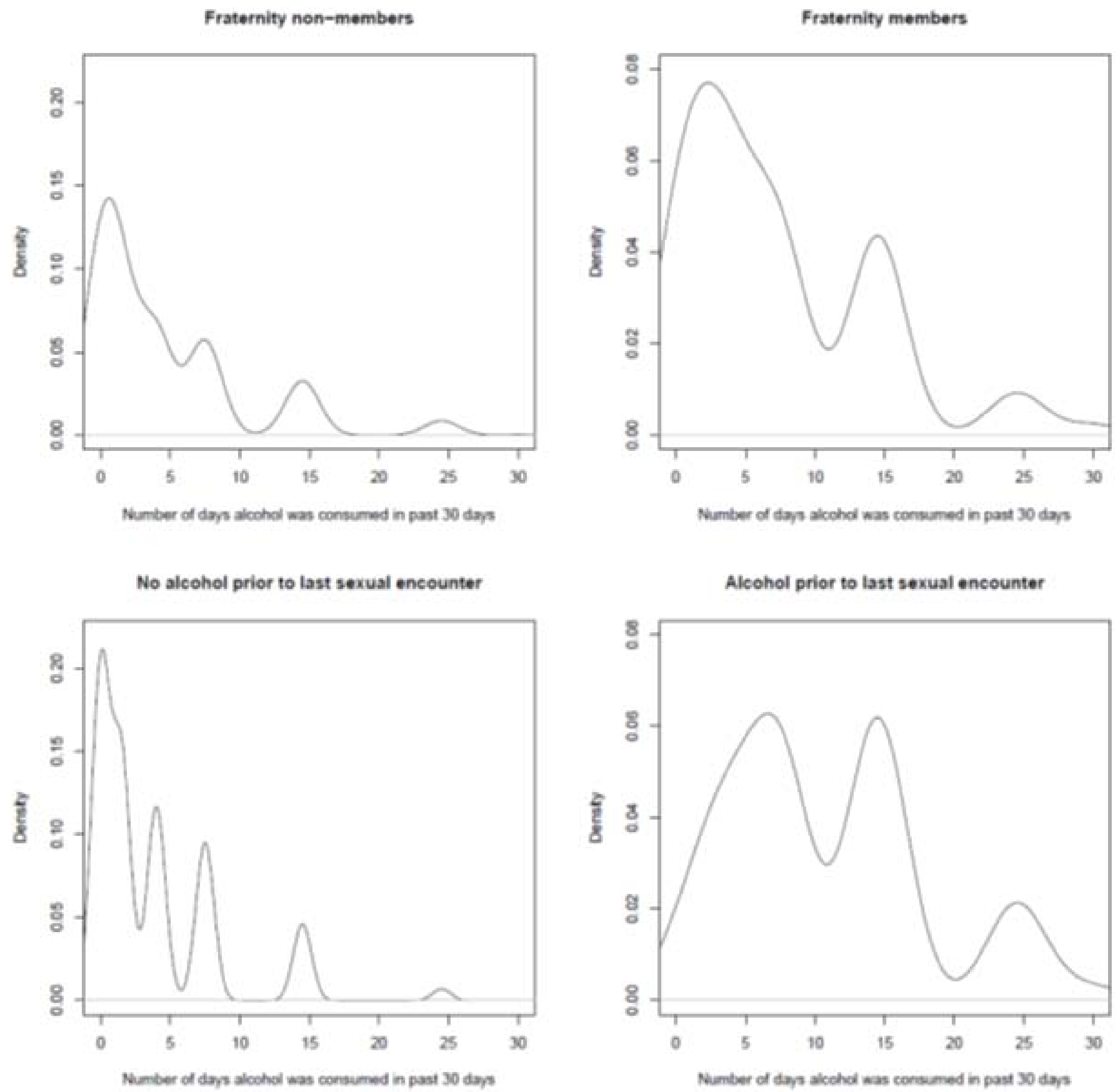


Figure 2 displays unconditional density plots of the number of days in which the respondent reported consuming alcohol in the last 30 days for fraternity members and non-members and for respondents who reported consuming alcohol prior to the last sexual encounter and for those that did not. Similar to Figure 1, fraternity members report consuming alcohol more frequently than non-members, yet the majority of respondents in both samples are clustered below 10 drinking days each month. The lower panel of Figure 2 shows that those who reported consuming alcohol prior to the last sexual encounter drink much more frequently than those who did not, while the majority of those who reported consuming alcohol prior to the last sexual encounter are grouped between 2 and 20 days per month. This is in contrast to the respondents who reported not consuming alcohol prior to the last sexual encounter, who appear to be clustered below 5 drinking days per month. Comparing the upper and lower right-hand panels, there is a mass of observations at both 15 and 25 days for respondents who reported consuming alcohol prior to the last sexual encounter that do not appear in the density for fraternity members. In addition, there are fewer observations who consumed alcohol fewer than 5 days in the past 30 days for respondents who consumed alcohol prior to the last sexual encounter than for fraternity members.

