Hold Their Beers? The Effects of Fraternity Moratoriums on Crime

Michael Topper

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Abstract

Fraternities maintain a presence at over 800 universities in the United States. While the literature has documented positive effects of membership such as increased graduation rates and future income, studies have also shown fraternities to be a reliable source of alcohol for underage students in addition to their members exhibiting more partying behavior than their non-member peers. In this paper, I exploit the variation in timing from 45 temporary university-wide halts on all fraternity activity with alcohol (moratoriums) across 38 universities over a six-year period (2014-2019). I construct a novel data set, merging unique incidence-level crime logs from university police departments to provide the first causal estimates of the effect of moratoriums on campus-wide reports of alcohol, drug, and sexual assault offenses. In particular, I find strong and robust evidence that fraternity moratoriums lower alcohol violations campus-wide by 27%. This effect is driven by decreases in weekend reports, consistent with the timing of most fraternity parties. Additionally, I find weaker evidence that moratoriums decrease reports of sexual assault on the weekends. However, both these effects are transcient, with moratoriums showing no evidence of long-run changes in student behavior.

1 Introduction

This paper is the first to estimate the causal effects of temporary campus-wide halts on fraternity social events with alcohol (henceforth, moratoriums) on reports of alcohol, drug, and sexual assault offenses. Since 2010, over 50 moratoriums have been enacted across university campuses, thus becoming a common policy used among school administrators. However, no prior research has investigated this topic; moratorium dates are difficult to find/confirm and there does not exist a centralized data source for university-specific crime with fine enough detail for casual inference. Despite this lack of research, administrators continue to use moratoriums as a disciplinary action on their fraternities.

Nonetheless, how these moratoriums effect student behavior, and thus on-campus crime, is theoretically unclear. On one hand, prohibiting alcohol from fraternity social events may reduce reports of crime. Fraternities are a common source of alcohol for underage drinking, as fraternities are typically a mix of lower and upperclassmen (Armstrong, Hamilton, and Sweeney 2006). The inclusion of legal-age drinkers and large social events allows for easy access to alcohol for underage students. Given that the literature has documented that alcohol causes higher prevalence of crimes such as assaults and alcohol offenses (Carpenter and Dobkin 2015), road accidents and arrests (Francesconi and James 2019), and reports of rape (Zimmerman and Benson 2007; Lindo, Siminski, and Swensen 2018), prohibiting such events could reduce the amount of on-campus crime. On the other hand, moratoriums may have the opposite effect. Without alcohol-fueled fraternity parties, students may substitute away from consuming alcohol at fraternity houses to potentially riskier places where behavior is less regulated. As a result, the net effect of moratoriums is ambiguous.

In this paper, I estimate the causal effect of 45 fraternity moratoriums across 38 universities over a six-year period (2014-2019) on university police reports of alcohol, drug, and sexual assaults offenses. I use a difference-in-differences identification strategy, leveraging the unanticipated nature of moratoriums. Intuitively, I compare academic-calendar days with a moratorium to academic-calendar days without a moratorium while accounting for expected differences across days of the week and different times of the year. I construct a novel data set, merging together two particularly unique data sources: university-specific Daily Crime Logs, which contain the universe of all reported incidences of crime to the university police at the incident-level, and moratorium start and end dates obtained through school newspapers and public records requests. Using this data, I find that moratoriums significantly decrease alcohol offenses campus-wide on academic-calendar days by 27%. This effect is driven by weekends (Fridays-Sundays) when college partying is more frequent and is robust across various specifications, estimation methods, and sensitively tests. Furthermore, I find weaker evidence that sexual assaults decrease by 26% on the weekends. Both of these decreases are concentrated only when a moratorium is in place suggesting that moratoriums possess no long-run effects on student behavior.

Most closely related to this paper is Lindo, Siminski, and Swensen (2018) who use increases in college partying from football games to estimate a 28% daily increase in rape. This paper differs from this work on several levels. First, I examine the effects of a *reduction* in partying coming from one prominent source (fraternities), rather than the effects of an *increase* in partying. As shown in Cunningham and Shah (2018), who study the effects of decriminalizing and criminalizing prostitution on rape, the effects are not necessarily the same in each direction. Hence, there is little reason to believe an increase/decrease in partying results in the same magnitude of change. Furthermore, this study focuses on sanctions against university fraternities which most exclusively affects university students—college football attracts a large demographic whom are not necessarily students of the university. Thus, the increases they find may not be as attributed to the university students themselves. Lastly, the novel data constructed in this paper contains all reports of alcohol offenses by the university police rather than only alcohol-related arrests as used in their secondary analysis. Given that students are unlikely to be arrested for underage drinking, this is a major advancement in determining how university drinking behavior is affected by decreases in partying.

