Fraternity Project Update: Full Sample (Document 2!)

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

1 Updates

Think of this document as a similar update to 3-weeks ago but with new staggered adoption event studies and poisson regressions. 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 Sample includes all universities

Note: this is document 2. The main updates to this progress report are as follows:

- *Additional never-treated schools.* 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 4 for this update.
- *Poisson Regressions.* 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.* How do these look here? Are they passable?
- *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.

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

[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.

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:

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

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. Each of these event studies do not look too convincing - especially when using OLS. However, I have not ran an F-test on the pre-period yet (on the to-do list).

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

[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.

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 and some of the OLS regressions (depending on the type of fixed effect I have). The results in each poisson 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 stronger in the weekends only table. In both Table 6 and Table 7, the the OLS regressions do not produce significant results if I use a university/month fixed effect - only a university-by-calendar-month fixed effect. This is very puzzling to me and I can't think of a good intuitive reason why this is happening.

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.

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

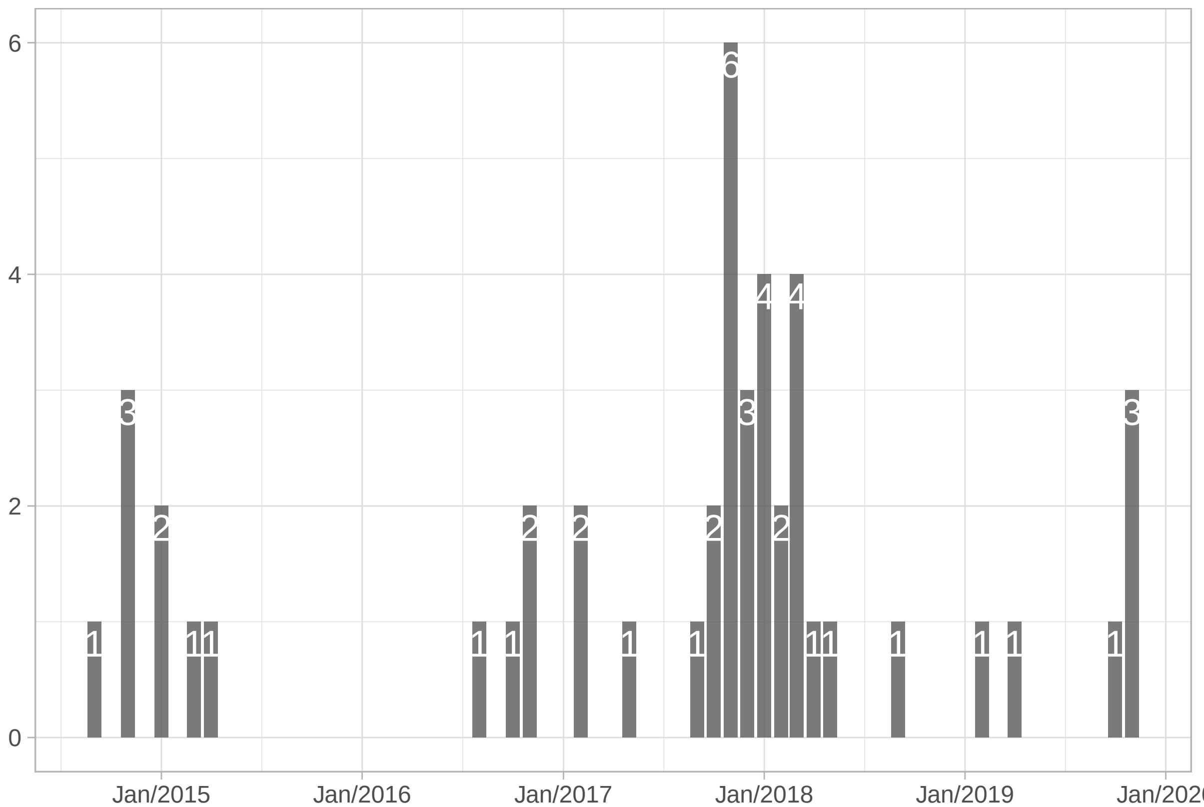


Table 2: The top 15 most frequent reported incidents after pattern matching into each category. Numbers in parenthesis denote the frequency of offense in the data.