FIGURE 2
UNCONDITIONAL DENSITIES OF THE NUMBER OF DAYS ALCOHOL WAS CONSUMED



It is clear that not only do those who report consuming alcohol prior to the last sexual encounter consume alcohol more frequently than fraternity members, but our indicator of alcohol use combined with sexual activity seems to provide more accurate prediction of drinking (and binge drinking) behavior. Moreover, many of the students who binge drank and drank alcohol prior to last sexual encounter were not fraternity members. These results further support the idea that risky behavior, specifically risky sexual activity, is more highly correlated with binge drinking than is membership in social fraternities. However, fraternity membership may be a cause of days of drinking, as well as, binge drinking showing an unobserved heterogeneity problem.

While the correlation between alcohol use and measures of risk preference has been identified in previous research (e.g., Ress et al., 2001 and Rashad and Kaestner, 2004, DeSimone, 2007), recent empirical work (e.g., DeSimone 2007, 2009) has argued that fraternity membership is a significant and potentially causal factor of binge drinking (while controlling for risk preference). We argue that simple analysis of the data casts doubt on the possibility that fraternity membership maintains robust and potentially causal significance in predicting binge drinking.

NONPARAMETRIC CONDITIONAL DENSITY

Correct Classification Ratio

We now evaluate the in-sample prediction accuracy of the nonparametric conditional density estimator and the probit model from DeSimone in order to select which model is more appropriate for predicting binge drinking. Our results suggest the parametric model is misspecified. We present the confusion matrices and correct classification ratio (CCR) for each estimator in Table 2.

TABLE 2
CONFUSION MATRICES AND CCR

Probit Model			Nonparametric Model		
A/P	0	1	A/P	0	1
0	699	72	0	737	34
1	114	516	1	38	592
	CCR 86.72%			CCR 94.86%	

The confusion matrices show the accuracy of our in-sample predictions for each outcome and the CCR measures the overall in-sample prediction accuracy of each estimator. The probit specification is able to predict with nearly 87% accuracy[8], while the nonparametric model predicts with nearly 95% accuracy. In a similar exercise, Li and Racine (2004) estimate a nonparametric conditional density specification that is able to outpredict the parametric counterpart by approximately 4 percentage points and conclude that the parametric model is misspecified. Hall, Racine and Li (2004) show the nonparametric estimator is better able to predict the left-hand-side variable only when the parametric model is misspecified. Following these results, we conclude that the probit model is misspecified.

Bandwidths

Now that we have established the nonparametric estimator as our preferred model, we analyze the nonparametric conditional density bandwidths to determine which of the covariates in the sample are relevant factors in predicting binge drinking. The results are shown in Table 3.

TABLE 3
CONDITIONAL DENSITY BANDWIDTHS

Variable	Bandwidth	Upper Bound	Relevance
Fraternity membership	0.4937	0.5000	Most likely no
Female	0.4954	0.5000	Most likely no
Age	0.8474	1.0000	Yes
Class standing	0.9257	1.0000	Yes
Ethnicity	0.2764	0.8000	Yes
Marital status	0.6667	0.6667	No
Mother's education	0.9677	1.0000	Yes
Father's education	1.0000	1.0000	No
Days drank in past 30 days	0.0456	11.8101	Yes
Years since first alcoholic drink	70011.1000	6.0634	No
Times used alcohol with drugs in past 30 days	39611.1300	5.8828	No
Times drank and drive in past 30 days	2.8622	2.9364	Yes
Used alcohol last time had sex	2.9025e-16	0.5000	Yes
Type of residence	0.6473	0.8333	Yes
Hours per week works for pay	55654357	24.1115	No
Height in inches	2044938	8.0793	No
Weight in pounds	34.4355	71.4062	Yes
Sports teams played for this year	1.4758	1.8456	Yes
Always wears seatbelt when riding in a car	0.1357	0.5000	Yes
Cigarettes smoked in past 30 days	81319143	215.9246	No
Times used marijuana in past 30 days	6.4846	11.8192	Yes
School indicator	0.9848	0.9848	No

The bandwidth on fraternity membership is 0.4937, which is just below the upper bound of 0.5. While it has not reached the upper bound exactly, it is likely that fraternity membership is in fact irrelevant[9]. Indeed, the weights assigned to both fraternity membership and non-membership are nearly identical. Taking the most conservative interpretation of the bandwidth, we conclude that fraternity membership carries little (if any) relevance in predicting binge drinking.