Additionally, this paper advances a small, but growing literature relating to fraternities. Two papers show the effects of fraternity membership on GPA using variation from deferred recruitment—a policy which prohibits freshman students from joining a fraternity until their second semester (De Donato and Thomas 2017; Even and Smith 2020). Each of the papers show that membership decreases GPA, while Even and Smith (2020) additionally find that membership causes students to select into easier courses and complete less course credits. More related to this paper is a working paper by Raghav and Diette (2021) who find that a larger percentage of enrolled students in fraternities is associated with an increase in the number of drug-law arrests. However, this work does not consider the differences between the types of fraternities (see Section 2) and due to their data limitations. Each type of fraternity has vastly different contributions campus party culture (e.g., an academic fraternity vs. a social fraternity), with social fraternities being a primary component. Furthermore, their main analysis uses Campus Safety and Security (CSS) data which is aggregated to a calendar-year level. Due to this limitation, they are unable to delineate between important differences in membership numbers between academic years and semesters.

Lastly, this paper more broadly contributes to the literature on the effects of restricting alcohol to college-aged students. Several studies have utilized the discontinuity in the minimum legal drinking age (MLDA) to show that alcohol causes large increases in mortality (Carpenter and Dobkin 2009), emergency room visits (Francesconi and James 2019), and crime (Carpenter and Dobkin 2015). In addition, two studies use the MLDA to show the academic effects of alcohol; Carrell, Hoekstra, and West (2011) find that drinking hinders the performance of the highest performing students, while Ha and Smith (2019) find that alcohol most significantly affects the performance of students who did not previously have access to underage drinking. Finally, Liang and Huang (2008) finds that placing harsher penalties on drunk driving (zero-tolerance laws) resulted in a 26% reduction in the probability of drinking and driving for those who reported drinking away from home, although the results are based on survey-data.

This paper proceeds as follows: Section 2 discusses the background on fraternities and moratoriums. Section 3 describes the construction of the data. Section 4 describes the empirical strategy used to estimate causal effects. Section 5 presents the results. Section 6 shows the differences in effectiveness between different types of moratoriums. Section 7 concludes.

2 Fraternities in the US

2.1 Background

Fraternities maintain a ubiquitous presence in the United States with chapters prevalent in over 800 universities (Hechinger 2017). 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), future income (Mara, Davis, and Schmidt 2018), and decreases in GPA (De Donato and Thomas 2017; Even and Smith 2020). Moreover, members spend approximately two more hours partying than nonmembers (Routon and Walker 2014), and binge drink on approximately 1.7 additional days (DeSimone 2007). While not causal, there is survey evidence that fraternity members are more accepting of sexual violence than nonmembers (Seabrook 2019) and that sorority women, whom frequently interact with fraternity men, are four times more likely to be a victim of sexual assault than nonmembers (Minow and Einolf 2009).

This paper focuses on the Interfraternity Council (IFC) fraternities otherwise known as social fraternities. These fraternities are the most common at universities, but differ from the professional, academic, or service fraternities. IFC fraternities participate in philanthropy and professional development, but according to their creed, they “exist to promote the shared interests and values of our member fraternities: leadership, service, brotherhood and scholarship” (Hechinger 2017). Importantly, it is the IFC fraternities that are always restricted by a moratorium in the sample.

Each IFC fraternity chapter[1] has three sources of oversight: the chapter national headquarters, the parent university, and the parent university's own IFC council—a group of student representatives from each recognized IFC fraternity chapter whom regularly meet with university staff to discuss rules/boundaries. Failure to abide by the rules outlined by these overseers' policies can result in a fraternity being unrecognized by the university which is costly—a fraternity relies on the university for new students to recruit.

2.2 Moratoriums

A moratorium is defined as a temporary ban on social events with alcohol for IFC fraternities.[2] The timing and length of a moratorium varies substantially. Figure 1 shows the start and end dates of each moratorium over time. Moratoriums can last as few as 6 calendar-days, or as long as 848 calendar-days. Additionally, moratoriums are the generally implemented because of a triggering event (see Figure A1). This event can be a prominent sexual assault allegation, a fraternity-related death (usually due to alcohol poisoning), or an extreme behavior violation.[3] Figure 2 shows the distribution of the triggering events: 18 are triggered by behavior violations, 10 by sexual assaults, 10 by a fraternity-related death, and 7 are unspecified. As alluded to in the introduction, moratoriums are enacted nation-wide. Figure 3 shows the locations of the 38 universities in the sample. While most universities are located in the mid-west and south, there are several universities from both the west and east coast.

Moratoriums can be implemented by two sources of jurisdiction: the university or the IFC. When a moratorium is implemented by the university, the university sets the guidelines

[1] A chapter, or otherwise known as a "house" is a unique fraternity. A fraternity can have many chapters across the US, with usually one per-school.

[2] This is the minimum requirement for a moratorium in this paper. Some universities ban alcohol at social events for all IFC fraternities in addition to the rest of their Fraternity and Sorority Life. However, IFC fraternities are generally the main focus.

[3] A behavior violation is a catchall term for hazing, rule violations, offensive behavior, and other disorderly conduct that results in a moratorium.

that fraternities must abide by during the moratorium. The minimum guideline in the sample is that all social events with alcohol are prohibited, although other guidelines can be enforced (e.g., additional sexual harassment training). On the other hand, an IFC-implemented moratorium is student-enforced. This means that the IFC council is responsible for oversight. Figure 2 shows that IFC-implemented moratoriums are less frequent (17) than university-implemented moratoriums (28) and Section 6 examines the heterogeneous effects involving this difference in oversight.

