Do Alpha Males impose a cost?

How Fraternity Moratorium Affect Alcohol Offenses and Sexual Assault

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Abstract

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1 Background on Fraternities

A fraternity, in the context of universities, is defined as a men's student organization formed chiefly for social purposes having secret rites and a name consisting of Greek letters. Fraternities are a ubiquitous, and longstanding tradition in the United States. They maintain a presence at 800 universities across the US (Hechinger 2017) with the oldest fraternities forming in the mid 1800s (IFC website).

Fraternities consist of students from families of higher-than-average educational attainment and income; they are predominantly white, and prior research has linked fraternity membership to increases in graduation rates (Routon and Walker 2014), income (Mara, Davis, and Schmidt 2018), and GPA (DeBard and Sacks 2011). However, members spend approximately 2 more hours partying than nonmembers (Routon and Walker 2014), and sorority[1] members, who socialize frequently with fraternity members, have been found to consume alcohol with greater frequency, delay assessments of threat, and have significantly higher rates of drugging victimization than non-sorority members (Lasky et al. 2017; Franklin 2016).

This paper focuses primarily on a group of fraternities known as the Interfraternity Council (IFC), a group of fraternities that consist of over 4 million alumni and more than 380k undergraduate members across the US which, according to their creed, "exist to promote the shared interests and values of our member fraternities: leadership, service, brotherhood and scholarship" (Hechinger 2017). IFC fraternities differ from professional development fraternities in that they exist mainly for social purposes and are typically the largest fraternity presence at a university. More importantly, IFC fraternities are the fraternities subject to moratoriums in the sample.

To become a member of an IFC fraternity, prospective members must apply during recruitment events that take place in the fall or spring semester (or both). Once a chapter and prospective member jointly accept membership, the new member (the "pledge") must abide by the chapter's guidelines. Figure **??** shows an example of the overarching rules within the

[1] A sorority is the female counterpart of fraternities.

chapter, Sigma Alpha Epsilon–one of the oldest and largest fraternity chapters across the US that has initiated over 336k members (Hechinger 2017). Each member must maintain a GPA over a certain threshold, pay an initiation and semester fee, attend chapter ritual events and meetings, be involved in one additional campus or community organization, and complete service hours. Upon membership, pledges may be invited to live within the fraternity house,[2] which can reside either on or off campus. However, chapter houses are not managed by university-housing, and hence, fraternities have been found to be the most reliable source of alcohol for first-year undergraduates (Mara, Davis, and Schmidt 2018).

2 Data

The main analysis utilizes Daily Crime Logs from 53 university's dedicated police department over a six year period (2014-2019). I omit the year 2020 due to the COVID-19 pandemic in which university activity varied substantially from the previous years. Under the Jeanne Clery Act, Universities that receive federal funding are mandated to keep Daily Crime Logs which specify the universe of crimes that university police officers report or are reported to the university police department over the last seven years. Daily Crime Logs are unique in that the data is unaggregated; each Daily Crime Log contains the date reported at the hourly level, in addition to a short description of the crime. Moreover, the Daily Crime Logs contain all incidents reported by or to the university police. Therefore, the data includes offenses such as alcohol offenses which are missing from national databases such as the Uniform Crime Reporting System (UCR) and the National Incidence-Based Reporting System (NIBRS). Additionally, the by-hour reporting makes the Daily Crime Logs preferable to other university crime databases such as Campus Safety and Security Data provided by the US Department of Education which features only yearly-level data on offenses.

[2] Not all universities have fraternity houses on their campus property, and not all fraternity chapters have houses at every university they are affiliated with.

2.1 Data Collection

Under the Jeanne Clery Act, university police must allow their Daily Crime Logs to be ready for inspection within two business days of an inquiry. The universities will then either send their Daily Crime Logs (usually in PDF format) through email, direct you to a website that holds their records, or arrange to set a time to inspect records.[3] Each of these records were parsed using PDF extracting and webscraping techniques. Figure SAMPLE OF CRIME LOG shows a sample of a Daily Crime Log.[4]

