Fraternity Project Update: Restricting to Death-Schools

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Last Updated: 2021-05-02

Please note that this is not a paper draft. This is 1 of 2 documents I provided for this update.

1 Updates

I am struggling right now on deciding how I want to restrict my sample. Hence, I am sticking this update into two portions: (1) the universities you had previously seen with the addition of 4 untreated schools (2) the universities that placed a moratorium on fraternities due to deaths only. The reason I am struggling with my decision is because of the pre-trends in each. The pre-trends look better in the death-only universities (more on this later), but the results also seem a little noisier when comparing OLS and Poisson. Essentially I wanted to make two versions of the same update with the same analysis for both samples and see which one seems "better". My personal opinion: I don't want to restrict to death-only universities, but those pre-trends have me very worried. **Apologies for sending two separate documents. . . it was MUCH easier to do it this way then put them together and get confused on which figure is which.**

2 Restricting sample to death-triggering universities only

The main updates to this progress report are as follows:

- *Restricted the sample of schools.* After talking with Kevin Schnepel and hearing his concerns relating to my previous event study pre-trends, he suggested that I try restricting the sample of universities to ones that are very plausibly exogenous. In this case, I decided to restrict the sample to only schools that experienced a death in a fraternity house. Hazing and drinking rituals are commonplace in fraternities, and events where an event was taken "too far" are plausibly random. However, this restricts my treated schools to 10, although I could get 1 more school if I really wanted to.
- *Additional never-treated schools.* Since my treated sample was reduced to 10, I thought it would be a good idea to add in some never treated schools. My criteria for the never-treated was that they must have experienced a death in a fraternity house in my time-frame, but failed to enact a moratorium. There are 17 plausible schools I can gather this information from (sourced from an online repository of fraternity-related deaths), and while I have collected 11 of these, I have only cleaned 5 for this update.
- *Poisson Regressions.* Schnepel also convinced me that a reviewer would likely want a poisson regression rather than OLS due to the count-nature of my outcome variables. Hence, I have changed my tables to show the poisson regressions.
- *New event studies.* Per last update, I decided to change the event studies to be staggered adoptions, focusing on only the first event, and disregarding the later events (if they exist). Hence, the event study graphs should now be interpreted differently.

- *All tables/graphs updated to reflect new sample.* Painful to read in some cases. I am particularly interested in whether university-by-calendar-month or university/month fixed effects make more sense.
- *(Not shown) Started to gather academic calendars.* I have started gathering data from schools academic calendars. This is a very painful process, and while I have completed many schools, I wanted to get some input on the following idea: finding the academic calendar for 1 year only, and then expanding the academic calendar by approximately 1 week on each side of each semester. This wouldn't be perfect, but it would be extremely close.

- *(Not shown) Read through the book True Gentlemen by John Hechinger.* This is a book on the history of fraternity culture with an emphasis on Sigma Alpha Epsilon. A great resource, and actually lead me to an online repository of fraternity deaths. Highly recommend to anyone if they are interested in the topic.

2.1 Feedback Wanted

Here are the major points I really would like feedback on:

- *What do you think of the never-treated units?* I want to be sure that these never-treated universities are reasonable counterfactuals. The identifying assumption here is that a university that experiences a fraternity-related death but does not implement a moratorium is a good counterfactual for a university that experiences a fraternity-related death and implements a moratorium. In other others, the random variation is the decision of the school administrators (or the Interfraternity Council) to implement a moratorium, and this needs to be unrelated to reports of sexual assaults and alcohol offenses. My guess is that the validity of this assumption is going to be most clearly displayed in the event study pre-trends.

- *Event studies are painful and sometimes inconsistent.* The results from the main specifications show clear decreases in alcohol offenses, and negative (although insignificant) decreases in reports of sexual assault. However, these results can't be found in the staggered event study. I think this is for a couple reasons: (1) the staggered event study does not reflect my actual treatment period since some schools' treatment can last far past 8 weeks (2) I am not excluding summer months. I would like to know thoughts on whether an event study is even appropriate to study, or whether anything I should be paying any attention to anything other than the pre-trends.

- *Academic calendar idea?* As stated earlier, I wanted to get some input on the following idea: finding the academic calendar for 1 year only, and then expanding the academic calendar by approximately 1 week on each side of each semester. This wouldn't be perfect, but it would be extremely close. This would save me SO many hours.

3 Data

The main analysis now uses data from each individual university police department. Using the Jeanne Clery Act[1], the Freedom of Information Act, webscraping, and pdf-extracting, I gathered Daily Crime Log data from 40 of the 44 schools in the sample[2]. The Daily Crime Log is a daily-level data set that features all reports and offenses logged by the university police department, provided the university has its own security department. Hence, this data is far richer than the UCR, as it contains records of all criminal incidents and alleged criminal incidents that are reported to the campus police or security department. Each entry must contain specific information about each crime including the date/time the crime was reported and occurred, a small description on the nature of the crime, the general location, and the disposition of the complaint. Additionally, these logs are more comprehensive than Clery Act statistics as they are reported at a daily level rather than yearly level, and include more categories of crime that may not fall under the Clery jurisdiction. However, these logs will **not necessarily** match Clery Act statistics when aggregated to the yearly level. This is mainly because the Daily Crime Logs contain only information **reported to the police**. For instance, if the Student Health Center has a rape victim confide in them, it is possible that Student Health will report the rape to the school's Clery Act compliance officer, but it may not be recorded within the university police's Daily Crime Log. Moreover, universities are only required to hold records for the past 7 years, and therefore I restrict my analysis from 2014-2019. Despite this shortcoming, the Daily Crime Log is the most detailed information on crime at each university that exists.