Sexual Assault	Alcohol Offense	Drug Offense	Theft/Larceny Offense	Burglary Offense	Noise Offense
(531) sex offense	(3347) alcohol offense	(3784) drug incident	(13318) theft	(2317) burglary	(771) noise complaint
(483) sexual assault	(3268) abcc violation	(3769) drugs	(9328) larceny	(1078) burglary alarm	(392) noise
(421) rape	(2342) dui	(2053) drug violation	(2397) petit larceny	(1042) alarm burglary	(73) city ordin viol-noise
(398) sex offenses	(1442) alcohol intoxication	(1885) drug violations	(1781) theft by unlawful taking or disposition(movable)	(832) auto burglary	(57) complaint noise
(251) indecent exposure	(1340) intoxicated person	(1865) possession of controlled substances	(1281) larceny from a building	(590) burglary/intrusion alarm	(27) university referral - excessive noise
(230) sexual battery	(1321) liquor law violation	(1184) possession - marijuana	(1181) larceny/theft	(441) burglary of vehicle	(23) loud-noise complaint
(146) csa report: rape	(1300) intx-intoxicated person	(1122) narcotics - possession	(1169) theft non-motor vehicle theft non-motor vehicle	(315) larceny/theft–auto burglary -report	(22) loud party
(115) criminal sexual conduct	(1165) public intoxication	(1004) narcotics	(1109) petit theft	(280) robbery	(16) loud music
(88) campus security authority-sex offense	(1070) public intox	(768) drug law violation	(1105) larc-larceny	(236) breaking and entering	(16) loud noise
(81) sex offense - rape	(1066) alcohol - minor in possession	(747) possession of drugs	(898) larceny-all types	(201) burg-burglary	(16) noise / alcohol offense
(77) assist other agency-sex offense	(903) liquor laws	(743) drug violation - vcsa	(884) theft _ without consent	(175) assist other agency-burglary	(15) disorderly conduct _ offensive gesture or noise
(73) sexual abuse 3rd degree	(902) minors in possession of alcohol	(708) possession of drug paraphernalia	(828) larceny/theft–petty theft -report	(131) burglary to auto, petit theft	(15) noise complaint/mip
(66) sex offense - anonymous	(823) minor in possession	(627) drug paraphernalia	(730) grand theft	(121) commercial burglary	(10) noise complaint / alcohol violation
(46) sex offense - other	(785) buying, consume while underage	(627) possession of drugparaphernalia	(695) theft: misdemeanor	(108) burglary–burglary -report	(9) noise complaint / alcohol
(45) sxof-sex offense	(771) possession/supply alcohol u/21	(591) controlled substance problem	(683) theft other	(95) theft by unlawful taking or disposition(movable) burglary by entering structure	(8) agency assist / noise

Table 3: University summary statistics of the 40 universities

	Mean	SD	Median	Min	Max
Total Students	27476.19	14001.09	27565.00	3127.00	69402.00
Total Undergrad Students	21337.71	11354.48	20666.50	2571.00	59371.00
Fraction Asian	0.06	0.07	0.04	0.01	0.36
Fraction Black	0.06	0.04	0.06	0.01	0.20
Fraction Hispanic	0.12	0.13	0.07	0.02	0.68
Fraction White	0.63	0.17	0.68	0.08	0.83
Total Full-time	18369.49	9163.22	18163.00	2433.00	42831.00
Graduation Rate	70.18	13.18	70.00	39.00	95.00
Fraction Private	0.14	0.34	0.00	0.00	1.00