2.2 Data Harmonization

Each university's Daily Crime Log varies in the description of the crimes reported. For instance, the report of "driving while intoxicated" may be represented in several ways across university police departments such as "DWI" or "operating while intoxicated." To achieve harmonization across university police departments, I pattern-matched key words using regular expressions relating to specific categories of crimes that are reported in the US Department of Education Campus Safety and Security Data: sexual assault, alcohol offenses, drug offenses, and robbery. I focus primarily on sexual assault, alcohol offenses, and drug offenses since these crimes have been previously linked to college partying (CITE) and fraternities (CITE), while robbery acts a placebo check; there is no literature pointing to robberies being correlated with fraternity or college partying behavior. and fraternity Table **KEYWORDS** shows the keywords used to pattern match to each offense type. These keywords were derived from surveying the most frequent descriptions of crimes within each university police department. For instance, if the phrase "liquor law violation" was a common description in a university's crime logs, then the keyword "liquor" was used to match to an alcohol violation.

[3]Universities did not have to allocate copies of the crime logs, they only had to make them available for inspection. Hence, there are **SEVERAL UNIVERSITIES** that may have had fraternity moratoriums, but were not able to be included in the sample. Additionally, **NUMBER OF UNIVERSITIES WITH UNREADABLE** universities provided Daily Crime Logs that were in formats that were completely unreadable by any software (e.g scanned documents). These **BLANK NUMBER** were

[4]Nearly every Daily Crime Log varied by university.

While this method is imperfect–it may underestimate the true reported offenses if particular keywords were not matched or it may overestimate the true reported offenses if particular keywords systematically match to incorrect crimes– Table **MOST COMMON WORDS** shows the 15 most frequently reported offenses after the pattern matching process. In each of the columns, there is no apparent mismatching. Furthermore, Figure **VENNDIAGRAM** shows that there is little overlap between the three main outcomes of alcohol, drug, and sexual assault offenses.

3 Fraternity Moratoriums

3.1 Collection of Dates and University Characteristics

University-wide fraternity moratoriums are defined as a temporary cease of fraternity-related social gatherings with alcohol. While there is variation in each university's guidelines (e.g. some universities may restrict third-party vendors for fraternity events during a moratorium, others may not), each of the universities in the sample restrict registered social events with alcohol.[5]. The existence of a moratorium was found searching school newspaper articles, Lexis Nexis, and a private repository of news articles relating to fraternities. Table FRATERNITY MORATIA DATES shows each of the university's moratorium start and end dates. Each date in Table FRATERNITY MORATORIA DATES was verified using either newspaper articles, conversations with Fraternity and Sorority Life employees, or Freedom of Information Act requests. However, Table FRATERNITY MORATORIA DATES is not an exhaustive list of all moratoria. NUMBER OF SCHOOLS LEFT OUT B/C DATA universities were omitted from the sample because either verification of exact start and end dates could not be achieved, or the university's police department did not provide Daily Crime Logs in a format readable by any software.[6] Hence, the 38 universities

[5]Fraternity social events typically need to be registered through their respective university. An example of the guidelines for one university can be found HERE.

[6]One particularly notable omission from the sample is Pennsylvania State University which registered a fraternity moratorium on PENN STATE DATE due to the cause of Timothy Piazza. The university police

experiencing moratoriums in the sample are a subset of all university-wide fraternity moratoriums that occurred between 2014 and 2019. Additionally, 15 universities (28.3%) that *did not* experience a fraternity moratorium, but experienced a fraternity-activity-related death are included as a 'never treated' control group. This amounts to a total of 53 universities that are widely dispersed among the US (see Appendix MAP). Table SUMMARY STATS shows summary statistics of university characteristics using data from the Integrated Post-secondary Education Data System (IPEDS). On average, the universities are large (~28k enrollment), predominantly white (~59% of undergraduates), mostly public (84%) and have a wide variation in terms of selectivity and graduation rate.

3.2 Who oversees fraternity moratoriums and why do they occur?

Fraternities have three sources of oversight: the university's IFC, the unique fraternity chapter's national headquarters, and the university itself. Of these three sources of oversight, only the IFC and university have the jurisdiction to impose a university-wide fraternity moratorium. IFC-imposed moratoriums account for 36% of the moratorium in the sample, while universities account for the remaining 64%.