[1] The Jeanne Clery Act is a law that states that any university that receives federal funding must hold Daily Crime Logs from their campus security department and send yearly aggregated statistics of certain crimes to the US Department of Education

[2] I am still waiting for 1 university's data. I am hopeful that I will get to 41 schools by next week.

3.1 Harmonizing the Daily Crime Logs

Each Daily Crime Log contains a small description the crime reported by the university police. However, since each of these incidents are being written by different police officers and departments, there is a vast amount of variation in how crimes are described. To harmonize these descriptions, I pattern-matched using regular expressions on each small description written in the Daily Crime Log. This was achieved by arranging all incidents at each university in descending order of frequency, and choosing the main words that describe the incident. Table 1 shows the key words and phrases used to match on the outcomes of sexual assault, alcohol offenses, drug offenses, theft, burglary, and noise violations. However, simply pattern matching causes some small, but noteworthy mistakes. For instance, pattern matching on "possession by a minor" for an alcohol offense could result in a match of "possession by a minor with marijuana". To mitigate this issue, I removed matches that contain words that frequently occur in *other* categories. For example, "possession by a minor" matches "possession by a minor with marijuana" for an alcohol offense, but is removed after the match since it contains the word "marijuana"- a word typically associated with a drug offense. Table 2 shows the 15 most frequently incidents matched through the algorithm. Note that each of these matches are within reason.

3.2 Cyclical Patterns

As shown in Figure 1, there are cyclical patterns to university reports of crime. Importantly, the summer months of June, July, and August, all have drastic dips in average frequencies. To account for this, the main analysis omits these summer months where students are less likely to be school. Moreover, Figure 2 shows the distribution of average reports crimes on each day of the week while omitting the summer months. Crimes tend to occur predominantly on weekends, and overall, alcohol offenses appear to be less common (on average) during fraternity moratoria.

3.3 Who is in the sample?

The sample consists of 14 US universities. Tables 3 and 5 show characteristics of these schools and their corresponding crime respectively. There is also a distribution of the moratoria in **??**.

4 Model

I estimate the following model:

$$Y_{u,t} = \beta_{fe} Moratorium_{u,t} + \mathbb{X}_{u,t} + \phi_{u,month} + \alpha_{year} + \epsilon_{u,t} \tag{1}$$

where $Y_{u,t}$ represents the daily/weekly reports of sexual assault and alcohol offenses at university u in time t. $Moratorium_{u,t}$ is an indicator equal to 1 if a university u is experiencing a moratorium at time t, $X_{u,t}$ is a vector of the covariates shown in Table 3 and week-day controls (if daily-level analysis), $\phi_{u,month}$ are university-by-calendar-month fixed effects to account for any time invariant differences within school-months[3], and α_{year} is a year fixed effect. I omit all summer months of June, July, and August from the sample.

4.1 Pre trends

To address the parallel trends assumption required by the model, I estimate an event-study under the following specification:

$$Y_{u,d} = \rho_{u,month} + \phi_{year} + \sum_{t=-8, w\neq -1}^{w=8} \beta_w \mathbb{I}(Moratorium_{u,w}) + \epsilon_{u,d} \tag{2}$$

[3]Note that I also try out university/month fixed effects as well. The effects seem to be less precise in this case.

where $Y_{u,d}$ is the outcome of interest for university u in a 7-day interval d, $\rho_{u,month}$ is a university-by-calendar-month fixed effect[4], ϕ_{year} is a year fixed effect, and $Moratorium_{u,d}$ is an indicator function equal to 1 if a university begins a fraternity moratorium in 7-day period d. Hence, I changed this to a staggered adoption, focusing only on the first moratorium for schools. Therefore, time periods 1,2,...,8 represent the number of weeks since the beginning of a fraternity moratorium, regardless of whether or not the university is still experiencing a moratorium. I estimated this model using both OLS and poisson regression, although I have never seen the latter done before in a paper, so I am unsure whether it is palatable. The estimated event studies in Figures 3 and 4. I have absolutely no idea what is going on with sexual assault - this will be something I look into more if I decide to go down this path.

4.2 Results

Results on alcohol offenses are shown in Table 6. I split the analysis by both the daily and weekly level, and used two different estimation methods (OLS and poisson) along with two different outcome variables (alcohol offenses per 25k students and alcohol offense counts). Table 6 shows significant decreases in alcohol offenses across the poisson regressions, but not the OLS estimates. The results in each regression seem robust to switching between university-by-calendar-month and university/month fixed effects (e.g. the differences between each pair of columns). Table 7 shows results estimating the model when restricting the sample to only Fridays/Saturdays/Sundays at both the daily and weekly level. Interestingly, the poisson regression effects are similar in magnitude, but much less precise compared to the full 7-day period. In both Table 6 and Table 7, the the OLS regresions do not produce significant results. This is interesting as these were typically rather significant in my full 45 school sample (see other document). I did not implement wild-cluster-bootstrap standard errors too due to time constraints and turning this document in at a reasonable time- I can put this on my list of things to do.

Results on reports of sexual assault are shown in Table 8 and Table 9 In each of these specifications, none show a significant decrease or increase.

4.3 My thoughts forward if chosen this route

If I choose this route, I would like to know whether this path forward seems reasonable:

1. Input in the final never-treated schools.
2. Finish the academic calendars and restrict the panel to only the academic calendar.
3. Use a university-by-semester fixed effect instead of a university-by-calendar-month fixed effect.
4. Try to use one of the new estimators for the event study.
5. Run an F-test on the point estimates of the event study pre-treatment - report these if the event study isn't pretty.
6. Figure out what the heck is going on in that sexual assault event study.
7. Use the bootstrapped standard errors.