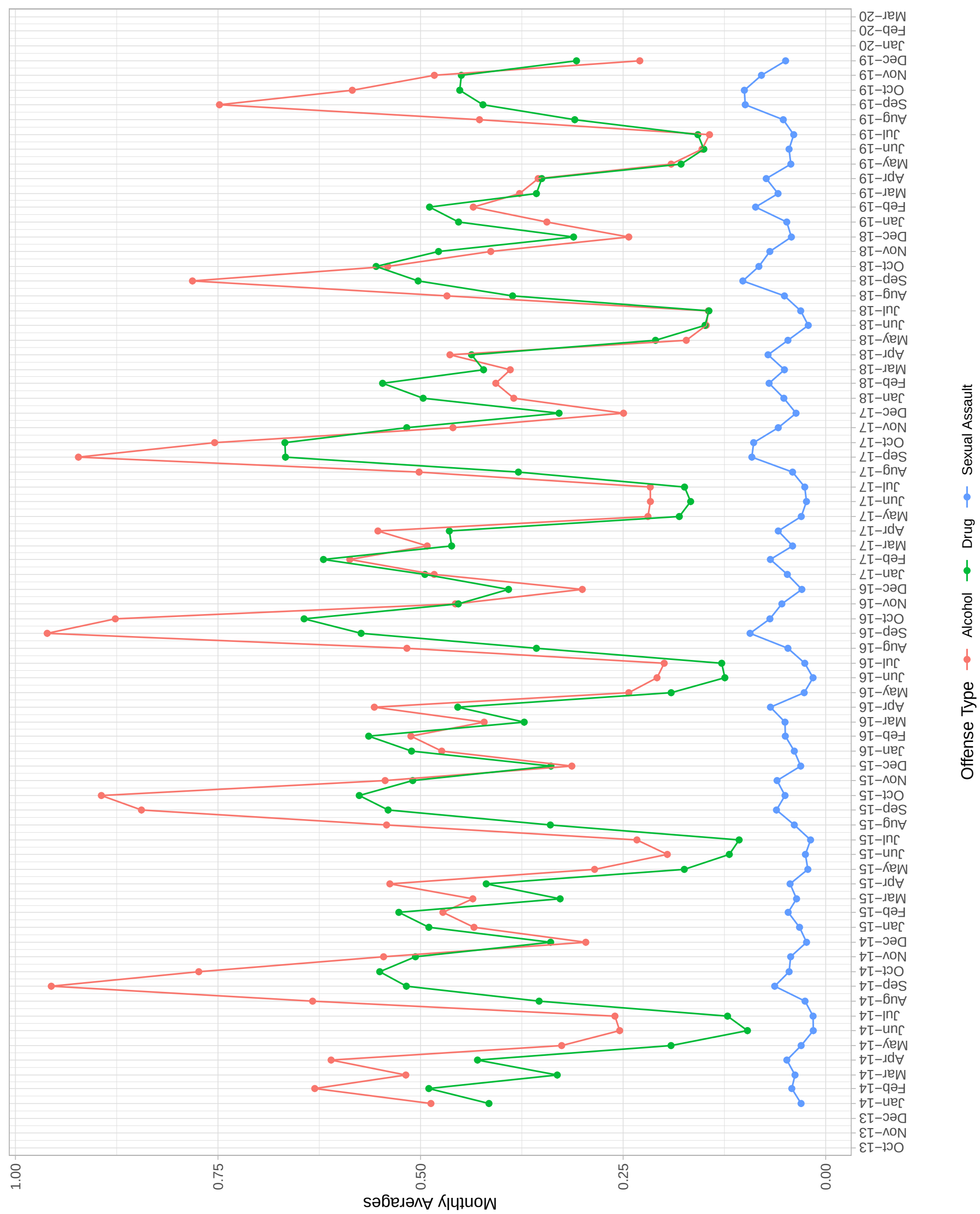
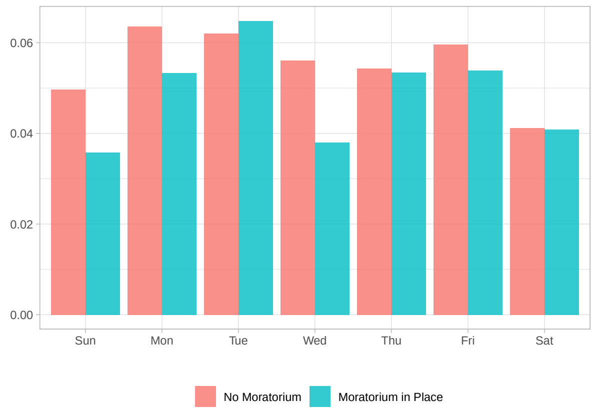
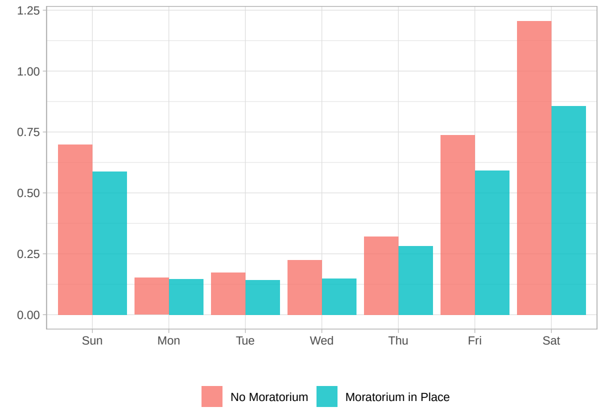


Figure 1: Reports of crimes over entire panel.