3 Data

The main analysis uses data from a variety sources. In particular, I construct a novel data set that links incidence-level crime from university police departments, fraternity moratorium dates, and university characteristics over a six-year period (2014-2019).

Daily reports of incidences are collected from Daily Crime Logs maintained by the 38 university's police departments resulting in approximately 500,000 distinct reports. The Daily Crime Log is an incidence-level source of information; each crime log contains the date occurred, date reported, time occurred, time reported, a short summary of the incident, the general location of the incident, and a distinct case number (see Figure A1 for an example).[4] The Daily Crime Log contains the universe of incidents that are reported by (or to) the university-specific police department. Hence, each of the incidences listed in these logs represent incidences that occurred on or nearby university property.[5] There are two main advantages of the Daily Crimes Logs over readily available crime data sources such as the National Incidence-Based Reporting System (NIBRS), Uniform Crime Reporting System (UCR), and the Campus Safety and Security Data (CSS). First, each university police de-

[4] While the date occurred is technically mandated under the Clery Act to include each of these categories, only 33 of the 38 universities contained the date occurred. However, these five schools contained the date reported. I use the date reported in lieu of the date occurred when the date occurred is missing.

[5] Sometimes, university police may respond to calls slightly outside of university property. Based on conversations with university police, this is usually when a student is involved.

partment is mandated under the Clery Act to maintain and make available a Daily Crime Log. Crime logs must be kept for seven years, although this mandate is subject to each university's interpretation.[6] Hence, only one university is missing data from a complete calendar-year.[7] Second, the Daily Crime Logs contain all daily incidences of alcohol offenses, drug offenses, and sexual assault offenses reported to or by the police—the primary outcomes used in the main analysis. This is a major advantage as the UCR does not contain alcohol offenses and the NIBRS only contains alcohol violations that end in arrests. Since most violations of underage drinking at universities do not end in arrests, the NIBRS data would under-report the prevalence of alcohol misuse. While the CSS data includes similar information as the Daily Crime Logs,[8] the CSS data is aggregated to the calendar-year which makes the effect of moratoriums difficult to study given their short-lived nature. See Table A3 for more details on the advantages of the Daily Crime Logs.

The existence of a fraternity moratorium is identified using Google and Lexis Nexis searches, in addition to documents from various fraternity associations. In total, there are 45 fraternity moratoriums in the sample. Importantly, these do not represent the universe of fraternity moratoriums that occurred from 2014-2019. In particular, there are five schools that are known to have experienced a moratorium in this time frame, but are excluded due to data issues or their definition of a moratorium.[9] Each moratorium's start and end dates are

[6]For instance, if a crime log from 2014 is requested in year 2021, most police departments will have this information as it falls within 7 years. However, some police departments may consider seven-years to be inclusive of their current year, and hence, may only contain records for 2015-2021.

[7]Rollins College is missing data from 2014. North Carolina State University is also missing data, although their missing data spans from January 2014-August 2014.

[8]There are important differences between these two sources. The CSS provides data on liquor and drug violations that occur in residence halls that may not be reported to the police and therefore not appear in the Daily Crime Logs. Hence, an aggregated Daily Crime Log should not (and will not) match the CSS exactly.

[9]Miami University is excluded due to being unable to verify the end-date of their moratorium. Pennsylvannia State University is excluded because they would not digitally release their Daily Crime Logs. University of Texas at Arlington is excluded because the crime logs are scanned images that can not be read reliably by any computer software. Cal State Northridge is excluded because it is unclear whether the moratorium includes a ban on alcohol. University of North Florida is excluded because of a discrepancy between public records information and newspaper articles: newspaper articles claim there is a moratorium beginning 12/4/17, but the public records department says this is untrue. There may exist other universities that experienced a moratorium, but may not have had any sort of news coverage-these are also be excluded from the sample.

obtained through public records requests, conversations with Fraternity and Sorority Life advisers, and school newspaper articles. All start and end date are verified by at least one of these sources.[10]

University characteristics such as total enrollment, student demographics, and academic calendars are obtained through the Integrated Postsecondary Education Data System (IPEDS) or directly from the university. However, not all academic calendars for each year in the sample are available. Therefore, only the most current academic calendar found on a university's website is utilized. To account for small changes in academic calendars year-to-year, a seven-day window is added to each start and end date of each semester.[11]

3.1 Matching and Harmonization

One of the challenges of using the Daily Crime Logs is their uniqueness to each university. While all crime logs contain daily reports of incidences, each university police department describes their incidences differently. For example, Indiana University's crime log describes driving under the influence as "driving under the influence" while Cal Poly San Luis Obispo's describes this as "dui." As such, there is a lack of harmonization between the crime logs—incidences do not have a standardized way of being reported between university police departments. To mitigate this issue, I use regular expressions to match on typical words, phrases, and abbreviations seen in each crime log for descriptions relating to alcohol, drug, and sexual assault offenses.[12] For each offense, I use the following definitions for matching the incident descriptions:

[10] There is one exception to this which is the first moratorium at San Diego State University. While the start date has been verified by a newspaper article, the exact end date is a little ambiguous. However, evidence shows that the moratorium ended before the start of the 2015 spring semester, and hence, this is the date used in the analysis. The newspaper article showing this evidence can be seen here: https://newscenter.sdsu.edu/sdsu_newscenter/news_story.aspx?sid=75357.