[4]Note that I also graph the university/month fixed effect as well. The trends here look better, but I prefer the university-by-calendar-month fixed effects intuitively.

Table 1: Words/phrases used to pattern match on outcomes of interest.

Outcome	Words to Match
Sexual Assault	sex, rape, fondling, fondle, indecent exposure
Alcohol Violations	alcohol, dwi, intox, drink, dui, drunk, liquor, driving under the influence, dip, abcc, underage, beverage, dwi, underage, container, pula, owi, mip, under age, beer, wine, booze, minor in possession, ovi
Drug Offense	drug, narcotic, marijuana, heroin, overdose, cocaine, controlled
Robbery/Burglary	robbery, burglary, unlawful entry, breaking and entering
Theft/Larceny	larceny, theft, shoplifting, pocket-picking, steal, shop lifting
Noise Complaints	noise, loud

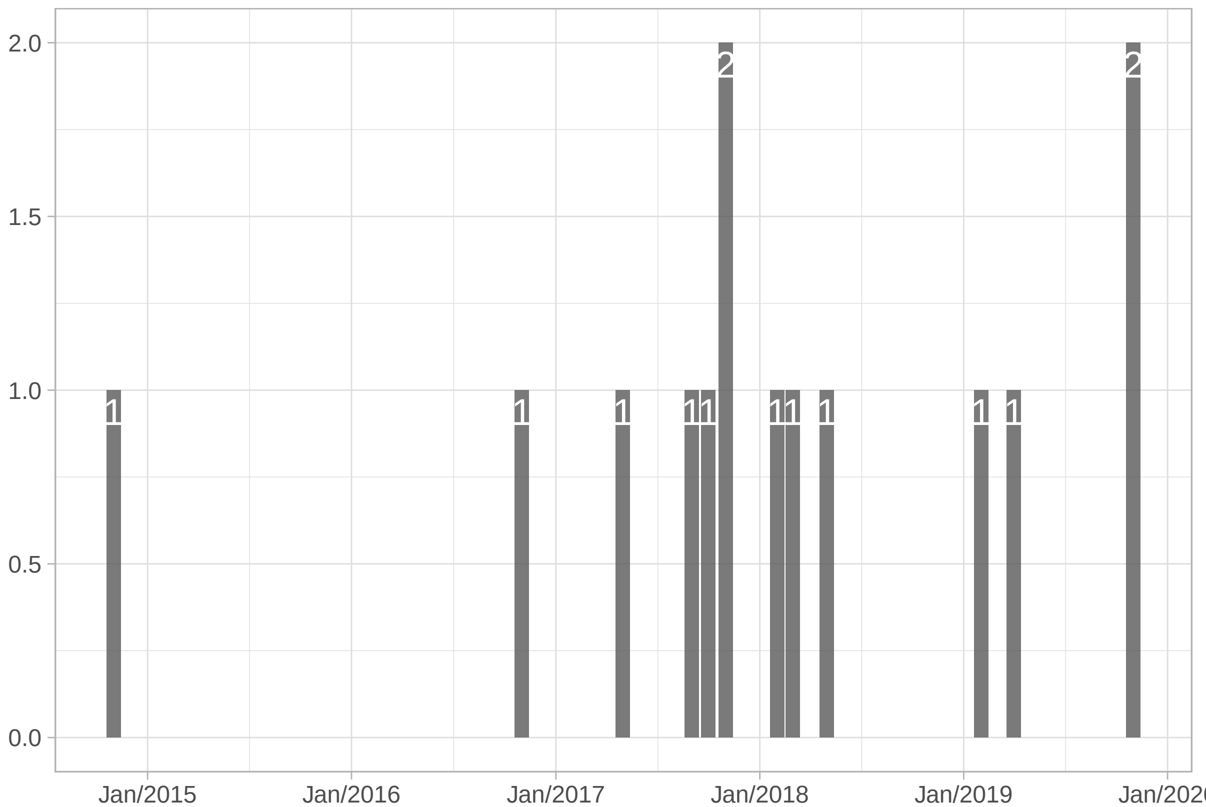


Table 2: The top 15 most frequent reported incidents after pattern matching into each category. Numbers in parenthesis denote the frequency of offense in the data.