(a) Sexual Assault



(b) Alcohol Offense

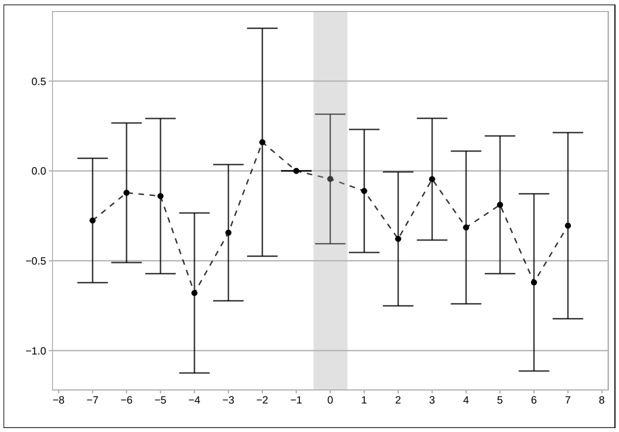
Figure 2: Average number of crimes by day-of-week.

Table 4: Summary Statistics of Offenses (excluding summer)

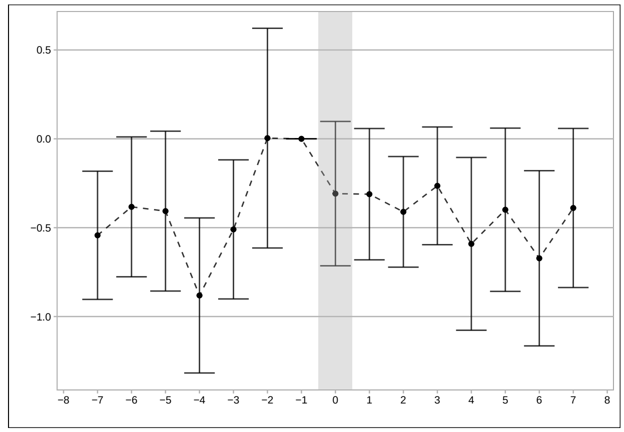
	Mean	SD	Median	Min	Max
Daily Reports					
Sexual Assault	0.05	0.26	0	0	8
Alcohol Offense	0.50	1.34	0	0	41
Drug Offense	0.44	0.91	0	0	20
Theft	0.66	1.10	0	0	29
Robbery/Burglary	0.13	0.48	0	0	33
Weekly Reports					
Sexual Assault	0.38	0.80	0	0	10
Alcohol Offense	3.37	5.03	1	0	62
Drug Offense	2.98	4.28	1	0	48
Theft	4.54	4.88	3	0	41
Robbery/Burglary	0.88	1.84	0	0	39

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

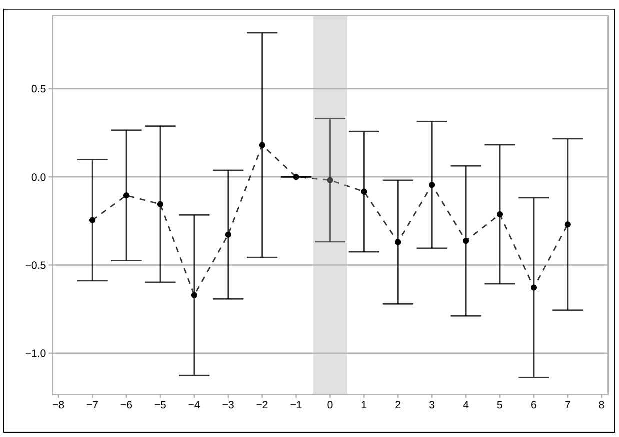
	Mean	SD	Median	Min	Max
Daily Reports Per 25k					
Sexual Assault	0.06	0.32	0.00	0	15.99
Alcohol Offense	0.49	1.35	0.00	0	40.84
Drug Offense	0.40	0.92	0.00	0	25.28
Theft	0.61	1.07	0.00	0	31.98
Robbery/Burglary	0.12	0.49	0.00	0	24.69
Weekly Reports Per 25k					
Sexual Assault	0.40	0.95	0.00	0	16.93
Alcohol Offense	3.34	4.96	1.46	0	70.01
Drug Offense	2.75	4.02	1.51	0	56.22
Theft	4.16	3.90	3.47	0	87.94
Robbery/Burglary	0.83	1.74	0.00	0	32.09