[11] To define the start of a semester, the first day of instruction is used. For the end of a semester, the finalized grade date is used.

[12] In particular, I found all unique descriptions of incidences in each Daily Crime Log, and then independently analyzed which descriptions matched to each offense.

- **Alcohol Offense** - Any incident description that refers to a public intoxication, underage drinking, or drinking in an unlawful manner. For instance, public drunkenness, a minor in possession, and driving while intoxicated refer to each of these definitions respectively.
- **Drug Offense** - Any incident description that relates to the possession or use of an illegal drug. Common descriptions may include a "drug incident" or "possession of marijuana."
- **Sexual Assault** - Any incident description that refers to a sexual assault or sex crime including rape and fondling. This corresponds to the types of sex crimes that are reported in the CSS data: rape, statutory rape, incest, and fondling. However, incest sex crimes are omitted as these are infrequent and less likely to be associated between college students.

Table 1 shows the corresponding words, phrases, and abbreviations used to match each incident description to its corresponding offense. Importantly, each of these phrases are only portions of an incident's description. For instance, the word "sex" is used as a word to match on sexual assaults. The advantage to this method is that the word "sex" will be matched to descriptions such as "sexual assault" or "sex offense" since the word "sex" appears in each of these descriptions. While this is an imperfect method, it is conservative—it is likely that this method is under-counting the true amount of offenses in each category since there are instances in incidence descriptions where words are misspelled (e.g., "aclohol" vs. "alcohol"). Table A4 shows a snapshot of the results of this matching process with the most frequent descriptions matched to each offense. In each category, there does not appear to be any clear misclassification.

3.2 Descriptive Statistics

Table 2 summarizes the characteristics of the 38 universities and their corresponding distribution of offenses and fraternity moratoriums. Panel A shows descriptive statistics of the universities' demographics. On average, the universities are large with total enrollment exceeding 28,000. Undergraduates are the majority population with 62% being white. Graduation rates vary substantially between schools and there is particularly large variation in the selectivity of each university. For instance, graduation rates and the fraction of students admitted range between 39-95 percent and 14-94 percent respectively. Panel B shows summary statistics of the three primary outcome measures: alcohol offenses, drug offenses, and sexual assaults. Each of these outcomes is measured as per-25000 enrolled students per-academic-calendar day. Therefore, the average amount of alcohol offenses per-25000 enrolled students in an academic-calendar day is approximately 0.5. Lastly, Panel C describes characteristics of the 45 moratoriums in the sample. On average, each university undergoes approximately one moratorium, although universities can experience up to three. Furthermore, the moratoriums persist for an average of 64 academic-calendar days. Notably, there is significant variation in the length of the moratoriums. In particular, the minimum length of a moratorium is only 6 academic-calendar days while the maximum is 541. Due to this large range, it is important to note that a median moratorium lasts for 46 academic-calendar days (approximately 1.5 months).

4 Empirical Strategy

4.1 Baseline and Preferred Specifications

The goal of this paper is to identify the average causal effect of fraternity moratoriums on alcohol, drug, and sexual assault offenses across universities that experience moratoriums. In a naive analysis, this would amount to taking a difference of means for moratorium days and non-moratorium days across all universities for each offense. However, there are several issues with identifying such difference of means as a causal effect. First, university police departments each vary considerably in the frequency of reporting offenses. This is the result of differing policing tactics, the departments' available resources—such as number of officers per-student—and the overall composition of students at the university. For instance, a police department that oversees a university with a reputation for partying may police differently than a police department that rarely encounters college partying. Second, frequencies of offenses vary depending on the day of the week and the time of year. As an example, alcohol offenses most commonly occur on Fridays, Saturdays and Sundays, and fraternity recruitment is typically in the fall semester. A simple difference of means fails to account for each of these systematic differences between universities, days of the week, and semester.

To circumvent these issues, I estimate the following baseline difference-in-differences specification using OLS:

$$Y_{u,t} = \beta Moratorium_{u,t} + \gamma_u + \lambda \mathbb{X}_t + \epsilon_{u,t} \tag{1}$$

where $Y_{u,t}$ is an outcome of alcohol offenses, drug offenses, or sexual assaults per-25000 enrolled students per academic-calendar day at university u in time t. $Moratorium_{u,t}$ is an indicator variable equal to one when university u is undergoing a moratorium at time t, γ_u is a university-specific fixed effect, $\mathbb{X}_t$ is a vector of time-varying controls that are shared across universities, and $\epsilon_{u,t}$ is the error term. In essence, Equation 1 is comparing moratorium days to non-moratorium days across universities that have, or will, experience a moratorium while accounting for expected differences across universities and time.