Sexual Assault	Alcohol Offense	Drug Offense	Theft/Larceny Offense	Burglary Offense	Noise Offense
(334) sex offenses	(3268) abcc violation	(3784) drug incident	(7570) theft	(1667) burglary	(388) noise
(233) sexual assault	(2580) alcohol offense	(3583) drugs	(1978) larceny	(1042) alarm burglary	(327) noise complaint
(95) rape	(1813) dui	(1820) drug violations	(1588) petit larceny	(795) burglary alarm	(57) complaint noise
(95) sex offense	(1442) alcohol intoxication	(1122) narcotics - possession	(683) theft other	(590) burglary/intrusion alarm	(20) loud party
(75) sex offense - rape	(1197) liquor law violation	(707) drug law violation	(608) larceny - stolen bike	(441) burglary of vehicle	(16) loud music
(73) indecent exposure	(1070) public intox	(627) possession of drugparaphernalia	(603) theft 5th degree	(160) robbery	(16) loud noise
(71) sexual abuse 3rd degree	(963) alcohol - minor in possession	(591) controlled substance problem	(593) petty theft	(82) burglary 3rd degree	(16) noise / alcohol offense
(46) sex offense - other	(861) public intoxication	(511) possession ofmarijuana	(445) theft of bicycle	(73) burglary - habitation	(8) agency assist / noise
(42) sex offense (except forcible rape or prostitution)	(771) possession/supply alcohol u/21	(219) owi/drugged 1st offense	(340) theft 4th degree	(68) burglary of building	(4) animal noise
(41) sex offenses - forcible	(612) alcohol - drunk	(158) drug paraphernalia possession:control substance	(276) larceny - from building	(61) breaking and entering	(4) drugs / noise
(36) anonymous sexual assault	(596) intoxication	(131) drug violation	(242) theft-under $500	(52) vehicle burglary	(4) noise / drugs
(32) 3rd party report sexual abuse 3rd degree	(453) intoxicated subjects	(130) drug possession	(236) theft 3rd degree	(48) burglary - building	(4) noise / drugs / alcohol offense
(27) late reported sexual assault	(402) alcohol - dwi	(123) possession of marijuana	(219) grand larceny:credit card	(43) burglary vehicle	(3) animal noise complaint
(25) sex offense - molest/fondling	(302) intox person 2	(121) drug related suspicious persons/activity	(211) petty theft shoplift	(36) burglary 2nd degree	(3) noise / agency assist
(25) sexual abuse	(255) mip-alcohol	(102) drugs / alcohol offense	(206) larceny - other or from open area	(29) burglary of residence	(2) alcohol offense / noise

Table 3: University summary statistics of the death-only universities and never treated universities

	Mean	SD	Median	Min	Max
Total Students	26862.95	9429.80	29727.00	9454.00	42450.00
Total Undergrad Students	21679.04	7699.18	22352.00	8056.00	34244.00
Fraction Asian	0.05	0.04	0.03	0.01	0.15
Fraction Black	0.06	0.03	0.05	0.01	0.13
Fraction Hispanic	0.13	0.10	0.07	0.02	0.40
Fraction White	0.65	0.14	0.69	0.33	0.82
Total Full-time	19242.13	6673.43	20528.00	6190.00	29879.00
Graduation Rate	66.92	9.19	67.00	49.00	83.00
Fraction Private	0.07	0.26	0.00	0.00	1.00

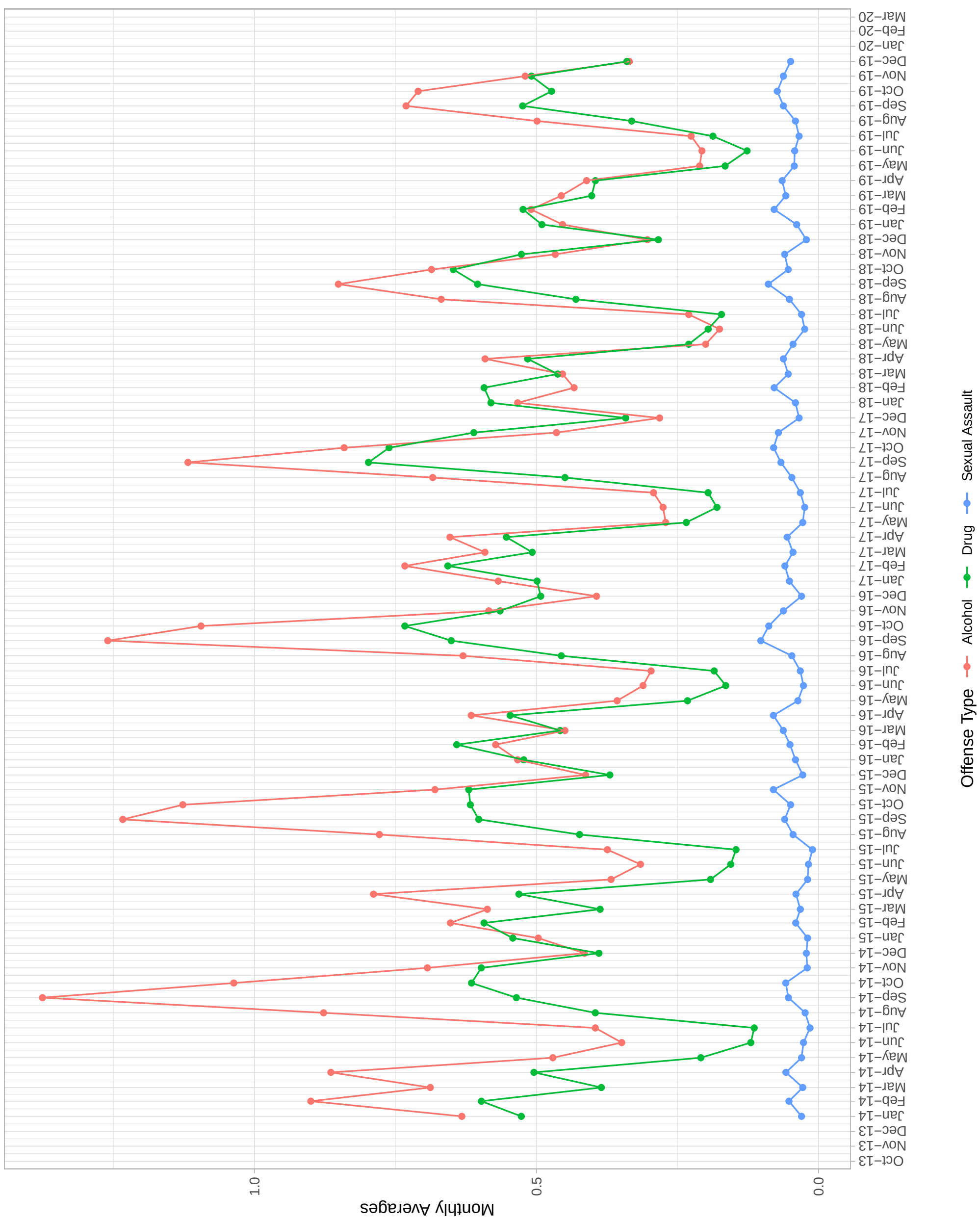
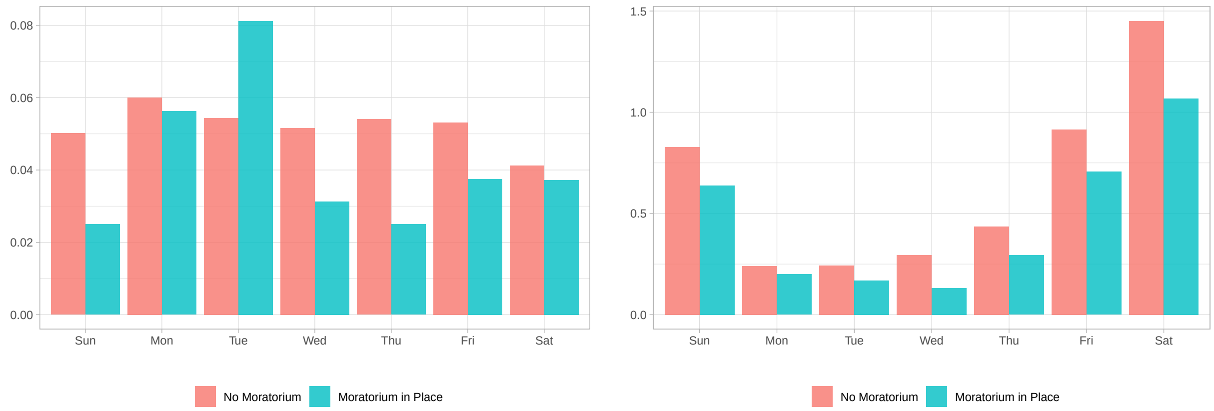