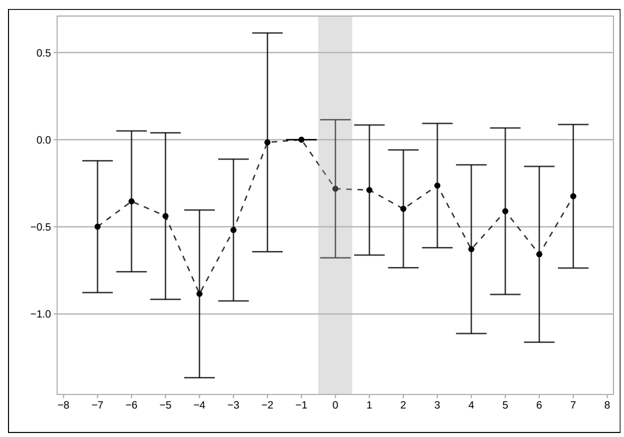
(a) Poisson w/ university-by-calendar-month/year fixed effects. Outcome is alcohol counts.



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

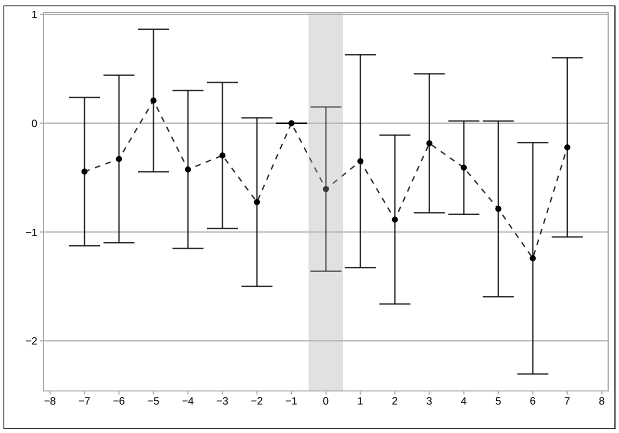


(c) Poisson w/ university/month/year fixed effects. Outcome I alcohol counts.

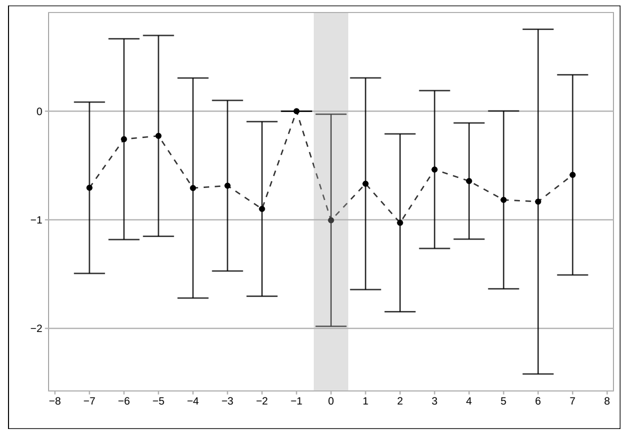


(d) OLS w/ university/month/year fixed effects. Outcome is Per25k

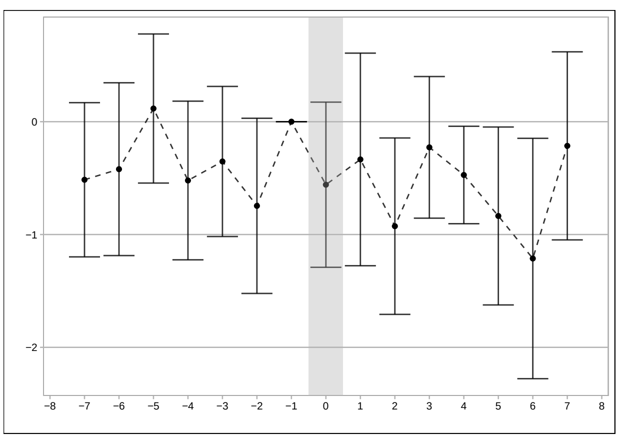
Figure 3: Event study of alcohol offenses. Units are in 7-day periods relative to the 7-day period before a moratorium occurs.