The bandwidth on the indicator for whether or not the respondent used alcohol prior to the last sexual encounter is approximately zero. This result suggests that those who consumed alcohol prior to the last sexual encounter belong in a separate sample than those who did not, when considering binge drinking behavior. We, therefore, confirm our previous result that suggests the binge drinking preferences of people who engage in risky sexual behavior are starkly different from those who do not engage in risky sexual activity. Numerous studies have found a strong link between drinking and risky sexual behavior, as alcohol use may lower inhibitions or reduce perceived risks. According to Morrison et al. (2003), Ress et al. (2001) and Rashad and Kaestner (2004) the relationship between drinking and risky sexual behavior is highly correlated. Unobserved personal characteristics, such as, time preference or degree of risk aversion (Rees et al. 2001) may more closely predict all sorts of risky behavior including risky sexual behavior and alcohol use. Therefore, we are unable to isolate causality between risky sexual behavior and binge drinking. However, we conclude that the binge drinking preferences of respondents who engage in risky sexual activity are fundamentally different than those who do not.

We find that all of our measures of risk preference are relevant with the exception of the number of years since the respondent first consumed alcohol, the number of times in the past 30 days in which the respondent used alcohol in combination with illegal drugs, and the number of cigarettes smoked in the past 30 days. The number of times alcohol was used in combination with illegal drugs is most likely irrelevant due to the relevance of the variable measuring the number of times marijuana was used in the past 30 days. We find in the entire sample, nearly every respondent who reported consuming alcohol in combination with illegal drugs also reported smoking marijuana in the past 30 days. The NCHRBS survey question is unspecific regarding what specifically are 'illegal drugs' when asking whether or not alcohol was used in combination with illegal drugs. Due to the consistencies between responses for the two variables, it is likely that the variable measuring marijuana use also identifies the effect on binge drinking of alcohol and drug use.

The irrelevance of the number of years since alcohol was first consumed is likely because college binge drinking preferences are influenced by the current social climate, rather than any past histories with alcohol use. For this same reason, cigarette use may be related more to social pressures instead of measuring risk preferences. In general, the risk associated with smoking cigarettes is long-term health effects, such as lung cancer or emphysema, and not short-term health effects. Other risky activities, for example, drinking and driving or engaging in risky sexual activities, pose immediate short-run risks, such as death, contraction of a serious or potentially incurable disease, or the possibility of facing serious legal repercussions. For these reasons, smoking cigarettes may not be considered risky for a cohort of college students and therefore does not adequately measure risk preference.

We further identify relevance in class standing and location of residence that were not otherwise identified in the parametric model. The relevance of class standing suggests that there are heterogeneous preferences for binge drinking based on the number of credit hours completed. In addition, we find female to not be relevant, as it just about reaches the upper bound. Since there are fundamental differences between fraternities and sororities, it would be interesting to run the model separately by gender, but we are unable to do so with the limited sample size[10].

We find sports participation to be relevant, noting its significance in the parametric model as well. Athletes typically participate in social gatherings and because of social pressure, are more likely to binge drink in order to fit in better with their teammates. In addition, athletes may use binge drinking as a means of showing off in order to attract members of the opposite sex. See, for example, Aries et al. (2004) for a discussion on differences between athletic and non-athletic college students.

The nonparametric model reveals a preference for risky behavior as the driving force behind binge drinking, not fraternity membership which was identified as a driving force in the parametric model. Furthermore, we find evidence that respondents who reported consuming alcohol prior to the last sexual encounter belong in a separate sample from those who did not, confirming the results found by analyzing the unconditional densities of binge drinking behavior.

POLICY RECOMMENDATION

Our results have direct policy implications, namely providing answers to the question of how should colleges and universities best focus their resources to curb binge drinking. We find that policies aimed primarily at restricting fraternity membership and participation may not produce the desired outcome because of the irrelevance of fraternity membership identified in this paper. Since fraternities offer positive influences, aims to reduce binge drinking by restricting fraternity membership and participation seem unjustified. Policies should be focused towards all students who partake in all types of risky behavior, with an added emphasis on risky sexual behavior.