Including university-specific fixed effects (γ_u) in the baseline model accounts for systematic differences between a university's police department and the corresponding student demographic they are are policing. As stated above, a police department may have systematic differences in the frequency of reporting due to the corresponding demographic of the university or their own policing practices. For example, some police departments may enforce policies against underage drinking stricter than others. Hence, including university-specific fixed effects ensures that moratorium days are compared to non-moratorium days while adjusting for these expected differences in universities. Moreover, $\mathbb{X}_t$ includes day of the week, semester type (spring/fall), holiday, and academic year controls. Day of the week controls are included since most offenses occur on the weekends, while semester controls are included to adjust for the fact that fraternity recruitment events usually occur in the fall semester. Lastly, holiday controls are included since there may be less student activity on holidays and academic year controls are included due to differences between fraternity rules and guidelines between academic years. Taken together, the corresponding interpretation of the parameter of interest, β, is the average difference in offense $Y_{u,t}$ on moratorium days relative to non-moratorium days, conditional on the expected differences between universities, days of the week, holidays, semesters, and academic years.

The preferred specification slightly modifies Equation 1's controls. In particular, I interact university-specific and academic-year fixed effects to allow more flexibility in controlling for differences within a university's academic year. Hence, the preferred specification (see column (3) in Table 5) compares only university-specific academic calendar days with a moratorium to university-specific academic calendar days without a moratorium. A more data-intensive specification using university-by-academic-year-by-semester fixed effect is analyzed in Section 5. However, this specification is not preferred as its coefficient estimates are less conservative and a large fraction (33%) of moratoriums span across multiple academic-year-semesters. Unless otherwise noted, all analysis in this paper utilizes the preferred specification which includes the interaction of university and academic year fixed effects.

4.2 Identification Assumptions

In order for β to be interpreted as a casual effect of fraternity moratoriums, there are four main assumptions that need to be satisfied. The first assumption is that the timing of a fraternity moratorium is as-good-as-random. This means that the enactment of a moratorium must not be correlated with unobserved factors in the error term that affect alcohol, drug, or sexual assault offenses. There are several reasons why this is a plausible assumption. First, fraternity moratoriums are the result of three types of triggering events: a fraternity-related death, a behavior violation, or a sexual assault (see Figure 2). Fraternity-related deaths and behavior violations are the result of alcohol poisoning from binge drinking and hazing/rule violations respectively. Since fraternities commonly engage in binge drinking and hazing frequently (DeSimone 2007; Hechinger 2017), it is reasonable to assume that the timing of these extreme instances were coincidental. Similarly, studies have linked a higher prevalence of partying to fraternity members (Routon and Walker 2014) which are linked to increased reports of sexual assault (Lindo, Siminski, and Swensen 2018) and therefore a more salient occurrence is likely to have come by-chance rather than the result of unusual behavior. Second, it is common that the start of each moratorium coincides with its corresponding triggering event. Table A1 shows a brief description of each triggering event in addition to the date of the triggering event and date of the enacted moratorium. In 14 of the 16 moratoriums in which the date of the triggering event is available, the moratorium is enacted within three days of the triggering event. Hence, there is little reason to expect that students are anticipating a moratorium. Lastly, according to an online repository of fraternity-related deaths from journalist Hank Nuwer,[13] there were 19 universities that experienced a fraternity-related death but *did not* undergo a moratorium in the sample period. Therefore, it is unlikely that fraternity members or students would expect a fraternity moratorium.

The second assumption is that there are no changes in policing or reporting of offenses between moratorium and non-moratorium days. For instance, if university police reduced

[13] See https://www.hanknuwer.com/hazing-deaths/.

the number of on-duty officers during moratorium days in anticipation of less crime, the number of offenses reported in the Daily Crime Logs would be mechanically smaller because of changes in officers rather than the moratorium itself. Furthermore, students may have more (or less) inclination to report crimes such as sexual assaults if they act in response to the public pressure that moratoriums place on fraternities. Since the Daily Crime Logs contain no information on number of on-duty officers or a student's affinity to report crimes, there is no direct way to test this assumption. However, as an indirect test, I analyze whether the time of occurrence to time of incident reported changes during moratorium days. In particular, I construct the proportion of offenses that are reported with a lag on a given day for each offense.[14] An offense is defined as reported with a lag if the date the incident occurred is not equal to the date the offense was reported. This test is motivated by the notion that the amount of time from an occurrence to an official report may be due to factors such as police force staffing or the willingness of students to report. Table 3 shows the results of this hypothesis. In each column, I change the definition of a lag to reflect a difference of one, three, seven, and fourteen days between the date occurred and date reported.[15] In each panel and column, the estimations show tight statistical zeros, therefore exhibiting no difference in the proportion of incidents reported with a lag.

The third assumption stems from the difference-in-differences design of the model: common trends. While it is impossible to know the number of offenses that university's would have experienced in absence of a moratorium, a difference-in-differences model requires only that universities were experiencing similar trends prior to a moratorium. To test this assumption, I estimate a multiple-event event study following the guidelines outlined in Schmidheiny and Siegloch (2020): I generalize a classic dummy variable event study to accommodate multiple moratoriums within a university. Importantly, the event study is not staggered—the indicator for being within a moratorium contains the *entire* moratorium period. Hence,

[14] Only 33 of the 38 universities had data for the date occurred of their incidents. Hence, this test only reflects a subset of the sample.