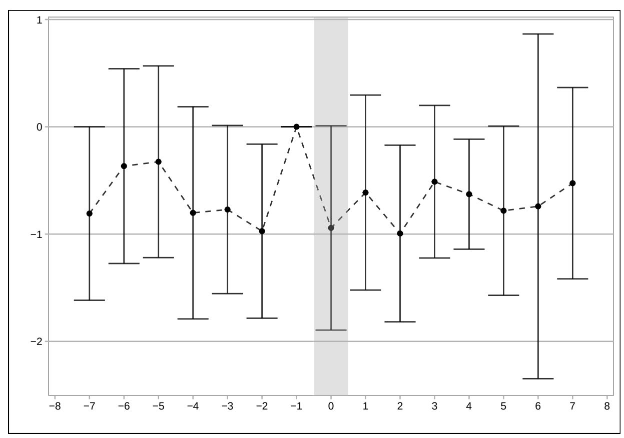
(a) Poisson w/ university-by-calendar-month/year fixed effects. Outcome is sex counts.



(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.

	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	-0.061	-0.072**	-0.179***	-0.196***	-0.260	-0.361	-0.118*	-0.144**
	(0.041)	(0.035)	(0.065)	(0.071)	(0.280)	(0.230)	(0.063)	(0.067)
Fraction Full-time Undergrad	-0.701	-0.702	-0.304	-0.297	-4.531	-4.625	-0.262	-0.278
	(0.996)	(0.997)	(1.167)	(1.164)	(6.904)	(6.934)	(1.181)	(1.185)
Fraction Undergrad Black	6.526*	6.614*	21.218	21.365	32.436	32.742	20.075	20.084
	(3.867)	(3.844)	(13.275)	(13.199)	(26.261)	(26.097)	(13.185)	(13.157)
Fraction Undergrad Asian	5.432*	5.334*	9.043	9.017	37.049*	38.240*	8.667	8.908
	(2.988)	(2.984)	(5.862)	(5.852)	(21.047)	(21.282)	(5.919)	(5.929)
Fraction Undergrad Hispanic	0.199	0.099	-13.160**	-13.149**	6.294	6.521	-12.718**	-12.717**
	(3.499)	(3.499)	(5.858)	(5.842)	(23.930)	(24.266)	(5.932)	(5.953)
Graduation Rate	0.015**	0.014**	0.022	0.023	0.099**	0.099**	0.023	0.023
	(0.006)	(0.006)	(0.019)	(0.019)	(0.045)	(0.045)	(0.019)	(0.019)
Num.Obs.	71197	71197	71197	68608	10296	10296	10296	9880
R2	0.189	0.215			0.420	0.515		
R2 Adj.	0.189	0.210			0.416	0.495		
R2 Pseudo			0.319	0.321			0.442	0.452
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	-0.138	-0.167**	-0.207**	-0.238***	-0.339	-0.454**	-0.164**	-0.205***
	(0.100)	(0.079)	(0.085)	(0.087)	(0.288)	(0.217)	(0.079)	(0.077)
Fraction Full-time Undergrad	-1.414	-1.454	-0.482	-0.479	-4.030	-4.168	-0.461	-0.490
	(1.838)	(1.857)	(1.091)	(1.090)	(5.443)	(5.508)	(1.111)	(1.113)
Fraction Undergrad Black	12.792*	13.143**	22.067*	22.330**	29.421	29.986	21.420*	21.443*
	(6.545)	(6.484)	(11.370)	(11.193)	(18.771)	(18.681)	(11.324)	(11.250)
Fraction Undergrad Asian	8.953*	8.833*	8.482	8.478	25.790	27.404*	8.145	8.441
	(5.258)	(5.224)	(5.674)	(5.611)	(15.851)	(16.045)	(5.716)	(5.726)
Fraction Undergrad Hispanic	-0.893	-0.895	-13.791**	-13.700**	0.243	0.636	-13.705**	-13.725**
	(5.871)	(5.921)	(5.367)	(5.332)	(17.081)	(17.396)	(5.463)	(5.481)
Graduation Rate	0.028**	0.027**	0.027	0.028	0.080**	0.081**	0.028	0.028
	(0.011)	(0.011)	(0.019)	(0.018)	(0.033)	(0.033)	(0.020)	(0.020)
Num.Obs.	30485	30485	29783	28694	10252	10252	10019	9606
R2	0.246	0.306			0.391	0.501		
R2 Adj.	0.244	0.297			0.388	0.480		
R2 Pseudo			0.292	0.296			0.412	0.423
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.