Policies to reduce risky behavior may benefit from focusing on the mental health quality of students. Poor emotional health and symptoms of depression are associated with reducing the perceived risks associated with dangerous behavior which, in turn, increases risky behavior (Harris et al., 2002). A greater emphasis on academic and personal counseling across college campuses may reduce the mental stress that often accompanies the college experience. In addition, encouraging campus sponsored recreation, such as outdoor adventures and day trips, might reduce social stress and provide a safe, fun alternative to engaging in risky behavior. One valuable medium through which the publication and implementation of such events may occur is through a joint sponsorship of events between fraternities and official campus departments.

Schools have also focused policies on modifying social norms to accurately reflect students' actual amount of risk taking. Students often overestimate norms in terms of drinking, sexual and other types of risky behavior, causing them to perceive their risky actions as normal. Campus policies encouraging greater awareness of risky behavior, as well as a realistic assessment of the consequences of partaking in such behavior may be effective in realigning perceived risk with actual risk and subsequently perceived norms with actual norms.

Many risky activities are also illegal, such as underage drinking, using illegal drugs, forced sexual activity or sexual activity with a minor. Alternative policy prescriptions include an increase in university police activity, which may result in the increased responsiveness of students' behavior to an increase in the likelihood of paying legal consequences for partaking in illegal and risky behavior. The effect may be a substitution away from risky activities if the cost from getting caught was sufficiently high.

While all of the above policy recommendations are aimed at generally reducing risky activities, the availability of contraceptives and STD screenings may directly affect the risk associated with college sexual activity. The effects of readily available contraceptives and STD screenings on sexual activity and other risky behaviors are not clear. On the one hand, providing contraceptives and screenings decreases the risk associated with sexual activity. On the other hand, it may substantially lower the price of risky sexual activity relative to alternative choices, thereby encouraging students to further partake in risky sexual activity. Either scenario may have indirect effects on all types of risky activities; therefore this topic warrants further study.

CONCLUSION

Our results show, contrary to previous research, that fraternity membership is not a relevant predictor of binge drinking, when controlling for risk preferences. Thus, we conclude that fraternity membership is not a causal factor of binge drinking. Rather, binge drinking is more closely related to overall risky behavior, specifically risky sexual behavior. While we make no assertions as to the direction of causality between binge drinking, risky behavior and risky sexual behavior, we recommend colleges and universities focus their efforts at curbing all types of risky behavior, perhaps with an emphasis on sex-related activities.

ENDNOTES

1. Throughout this paper, the term fraternity refers to both fraternities and sororities.
2. DeSimone (2007) also uses an interval regression model to predict the number of binge drinking days. Both the probit and interval regression models yield qualitatively similar results.
3. Of course, one can include interactions and nonlinearities of the regressors, but this must be exactly specified and is usually ad hoc.
4. The nonparametric estimation conducted during this analysis was done using version 0.30-3 of the ``np'' package available in R version 2.9.2. See Hayfield and Racine (2008) for details.
5. The neighborhood is determined by the magnitude of the bandwidth.
6. Alternative bandwidth selections methods include `rule-of-thumb' and plug-in methods, however, selection of the optimal bandwidths through these methods is difficult in applied work.
7. In general, different criteria can be used to evaluate the relative performance of an estimator. The present paper uses the accuracy of in-sample predictions; see Bontemps et al. (2009).
8. These results are for the unweighted probit specification. The weighted probit specification predicts with 86.58% accuracy, which is virtually identical to the unweighted results.
9. Henderson and Millimet (2008) make similar assumptions regarding irrelevance of categorical regressors.
10. DeSimone (2007) runs a probit model separately by gender and finds no significant difference between the results.

REFERENCES

Aries, E., D. McCarthy, P. S. & Banaji, M. R.(2004).A Comparison of Athletes and Nonathletes at Highly Selective Colleges: Academic Performance and Personal Development. *Research in Higher Education*, 45(6), 577-602.

Astin, A. W. (1993). *What Matters in College: Four Critical Years Revisited*, San Francisco: Jossey-Bass.

Baier, J. L. & Whipple, E. G. (1990). Greek Values and Attitudes: A Comparison With Independents *NASPA Journal*, 28, 43–53.

Bontemps, C., Racine, J. S. & Simioni, M. (2009) Nonparametric vs Parametric Binary Choice Models: An Empirical Investigation, working paper.