Figure 1: Reports of crimes over entire panel.



(a) Sexual Assault

(b) Alcohol Offense

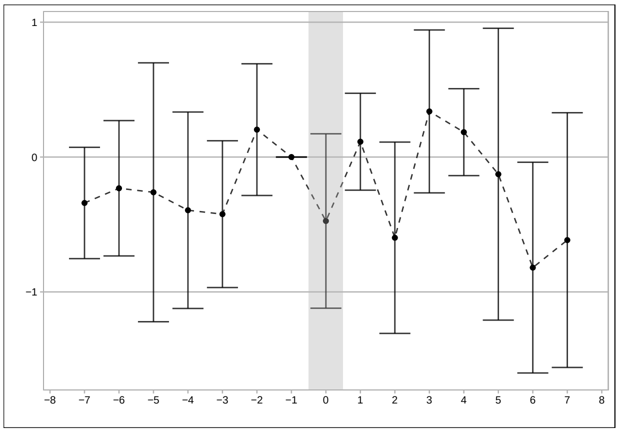
Figure 2: Average number of crimes by day-of-week.

Table 4: Summary Statistics of Offenses (excluding summer)

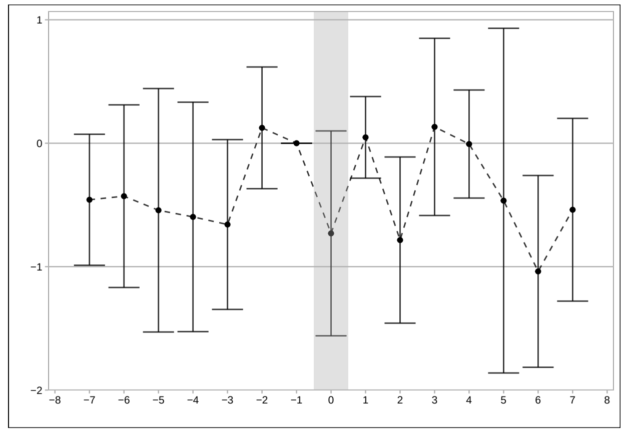
	Mean	SD	Median	Min	Max
Daily Reports					
Sexual Assault	0.05	0.24	0	0	4
Alcohol Offense	0.62	1.52	0	0	36
Drug Offense	0.50	0.96	0	0	13
Theft	0.59	0.99	0	0	29
Robbery/Burglary	0.18	0.56	0	0	14
Weekly Reports					
Sexual Assault	0.36	0.73	0	0	6
Alcohol Offense	4.26	5.75	2	0	62
Drug Offense	3.43	4.52	2	0	33
Theft	4.09	4.06	3	0	41
Robbery/Burglary	1.27	2.38	0	0	20

Table 5: Summary Statistics of Offenses Per 25k (exluding summer)