[15] Literature such as Sahay (2021) use a 3-day lag when applying this test.

the leads and lags only represent periods where a moratorium is not in effect. This decision was made due to the differences in moratorium lengths—moratorium lengths can vary considerably across universities (see Table 2). Figures 4, 5, and 6 show the results of the multiple-event event study. The shaded area represents an entire moratorium period while each point estimate before and after represents a 14-day period prior to or proceeding a moratorium (normalized by the 14-day period immediately before a moratorium). 14-day periods are chosen in lieu of 7-day periods to allow for a more precise point estimate. Five periods before and after are estimated, but only four are included. The fifth lead and lag are binned endpoints as described in Schmidheiny and Siegloch (2020). The errorbars represent 95% confidence intervals while the event window (e.g., the number of periods before/after the moratorium period) was chosen to give approximately a median moratorium length of days (46) before and after the moratorium period. In each figure, there is no evidence of a downward or upward trend prior to a moratorium. This is reinforced with a joint F-test that the three pre-periods are zero are statistically insignificant at the 5 or 10 percent level. As a measure of robustness, an alternative event-study is estimated using 46-day periods before and after a moratorium in Figures A2, A3, and A4. Each of these figures fails to show evidence of a decreasing or increasing pre-period trend.

The fourth and final assumption is that moratoriums have no lasting effects. Equation 1 implicitly assumes that student behavior changes only during moratoriums and that this behavior change does not persist over time. This is demonstrated through the fact that six universities in the sample experience more than one moratorium in the six-year period. If behavior truly changed, there would be no reason to enact multiple moratoriums. Moreover, in Section 5, I test this assumption by enriching the model with an indicator function for the week before and week after a moratorium. As discussed later, there is no evidence that there are persistent effects in the week following a moratorium.

5 Results

In this section, the causal effects of a fraternity moratorium on alcohol, drug, and sexual assault offenses are estimated using OLS. To reduce potential noise in the estimates, the sample is restricted to only the academic calendar days unique to each university.[16] Furthermore, I perform numerous robustness and sensitivity checks—each resulting in estimates that are consistent with the main findings discussed above.

5.1 Main Results

Table 4 reports that fraternity moratoriums lead to substantially lower alcohol offenses across university campuses while showing weaker evidence of decreases in both drug offenses and sexual assaults. Column (1) exhibits the naive regression with no controls—it compares only the difference in means between moratorium and non-moratorium days. While none of the panels in this column contain significant results, this specification acts as a demonstration of the importance of accounting for the factors described in Section 4. On the other hand, Column (2) shows the baseline specification from Equation 1. This baseline specification includes day of the week, holiday, semester, and academic year fixed effects in order to address the potential concerns described earlier. Moreover, columns (3) and (4) show results from progressively adding more flexible fixed effects. In Panel A, alcohol offenses decrease during moratorium days relative to non-moratorium days in the academic calendar. In particular, an average moratorium day exhibits between 26 and 29 percent less alcohol offenses in comparison to an average academic calendar day. These estimates are statistically significant across each specification, maintaining that moratoriums decrease campus-wide alcohol offenses. Although alcohol offenses are robust, both drug offenses and sexual assaults fail to achieve statistical significance across each specification and the magnitude of each effect varies considerably; drug offenses exhibit a 3-17 percent reduction from the mean

[16] See the Data section for more details.

and sexual assaults show an 18-26 percent reduction. One reason for this discrepancy in magnitude may be that the inclusion of the university by academic year fixed effect (column (3)) changes the comparison groups; intuitively, a university by academic year fixed effect allows only for comparisons of moratorium days to non-moratoriums within a particular university's academic calendar. Similarly, interacting university, academic year, and semester fixed effects (column (4)) only allows for comparisons of moratorium days to non-moratorium days within a particular university's semester in a particular academic year. In light of these differences, all further analysis uses the controls from column (3) as the preferred specification due to their conservative estimates. Under this specification, alcohol offenses are the only offense that are significantly reduced in moratorium days when considering the entire sample period.

The effects of moratoriums are most evident during the weekends (Friday-Sunday), consistent with the literature that most college partying occurs on weekends rather than weekdays (Lindo, Siminski, and Swensen 2018). Table 5 shows column (3) from Table 4 separated by weekends, and weekdays; the column "All Days" corresponds to the estimates of column (3) from Table 4. During the weekends, alcohol offenses decrease by 29% relative to an average academic calendar weekend as shown in Panel A. On the other hand, weekdays show no statistically significant decreases. This is due to the nature of alcohol drinking at universities—most consumption occurs on the weekends rather than weekdays. Likewise to alcohol, sexual assaults show larger decreases on the weekend in comparison to weekdays in Panel C. A weekend during a moratorium can expect 26% fewer sexual assaults relative to an average academic calendar weekend. These results align with previous literature that indicate college partying increases both alcohol and sexual assaults (Lindo, Siminski, and Swensen 2018), although notably, these results indicate that *decreases* in college partying result in *decreases* of both alcohol and sexual assaults.

While both alcohol offenses and sexual assaults decrease significantly on the weekends, these effects are concentrated only within a moratorium. Figure 7 shows estimates from specification (3) in Table 4 with the inclusion of an indicator variable for the week after and week before a moratorium. When considering the entire sample, each offense exhibits decreases that persist only during the moratorium period. This pattern persists when restricting the sample to weekends where the effects of the moratorium are most prominent. While drug offenses show significant increases in the week following a moratorium, these results are likely the result of multiple hypothesis testing as drug offenses showed the least amount of robustness in Table 4 and there is little reason to suspect that only drug offenses increase after moratoriums without similar increases for alcohol offenses and sexual assaults. If this significant increase in drug offenses was the result of pent-up demand for hard partying, large increases in alcohol offenses and sexual assaults should also be expected. However, no accompanying increases are found.