Cashin, J. R., Presley, C. A. & Meriland, P. W. (1998). Alcohol Use in the Greek System: Follow the Leader? *Journal of Studies on Alcohol*, 63-70.

Centers for Disease Control and Prevention (1997). Youth risk behavior surveillance: National College Health Risk Behavior Survey - United States, 1995 *Morbidity and Mortality Weekly Report*, 46(SS-6), 1-54.

Chaloupka, F. J. & Wechsler, H. (1996). Binge Drinking in College: The Impact of Piece Availability, and Alcohol Control Policies. *Contemporary Economic Policy*, 14(4), 112-124.

De Los Reyes, G. & Rich, P. (2003). Housing Students: Fraternities and Residential Colleges. *Annals of the American Academy of Political and Social Science*, 585, 118-123.

DeSimone, J. (2007). Fraternity membership and binge drinking. *Journal of Health Economics*, 26, 950-967.

DeSimone, J. (2009). Fraternity Membership and Drinking Behavior. *Economic Inquiry*, 47(2), 337-350.

Grubb, F. (2006). Does Going Greek Impair Undergraduate Academic Performance. *American Journal of Economics and Sociology*, 65(5), 1085-1110.

Hall, P., Racine, J. S. & Li, Q. (2004). Cross-Validation and the Estimation of Conditional Probability Densities. *Journal of the American Statistical Association*, 99(468), 1015-1026.

Hall, P., Li, Q. & Racine, J. S.(2007). Nonparametric estimation of regression functions in the presence of irrelevant regressors. *Review of Economics and Statistics*, 89(4), 784-789.

Harris, K. M., Duncan, G. J. & Boisjoly, J. (2002). Evaluating the Role of `Nothing to Lose' Attitudes on Risky Behavior in Adolescence. *Social Forces*, 80(3), 1005-1039.

Harrison, W. B., Mitchell, S. K. & Peterson, S. P. (1995). Alumni Donations and Colleges' Development Expenditures: Does Spending Matter? *American Journal of Economics and Sociology*, 54(4), 397-412.

Hayfield, T. & Racine, J. S. (2008). Nonparametric Econometrics: The np Package. *Journal of Statistical Software*, 27. URL http://www.jstatsoft.org/v27/i05/.

Henderson, D. J. & Millimet, D. L. (2008). Is Gravity Linear? *Journal of Applied Econometrics*, 23, 137-172.

Hunt, S. & Rentz, A. L. (1994). Greek Letter Social Group Members’ Involvement and Psychosocial Development. *Journal of College Student Development*, 35(4), 289-296.

Li, Q. & Racine, J. S. (2004). Predictor Relevance and Extramarital Affairs. *Journal of Applied Econometrics*, 19(4), 533-535.

Li, Q. & Racine, J. S. (2007). *Nonparametric Econometrics: Theory and Practice*, Princeton University Press.

Marmaros, D.& Sacerdote, B. (2002). Peer and Social Networks in Job Search. *European Economic Review*, 46(4-5), 870-879.

Morrison, D. M., Gillmore, M. R., Hoppe, M. J.,Gaylord, J., Leigh, B. C. & Rainey, D. (2003). Adolescent Drinking and Sex: Findings from a Daily Diary Study. *Perspectives on Sexual and Reproductive Health*, 35(4), 162-168.

R Development Core Team (2009). *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.Rproject.org.

Racine, J. S. & Li, Q. (2004).Nonparametric Estimation of Regression Functions with Both Categorical and Continuous Data. *Journal of Econometrics*, 119, 99-130.
Racine, J. S. (2008). Nonparametric Econometrics: A Primer. *Foundations and Trends in Econometrics*, 3, 1-88.
Rashad, I. & Kaestner, R. (2004). Teenage Sex, Drugs and Alcohol Use: Problems Identifying the Cause of Risky Behaviors. *Journal of Health Economics*, 23, 493-503.
Rees, D. I., Argys, L. M. & Averett, S. L. (2001). New Evidence on the Relationship Between Substance Use and Adolescent Sexual Behavior. *Journal of Health Economics*, 20, 835-845.
Sacerdote, B. (2001). Peer Effects with Random Assignment: Results for Dartmouth Roommates. *Quarterly Journal of Economics*, 116(2), 681-704.
Wechsler, H., Dowdall, G. W., Davenport, A. & Castillo, S. (1995). Correlates of College Student Binge Drinking. *American Journal of Public Health*, 85(7), 921-926.