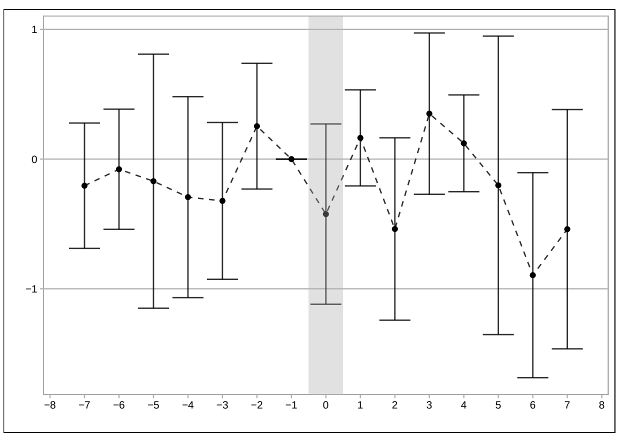
	Mean	SD	Median	Min	Max
Daily Reports Per 25k					
Sexual Assault	0.06	0.32	0.00	0	5.85
Alcohol Offense	0.67	1.69	0.00	0	40.84
Drug Offense	0.52	1.10	0.00	0	25.28
Theft	0.60	1.00	0.00	0	23.35
Robbery/Burglary	0.17	0.52	0.00	0	11.35
Weekly Reports Per 25k					
Sexual Assault	0.44	1.01	0.00	0	11.24
Alcohol Offense	4.61	6.25	2.29	0	70.01
Drug Offense	3.59	5.07	2.00	0	56.22
Theft	4.13	3.71	3.46	0	34.79
Robbery/Burglary	1.18	2.04	0.00	0	17.43



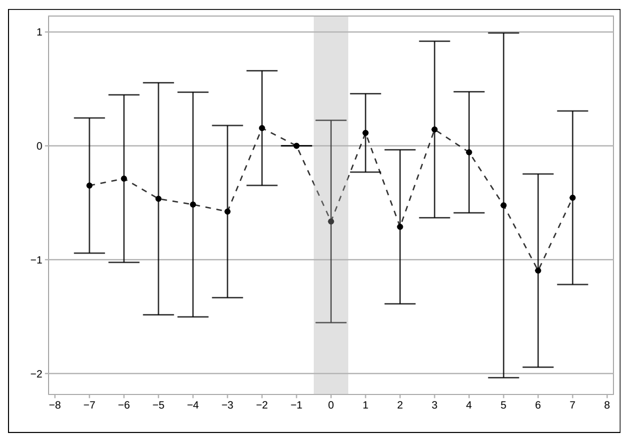
(a) Poisson w/ university-by-calendar-month/year fixed effects. Outcome is alcohol counts.



(b) OLS w/ university-by-calendar-month/year fixed effects. Outcome is Per25k

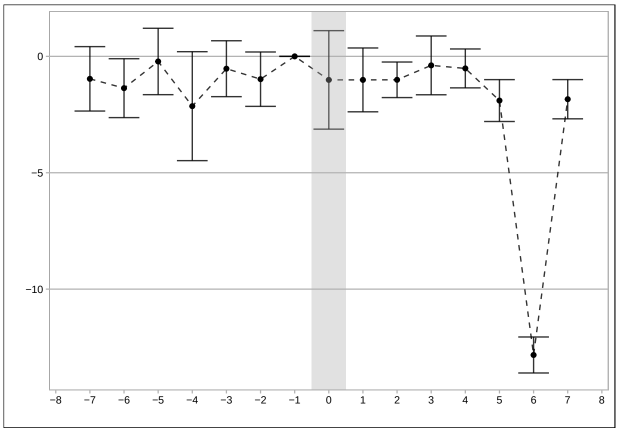


(c) Poisson w/ university/month/year fixed effects. Outcome is alcohol counts.

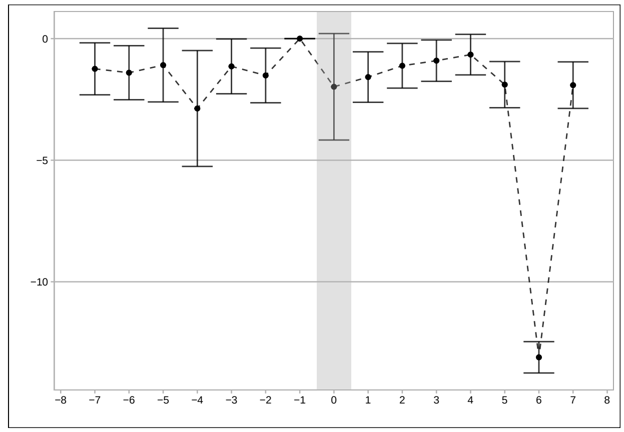


(d) OLS w/ university/month/year fixed effects. Outcome is Per25k

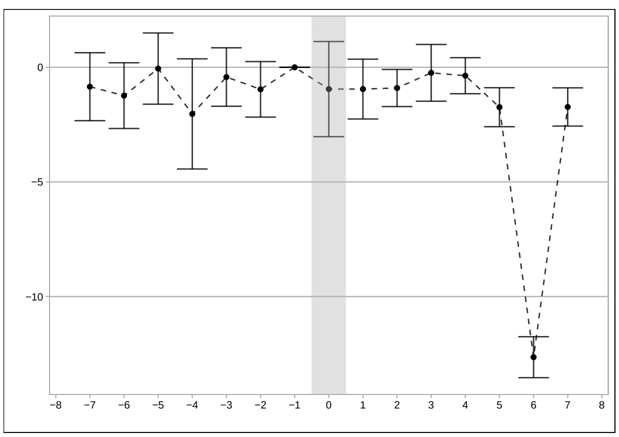
Figure 3: Event study of alcohol offenses. Units are in 7-day periods relative to the 7-day period before a moratorium occurs.