Moratoriums are the result of a plausibly exogenous shock to a university such as fraternity-related deaths, sexual assaults, hazing violations, or racist activity gone viral. Figure TRIGGER GRAPH shows the 45 moratoriums in the sample by the event that triggered the moratorium. The most frequent (42%) are behavior violations which include alcohol violations, racist activity gone viral, and hazing allegations, while second are fraternity related deaths (22%), and third are sexual assault allegations (20%). Of these triggering events, death results in the longest average moratorium at approximately 103 university-calendar days, while behavior and sexual assault allegations result in approximately 58 and 31 average university-calendar days respectively. 7 (16%) of these moratoriums had no clarifying explanation for the resulting moratorium. To test the plausible exogeneity of these

department did not allow copies of their Daily Crime Logs to be distributed- only inspected in person.

triggering events, I estimate both a linear probability and logit model on pre-treatment characteristics to predict a fraternity moratorium based on observables. I estimate Equation 1 where $EverMoratorium_u$ represents whether university u ever experiences a fraternity moratorium, $\mathbb{X}_u$ is a vector of observable characteristics including enrollment, demographics, pricing, and source of income for each university averaged over all years prior to the first moratorium, and ϵ_i is the error term. Standard errors are clustered by university, and an indicator for missing data is added to the model as revenues and SAT data is missing among a large portion of the sample.

$$EverMoratorium_u = \gamma \mathbb{X}_u + \epsilon_u \tag{1}$$

Table PREDICTION TABLE shows the results of this prediction exercise. Overall, there is little evidence that university characteristics can predict whether or not a moratorium is implemented. While there appears to be slight evidence that selectivity and total cost are predictors of moratoriums, these are weakly significant, not robust across both specifications, and likely represent 'by-chance' significance due to the multiple hypothesis tests problem. A Bonferroni p-value correction (e.g. multiplying the p-value by the number of hypothesis tests) yields no significance across any of the observable covariates, thus providing further evidence of the plausible exogeneity of these events.

4 Empirical Strategy

4.1 Primary Model

I estimate the effect of fraternity moratoriums on reports of sexual assault and alcohol offenses by exploiting across-time and within-university variation induced by the plausibly exogenous nature of the moratoriums. The model's identifying assumption is that universities that have experienced, will experience, or have never experienced a campus-wide fraternity moratorium are a good counterfactual for a university experiencing a campus-wide fraternity moratorium. In particular, the baseline approach to this model is estimated using Equation 2, where $Y_{u,t}$ represents the outcome of either sexual assault, alcohol offenses, or drug offenses at university u in time t, $\mathbb{X}_{u,t}$ is a vector of observable university characteristics that are complete across all universities[7] to minimize the impact of missing data, $\gamma_{u,semester}$ is a university-by-semester fixed effect, $\alpha_{weekday}$ is a weekday fixed effect, and $\epsilon_{u,t}$ is the error term.

$$Y_{u,t} = \beta Moratorium_{u,t} + \mathbb{X}_{u,t} + \gamma_{u,semester} + \alpha_{weekday} + \epsilon_{u,t} \tag{2}$$

University-by-semester fixed effects are included to remove any time-invariant differences between university-semesters. For instance, fraternity recruitment events vary across university-semesters (e.g. some universities may only allow spring recruitment, while others may allow fall and spring recruitment) which may enhance fraternity-related activities within a semester (De Donato and Thomas 2017). The inclusion of these fixed effects ensures that the estimated effects are driven by moratoriums instead of a cyclical increase in fraternity activities.

I include day-of-week fixed effects to address the fact that most fraternity-related activities occur on Fridays/Saturdays. Hence, the estimates should be interpreted as an additional effect of the crimes that are typically reported on a given weekday.

To increase precision of the estimates, I use only academic calendar days for each specific university. In particular, I extracted academic calendars[8] using the "first-day of classes" as the start-date of the fall semester, the "finalized grade date" for the end of the semester, and added a seven-day period to each beginning and end of a semester to account for slight variations across years.[9] To harmonize the 4% of the universities in the sample that use

[7]List out the observables here

[8]Academic calendars are based on the most recent calendar that was relevant to my sample period. Most academic calendars are based on academic years 2019-2020.

[9]However, I do not add a seven-day period to the end of the fall semester as this would bleed into Christmas vacation for many of the schools. Considering I use an extremely conservative end date (e.g. the

the quarter system, the fall quarter is defined as the fall semester, and the winter/spring quarters are defined as the spring semester.