5.2 Robustness

Given the low number of universities in the sample (38), the results shown above lack precision—while both alcohol and sexual assault offenses show statistically significant decreases on the weekend, the standard errors are not small: weekend offenses for alcohol decrease by 17-41 percent from the mean, while sexual assaults decrease by 10-42 percent with 95% confidence. To address this issue and increase power, I include 14 additional universities in the sample that never underwent a moratorium in the period of analysis. This amounts to 52 total universities for a total of approximately 75,000 academic calendar days. Each of the additional universities was chosen from the Colleges with the Best Greek Life list on niche.com.[17] Universities were selected if they were regarded as a top 50 Greek Life school.[18] However, 17 of these universities were already included in the sample due to experiencing a fraternity moratorium. As such, 14 of remaining 33 universities were able to provide

[17] I use niche.com since it is the top search result on Google when searching for the "best fraternity colleges' ". The Princeton Review, notable for its annual list of party schools, does not a list regarding fraternity life.

[18] Notably, it is known that at least one university (Chico State) had a moratorium outside of the sample period (2013). This, however, only further validates the selection of the never-treated universities.

Daily Crime Logs for the 2014-2019 period. Table A5 shows the effects of moratoriums when including these never-treated universities. Overall, the results remain similar, with weekend decreases of alcohol between an 11-34 percent reduction from the mean and sexual assault decreases between 10-39 percent. While the precision is only enhanced by 1-3 percentage points, the stability of the estimates and significance instill further confidence in the results of the model.

Figures A5, A6, and A7 show leave-one-out coefficient estimates for each corresponding offense. This analysis ensures that the results described above are not driven by a single university. In particular, 38 unique regressions are estimated for every offense, omitting one university within each iteration. This exercise is repeated for the entire sample in addition to weekends and weekdays only. In each figure, the results remain consistent with the estimates shown in Table 5; alcohol offenses significantly decline overall (with particularly strong effects on the weekends) while there is weaker evidence of declines in sexual assaults on the weekends. This analysis verifies that the effect of the moratorium is not driven by only one particularly stringent university.

Furthermore, given the non-negative count nature of the offense data and the sensitivity of OLS estimation to outliers, Tables A6 and A7 show Tables 4 and 5 using poisson estimation in lieu of OLS.[19] The results are consistent with Table A7 showing the preferred specification leading to 27 and 16 percent average reductions for alcohol offenses and sexual assaults respectively.

Lastly, several recent journal articles have found that using OLS in a two-way-fixed-effects (TWFE) difference-in-differences design can cause problematic issues with the coefficient estimates when there are heterogeneous treatment effects between groups over time (Chaisemartin and D'Haultfœuille 2020; Sun and Abraham 2021; Goodman-Bacon 2021; Athey and Imbens 2022). In particular, the parameter of interest (e.g., the coefficient on the treatment

[19]Despite these advantages of poisson estimation, OLS is the preferred method since the results are more conservative.

variable) is a weighted sum of average treatment effects where some of the weights may be negative. This negative weighting issue can potentially lead to coefficient estimates switching signs. For instance, a negative-signed treatment effect implicating reductions may actually be positively-signed once corrected for the problematic negative weights. While this paper's research design is not a typical TWFE design since the preferred specification uses interacted fixed effects and university's switch between moratorium days and non-moratorium days (and in some cases multiple times), there maintains a possibility that the negative weights issue could extend to the preferred model used in this paper. Appendix A analyzes a typical TWFE design in this setting using university and day by month by year fixed effects. I show that this design does not contain negative weights and that the coefficient estimates are consistent with the results described earlier.

6 Heterogeneity

In this section, I analyze three types of heterogeneous effects. First, I examine which type of triggering event of a moratorium causes the most significant decreases of offenses and find that fraternity-related deaths exhibit the strongest results for alcohol offenses. Second, I estimate the optimal length of a moratorium. While there is no clear answer to this, the estimates show that moratoriums should last at least a month to give effects. Last, I show that moratoriums are most effective when overseen by the university rather than the fraternity members themselves.

6.1 Triggering Event

As described in Section 2, there are several reasons why a moratorium is triggered: a fraternity-related death, a prominent sexual assault, or a behavior violation. There is little reason to expect that each of these cause similar effects. As an illustration, a death may be more salient than a behavior violation,[20] resulting in a stronger belief among fraternity members that their behaviors need to be modified. Moreover, both deaths and sexual assaults are less subjective results of risky behavior—a moratorium may seem more justified than an instance of hazing.

Figure 8 demonstrates that when a moratorium occurs due to a fraternity-related death or sexual assault, the effects of the moratorium are most prominent. Alcohol offenses decline significantly when a fraternity-related death is the triggering event. However, this may be due to a shock mechanism in which students across campus are changing their behavior in response to the death rather than the moratorium. For instance, students may be mourning the death of a student and partying behavior is reduced in response. This effect would contaminate the effect of a moratorium, as it would be unclear whether the moratorium is changing behavior or the death itself. To mitigate this issue, I include an additional 15 universities that experienced a fraternity-related death in the sample period, but *did not* undergo a moratorium.[21]. With the inclusion of these universities, alcohol offenses maintain strong and significant decreases signaling that the moratorium itself is changing behavior rather than the occurrence of a death.