	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	-0.004	-0.009	-0.130	-0.192	-0.017	-0.048	-0.107	-0.156
	(0.006)	(0.006)	(0.103)	(0.121)	(0.039)	(0.036)	(0.095)	(0.109)
Fraction Full-time Undergrad	0.168	0.168	2.037	2.051	1.293	1.278	2.143	2.085
	(0.190)	(0.190)	(3.240)	(3.248)	(1.339)	(1.341)	(3.290)	(3.298)
Fraction Undergrad Black	0.704	0.717	26.958*	27.114*	1.791	1.775	24.674	24.974
	(0.976)	(0.980)	(15.877)	(15.823)	(7.366)	(7.389)	(16.597)	(16.459)
Fraction Undergrad Asian	-0.109	-0.119	2.358	2.411	-0.529	-0.612	2.399	2.350
	(0.725)	(0.726)	(10.602)	(10.615)	(4.824)	(4.827)	(10.839)	(10.890)
Fraction Undergrad Hispanic	-0.586	-0.596	-4.562	-4.795	-2.672	-2.470	-3.703	-3.498
	(0.458)	(0.459)	(7.639)	(7.701)	(3.571)	(3.613)	(7.363)	(7.343)
Graduation Rate	0.000	0.000	0.025	0.025	-0.002	-0.002	0.029	0.029
	(0.001)	(0.001)	(0.022)	(0.022)	(0.008)	(0.008)	(0.022)	(0.023)
Num.Obs.	71197	71197	71197	68487	10296	10296	10296	9775
R2	0.027	0.036			0.145	0.196		
R2 Adj.	0.026	0.031			0.140	0.163		
R2 Pseudo			0.087	0.095			0.157	0.168
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

	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	-0.005	-0.008	-0.116	-0.130	-0.014	-0.018	-0.118	-0.104
	(0.007)	(0.007)	(0.154)	(0.154)	(0.021)	(0.019)	(0.151)	(0.157)
Fraction Full-time Undergrad	0.036	0.032	-0.506	-0.511	0.139	0.118	-0.390	-0.515
	(0.177)	(0.175)	(3.574)	(3.550)	(0.539)	(0.543)	(3.675)	(3.688)
Fraction Undergrad Black	0.127	0.138	16.818	16.698	-0.191	-0.165	16.126	16.651
	(0.868)	(0.863)	(16.672)	(16.659)	(2.575)	(2.574)	(17.605)	(17.591)
Fraction Undergrad Asian	0.425	0.421	8.482	8.607	1.072	1.058	7.380	7.030
	(0.633)	(0.629)	(9.405)	(9.363)	(1.755)	(1.761)	(9.590)	(9.757)
Fraction Undergrad Hispanic	-0.301	-0.317	2.568	2.294	-0.639	-0.537	3.227	3.598
	(0.448)	(0.441)	(10.131)	(10.138)	(1.333)	(1.342)	(10.114)	(10.153)
Graduation Rate	-0.001	-0.001	-0.005	-0.004	-0.004	-0.004	-0.003	-0.006
	(0.001)	(0.001)	(0.024)	(0.024)	(0.003)	(0.003)	(0.025)	(0.024)
Num.Obs.	30485	30485	30485	25961	10252	10252	10252	8565
R2	0.026	0.042			0.069	0.113		
R2 Adj.	0.024	0.029			0.064	0.077		
R2 Pseudo			0.086	0.083			0.120	0.114
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.