4.2 Threats to Identification

Based on this empirical strategy, the main challenges with interpreting β as the causal effect of fraternity moratoriums come from two separate channels: changes in reporting and ex-ante trends. First, it is important that the propensity to report a crime does not change between moratorium days and non-moratorium days. For instance, β would be overestimating the effect of fraternity moratoriums if victims of sexual assault were more inclined to report (e.g. increased pressure on fraternities) or if there was more surveillance (e.g. more police officers on-duty to prevent bad behavior) on moratorium days which could result in higher reports of sexual assault and more discoveries of alcohol offenses respectively. On the other hand, β may be underestimating the effect of fraternity moratoriums if sexual assault victims are less inclined to report an offense (e.g. fear of retaliation) or if police surveillance decreased (e.g. less need for police officers when little fraternity activity) during moratoriums. To indirectly test these possibilities of reporting differences, I test whether there is a significant change in the proportion of offenses that are reported with a lag on moratorium days. I follow Sahay (2021) and define a crime reported with a lag as any crime that has a date reported that is more than three days[10] past the date occurred. While only 46 universities feature the date occurred in their Daily Crime Logs made available, this still amounts to 87% of the universities used for the main analysis. I estimate Equation 2, where $Y_{u,t}$ is the proportion of either sexual assaults or alcohol offenses reported with a lag at university u in time t. Estimates of this specification are shown in Table **??** Neither sexual assault nor alcohol offenses are reported differently during moratorium days, with both point

finalized grade date), there is little possibility that I will be excluding a significant amount of meaningful university-student-life activity. Additionally, if a start date was January 7th or earlier, I do not add a seven-day buffer. Exact academic calendars were not used because a significant portion of schools do not retain their old academic calendars.

[10] In Appendix Table BLANK, I change the definition of reporting with a lag to encapsulate a large variety of intervals. None of which are statistically significant.

estimates being precisely estimated around 0.

Moreover, β would not represent the causal effect of fraternity moratoriums if university police incidences/reports of crimes were already trending downward prior to the moratorium and would have continued downward absent the moratorium (e.g. Ashenfelter's Dip). Hence, I estimate an event study, aggregating the data to the weekly level,[11] following Equation 3.

$$Y_{u,t} = \sum_{j}^{J_u} \sum_{d=-8, d\neq -1}^{8} 1(t - e_j^u = d)\beta_d + \gamma_{u,semester} + \epsilon_{u,t} \tag{3}$$

Note that universities can experience multiple moratoriums in the sample time frame, and hence, J_u denotes the number of events ever occurring for university u, e_j^u denotes the time when university u experiences their jth event, and $1(t - e_j^u = d)$ is an indicator function. The remaining parameters are described similarly as in Equation 2. The treatment effects are normalized by setting $\beta_{-1} = 0$ (e.g. the reference period), and the earliest lead (β_{-8}) and latest lag (β_8) are binned to allow for identification with the presence of never-treated units (Schmidheiny and Siegloch 2020).[12]. Figure **??** and **??** show the estimated coefficients and confidence intervals for alcohol offenses and reports of sexual assault respectively. Figure **??** displays no signs of ex-ante trends for alcohol offenses- the estimated coefficients are all statistically insignificant and oscillate around 0 prior to a moratorium. While Figure **??** features less conventional satisfaction of ex-ante trends (e.g. all estimated coefficients are negative), the confidence intervals still encapsulate 0 pre-moratorium, signifying no statistically significant changes in reporting sexual assaults before the moratoriums.

[11] I define the start of a week as Monday since most fraternity activity and college partying activity occurs Friday-Sunday. Additionally, moratorium dates are 'floored' to the nearest week. As an example, if a moratorium occurs on a Wednesday, the full week beginning on Monday is considered the start of the moratorium week.

[12] Moreover, the binned endpoints are the sum of all the events that have occurred. For instance, if university u experienced two moratoriums, their final lag would consist of 0s, 1s, and 2s.