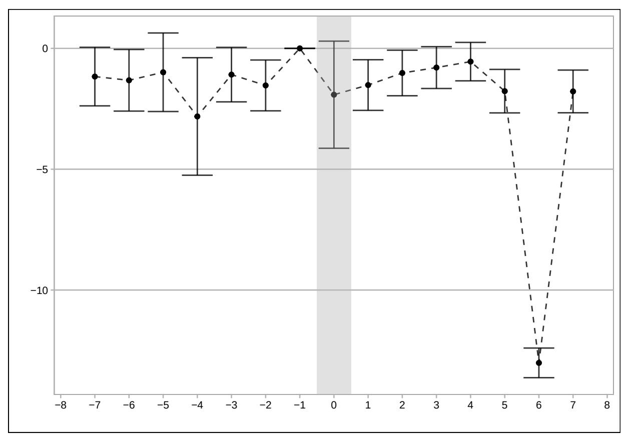
(a) Poisson w/ university-by-calendar-month/year fixed effects. Outcome is sex counts.



(b) OLS w/ university-by-calendar-month/year fixed effects. Outcome is Per25k



(c) Poisson w/ university/month/year fixed effects. Outcome I sex counts.



(d) OLS w/ university/month/year fixed effects. Outcome is Per25k

Figure 4: Event study of reports of sexual assault offenses. Units are in 7-day periods relative to the 7-day period before a moratorium occurs.

Table 6: Effect of fraternity moratoria on alcohol offenses. June, July, August excluded. Death-trigger universities only

	Daily Level				Weekly Level			
	OLS - Per 25000 Students	OLS - Per 25000 Students	Poisson	Poisson	OLS - Per 25000 Students	OLS - Per 25000 Students	Poisson	Poisson
Moratorium	-0.085	-0.103	-0.232**	-0.245***	-0.473	-0.622	-0.192*	-0.206***
	(0.089)	(0.075)	(0.101)	(0.080)	(0.604)	(0.504)	(0.106)	(0.079)
Fraction Full-time Undergrad	0.165	0.131	4.508*	4.368*	-0.379	-0.903	4.191	4.222
	(4.398)	(4.360)	(2.500)	(2.491)	(31.911)	(31.952)	(2.775)	(2.706)
Fraction Undergrad Black	11.849	11.902	12.010	12.790	83.245	83.143	13.643	13.562
	(7.969)	(7.920)	(20.220)	(20.210)	(55.414)	(55.686)	(20.225)	(20.222)
Fraction Undergrad Asian	0.249	0.216	-4.779	-4.104	-4.273	-1.956	-7.746	-7.468
	(13.544)	(13.535)	(14.531)	(14.651)	(94.323)	(96.387)	(14.871)	(14.841)
Fraction Undergrad Hispanic	3.340	3.329	-8.538	-8.742	24.425	25.109	-8.700	-8.617
	(7.025)	(7.013)	(9.072)	(9.103)	(49.546)	(50.176)	(9.208)	(9.179)
Graduation Rate	0.010	0.011	0.003	0.003	0.070	0.072	0.002	0.002
	(0.014)	(0.014)	(0.022)	(0.022)	(0.100)	(0.101)	(0.023)	(0.023)
Num.Obs.	22946	22946	22946	22946	3276	3276	3276	3276
R2	0.206	0.229			0.448	0.533		
R2 Adj.	0.205	0.224			0.442	0.513		
R2 Pseudo			0.298	0.309			0.433	0.460
FE: month	X		X		X		X	
FE: uni_month		X		X		X		X
FE: university	X		X		X		X	
FE: weekday	X	X	X	X				
FE: year	X	X	X	X	X	X	X	X
Std. errors	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)

* p < 0.1, ** p < 0.05, *** p < 0.01

[a] Poisson regressions are based on counts and not per-25000-students.

[a] Fixed effects of uni_month mean university-by-calendar-month.

Table 7: Effect of fraternity moratoria on alcohol offenses restricting to only weekends

	Daily Level (Fri/Sat/Sun)				Weekly Level (Fri/Sat/Sun)			
	OLS - Per 25000 Students	OLS - Per 25000 Students	Poisson	Poisson	OLS - Per 25000 Students	OLS - Per 25000 Students	Poisson	Poisson
Moratorium	-0.217	-0.259	-0.266*	-0.305**	-0.537	-0.675	-0.223	-0.262**
	(0.218)	(0.177)	(0.147)	(0.123)	(0.634)	(0.486)	(0.150)	(0.122)
Fraction Full-time Undergrad	-5.999	-6.389	-1.701	-1.968	-18.785	-19.398	-2.074	-2.078
	(5.673)	(5.803)	(2.775)	(2.774)	(17.773)	(17.866)	(3.032)	(3.004)
Fraction Undergrad Black	19.071	19.174	12.611	13.874	57.005	58.402	14.903	15.059
	(13.822)	(13.776)	(18.272)	(18.273)	(40.742)	(41.391)	(18.411)	(18.389)
Fraction Undergrad Asian	-8.271	-8.231	-13.497	-12.553	-32.012	-29.372	-17.071	-16.322
	(22.879)	(22.852)	(13.456)	(13.546)	(68.118)	(70.056)	(13.767)	(13.874)
Fraction Undergrad Hispanic	3.717	3.890	-11.079	-11.336	11.276	11.835	-11.370	-11.386
	(10.852)	(10.963)	(8.590)	(8.613)	(32.636)	(33.238)	(8.769)	(8.761)
Graduation Rate	0.027	0.028	0.007	0.008	0.076	0.077	0.005	0.006
	(0.023)	(0.023)	(0.024)	(0.024)	(0.071)	(0.071)	(0.026)	(0.026)
Num.Obs.	9828	9828	9828	9828	3262	3262	3262	3262
R2	0.272	0.329			0.428	0.528		
R2 Adj.	0.269	0.320			0.422	0.507		
R2 Pseudo			0.288	0.302			0.410	0.434
FE: month	X		X		X		X	
FE: uni_month		X		X		X		X
FE: university	X		X		X		X	
FE: weekday	X	X	X	X				
FE: year	X	X	X	X	X	X	X	X
Std. errors	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[a] Poisson regressions are based on counts and not per-25000-students.

[a] Fixed effects of uni_month mean university-by-calendar-month.

Table 8: Effect of fraternity moratoria on reports of sexual assault. June, July, August excluded. Death-trigger universities only.

	Daily Level				Weekly Level			
	OLS - Per 25000 Students	OLS - Per 25000 Students	Poisson	Poisson	OLS - Per 25000 Students	OLS - Per 25000 Students	Poisson	Poisson
Moratorium	-0.001	-0.009	-0.127	-0.220	0.029	-0.017	-0.079	-0.153
	(0.007)	(0.007)	(0.175)	(0.208)	(0.069)	(0.050)	(0.182)	(0.205)
Fraction Full-time Undergrad	0.063	0.048	-5.173*	-5.407*	0.211	0.073	-5.336*	-5.677*
	(0.385)	(0.378)	(2.879)	(2.895)	(2.596)	(2.540)	(2.916)	(3.018)
Fraction Undergrad Black	0.280	0.304	11.192	11.762	1.662	1.738	10.507	10.782
	(0.734)	(0.735)	(16.422)	(16.248)	(4.972)	(4.929)	(16.990)	(16.866)
Fraction Undergrad Asian	0.209	0.191	18.366	18.436	1.611	1.693	17.265	18.278
	(1.361)	(1.359)	(23.484)	(23.470)	(9.453)	(9.421)	(24.445)	(24.530)
Fraction Undergrad Hispanic	-1.264*	-1.269*	-12.026**	-12.439**	-8.127*	-8.171*	-11.355*	-11.867**
	(0.610)	(0.615)	(5.944)	(5.954)	(4.070)	(4.147)	(5.873)	(6.046)
Graduation Rate	-0.003	-0.003	-0.033	-0.033	-0.019	-0.018	-0.031	-0.030
	(0.002)	(0.002)	(0.026)	(0.026)	(0.013)	(0.013)	(0.026)	(0.026)
Num.Obs.	22946	22946	22946	22946	3276	3276	3276	3225
R2	0.045	0.053			0.224	0.268		
R2 Adj.	0.043	0.047			0.216	0.236		
R2 Pseudo			0.074	0.086			0.136	0.156
FE: month	X		X		X		X	
FE: uni_month		X		X		X		X
FE: university	X		X		X		X	
FE: weekday	X	X	X	X				
FE: year	X	X	X	X	X	X	X	X
Std. errors	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)

* p < 0.1, ** p < 0.05, *** p < 0.01

[a] Poisson regressions are based on counts and not per-25000-students.

[a] Fixed effects of uni_month mean university-by-calendar-month.

Table 9: Effect of fraternity moratoria on reports of sexual assault. Restricting schools to death-trigger only.

	Daily Level (Fri/Sat/Sun)				Weekly Level (Fri/Sat/Sun)			
	OLS - Per 25000 Students	OLS - Per 25000 Students	Poisson	Poisson	OLS - Per 25000 Students	OLS - Per 25000 Students	Poisson	Poisson
Moratorium	-0.009	-0.009	-0.312	-0.251	-0.025	-0.018	-0.292	-0.212
	(0.007)	(0.007)	(0.252)	(0.255)	(0.021)	(0.024)	(0.253)	(0.293)
Fraction Full-time Undergrad	-0.188	-0.195	-9.877	-9.913	-0.794	-0.756	-10.867*	-10.635*
	(0.544)	(0.544)	(6.395)	(6.507)	(1.538)	(1.515)	(6.142)	(6.082)
Fraction Undergrad Black	-0.037	-0.037	-2.326	-2.508	-0.573	-0.607	-6.914	-8.004
	(1.138)	(1.152)	(23.203)	(23.519)	(3.286)	(3.194)	(22.532)	(22.419)
Fraction Undergrad Asian	-0.659	-0.637	-17.536	-18.133	-2.183	-1.815	-19.519	-15.668
	(1.479)	(1.489)	(25.362)	(25.297)	(4.439)	(4.397)	(26.683)	(27.016)
Fraction Undergrad Hispanic	-1.224*	-1.206*	-9.128	-8.655	-3.422	-3.413	-8.599	-9.043
	(0.671)	(0.666)	(8.320)	(8.414)	(1.988)	(1.977)	(8.340)	(8.481)
Graduation Rate	-0.005**	-0.005**	-0.078***	-0.080***	-0.012**	-0.013**	-0.076***	-0.076***
	(0.002)	(0.002)	(0.029)	(0.029)	(0.006)	(0.006)	(0.029)	(0.029)
Num.Obs.	9828	9828	9828	8962	3262	3262	3262	2873
R2	0.034	0.046			0.092	0.122		
R2 Adj.	0.031	0.032			0.083	0.084		
R2 Pseudo			0.073	0.082			0.104	0.108
FE: month	X		X		X		X	
FE: uni_month		X		X		X		X
FE: university	X		X		X		X	
FE: weekday	X	X	X	X				
FE: year	X	X	X	X	X	X	X	X
Std. errors	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)	Clustered (university)

* p < 0.1, ** p < 0.05, *** p < 0.01

[a] Poisson regressions are based on counts and not per-25000-students.

[a] Fixed effects of uni_month mean university-by-calendar-month.