5 Results

5.1 Main Estimation

In Table ??, I estimate Equation 2 with OLS using both reports of sexual assault and alcohol offenses per 25 thousand enrolled students as the dependent variables. Standard errors are clustered at the university level, and university-by-semester and weekday fixed effects are included in all specifications. Columns (1)-(3) represent the effect of fraternity moratoriums on alcohol offenses. The estimation shows large and statistically significant decreases in alcohol offenses when there are no restrictions on days of the week (e.g. including Monday-Sunday), representing a 25% reduction from the mean, thus showing that moratoriums have a strong impact on campus-wide drinking behavior. These effects appear to be driven by weekend days (Friday/Saturday/Sunday), as shown in column (2), which is consistent with evidence that alcohol consumed more frequently on the weekends (CITE). Moreover, there is no evidence of significant decreases in alcohol offenses during weekdays. This is in-line with current literature showing that drinking behavior is less common on weekdays (CITE). On the other hand, reports of sexual show a small and statistically insignificant change during moratorium days. However, when restricting the sample to only weekends (Friday/Saturday/Sunday), there is weak evidence that reports of sexual assaults decrease during moratorium days. While this is only significant at the 10% level, this represents a 31% reduction from the mean. Next, I test whether the results from columns (1) and (4) are the result of OLS' sensitivity to outliers. I estimate Equation 2 using a leave-one-out regression framework. More specifically, I estimate 53 separate regressions, with each estimation omitting one university. Figure ?? shows the distribution of the coefficient estimates and standard errors. In each iteration, the results remain similar across both alcohol offenses and sexual assault as there appears to be no deviation in statistical significance and little deviation in the magnitude of the effects.

As an alternative, I replicate the results shown in Table ?? in Table (Appendix?) ??

using poisson estimation due to the discrete, count-nature of the offenses. The estimates have similar interpretation: alcohol offenses decline substantially during moratoriums while sexual assaults remain unchanged. The coefficients show a 33% decrease in alcohol offenses, with this effect being attributed to large decreases on the weekends. Similarly to OLS, there is weak evidence of reductions in reports of sexual assault on the weekends, but no effect when using the entire sample. Despite slightly larger magnitudes, poisson regression is not my preferred estimation method for two reasons: (1) OLS provides more conservative estimates and (2) poisson regression with fixed effects may drop observations when no variation is observed.

5.2 Placebo Checks

Use robbery offenses here.

Maybe randomize treatment?

5.3 Robustness

Leave-one-out regressions here. Poisson regressions here. Same offenses and using similar table as above.

References

De Donato, Andrew, and James Thomas. 2017. “The Effects of Greek Affiliation on Academic Performance.” *Economics of Education Review* 57 (April): 41–51. https://doi.org/10.1016/j.econedurev.2017.01.004.

DeBard, Robert, and Casey Sacks. 2011. “Greek Membership: The Relationship with First-Year Academic Performance.” *Journal of College Student Retention: Research, Theory & Practice* 13 (1): 109–26. https://doi.org/10.2190/CS.13.1.f.

Franklin, Cortney A. 2016. “Sorority Affiliation and Sexual Assault Victimization: Assessing Vulnerability Using Path Analysis.” *Violence Against Women* 22 (8): 895–922. https://doi.org/10.1177/1077801215614971.

Hechinger, John. 2017. *True Gentlemen: The Broken Pledge of America’s Fraternities*. 1st ed. Hachette Book Group, Inc.

Lasky, Nicole V., Bonnie S. Fisher, Caitlin B. Henriksen, and Suzanne C. Swan. 2017. “Binge Drinking, Greek-Life Membership, and First-Year Undergraduates: The ‘Perfect Storm’ for Drugging Victimization.” *Journal of School Violence* 16 (2): 173–88. https://doi.org/10.1080/15388220.2017.1284470.

Mara, Jack, Lewis Davis, and Stephen Schmidt. 2018. “Social Animal House: The Economic and Academic Consequences of Fraternity Membership.” *Contemporary Economic Policy* 36 (2): 263–76. https://doi.org/10.1111/coep.12249.

Routon, P. Wesley, and Jay K. Walker. 2014. “The Impact of Greek Organization Membership on Collegiate Outcomes: Evidence from a National Survey.” *Journal of Behavioral and Experimental Economics* 49 (April): 63–70. https://doi.org/10.1016/j.socec.2014.02.003.

Sahay, Abhilasha. 2021. *The Silenced Women: Can Public Activism Stimulate Reporting of Violence Against Women?* Policy Research Working Papers. The World Bank. https://doi.org/10.1596/1813-9450-9566.

Schmidheiny, Kurt, and Sebastian Siegloch. 2020. "On Event Studies and Distributed-Lags in Two-Way Fixed Effects Models: Identification, Equivalence, and Generalization." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3571164.