Additionally, Figure 8 also shows significant decreases in sexual assaults when a triggering event involves either a sexual assault or behavior violation. However, the shortcomings of the estimations underlying these results must be carefully considered. Specifically, sexual assaults are a significantly under-reported offense—survey evidence shows that nearly 80% of sexual assaults go unreported.[22] Because of this, sexual assaults are relatively rare in police reports, thus resulting in small amounts of observations needed for identification. In addition, these estimates are based on a small subset of universities (18 universities for

[20] Recall that a behavior violation includes hazing, offensive behavior, rule violations, and other disorderly conduct.

[21] These universities were found using Hank Nuwer's repository of hazing-related deaths in the US: https://www.hanknuwer.com/hazing-deaths/.

[22] This is based on statistics from the AAU Campus Climate Survey on Sexual Assault and Sexual Misconduct. See here: https://ira.virginia.edu/sites/ias.virginia.edu/files/University%20of%20Virginia_2015_climate_final_report.pdf

Trigger: Behavior and 10 for Trigger: Sexual Assault). Taken together, the results indicate evidence of decreases in sexual assaults, although more evidence is needed to substantiate this claim.

6.2 Length of Moratorium

Each moratorium varies in its length. As shown in Table 2, the average length of a moratorium is 63 academic calendar days, with a minimum of 6 days and a maximum of 541 days. This is a large discrepancy, and to inform best practices, it is important to know which length is optimal. Short-lived moratoriums may not be effective since there is little time for behavior to change, although longer moratoriums' benefits may diminish if imposed too lengthy.

In an ideal dataset, a model that shows the effects of a moratorium along each day/week of enforcement would be estimated. More specifically, the model would show an optimal number of days/weeks that produces the strongest effects. Unfortunately, it is challenging to model such regression since every moratorium has a different length; only the longest moratoriums will identify the later days/weeks' effect since short moratoriums will have ended. While imperfect, Figure 9 examines such model by analyzing each week of a moratorium across the sample. The figure shows evidence that the largest effects for alcohol are observed in the 5th and 6th weeks of a moratorium, although it should be noted that this estimate is identified by only 27/38 universitsies.

In light of these shortcomings, I analyze the heterogeneous effects of length with a second approach: I bin each moratorium into three percentiles based on length (33rd, 66th, 100th). The three percentiles correspond to [0-32], [33-57], and [58-541] academic calendar day intervals under moratorium respectively. Table 7 shows that when moratoriums are under 33 days (Panel A), there is little effect on any of the offenses. On the other hand, Panel B exhibits the strongest effects among the three quantiles. In particular, alcohol offenses decrease significantly by an approximately 32% from the mean. Notably, the magnitude of both alcohol offenses and sexual assaults are the largest among the three panels although sexual assaults are not significant. Panel C shows weaker evidence of significant decreases in alcohol offenses from the moratoriums that last between 58 and 541 days with alcohol offenses decreasing 28% from the mean. Overall, this evidence shows that moratoriums need to be implemented for at least a month's worth of academic calendar days to have effects across campus while there is evidence of diminishing returns if imposed for too long. On the contrary, short moratoriums have no effect on student behavior.

6.3 University vs. IFC Enforcement

Recall that there are two sources of enactment/oversight for campus-wide moratoriums—the university itself and the university-specific IFC. In the sample, 28 of the 45 (62%) moratoriums are enacted by a university. While a university-enacted moratorium is overseen by the university, an IFC university is only overseen by the fraternity members themselves. More specifically, an IFC-enacted moratorium is purely an agreement among fraternity members to restrict behavior. Hence, there is reason to suspect differences between these two sources of jurisdiction since IFC moratoriums may lack the oversight and punitive measures that university moratoriums have. Without this additional incentive to oblige, fraternities could "look away" from the guidelines set forth by the IFC.

In Table 6 alcohol offenses are shown to significantly decline when a university imposes the moratorium as shown in Panel A. Notably, each coefficient estimate in Panel A is negative, unlike the estimates shown in Panel B. While the estimates in Panel B fail to be statistically significant, it is noted that the magnitudes of the estimates for alcohol and sexual assault offenses are similar. Despite this, the results show that universities are the best source of oversight for moratoriums rather than the fraternity members themselves.

7 Discussion and Conclusion

In this paper, I estimate the causal effect of temporary restrictions of fraternity social events with alcohol (moratoriums) on campus-wide reports of alcohol, drug, and sexual assaults across 38 universities in the US. I construct a novel dataset which includes daily-level incidence reports from each university-specific police department. Using this data, I compare academic calendar days with a moratorium to academic calendar days without a moratorium while controlling for expected differences in the days of the week, holidays, semesters (spring/fall), academic years, and universities. I find that moratoriums decrease the average incidence of alcohol offenses on a given academic calendar day by approximately 27%. This result is most prominent on the weekends when partying is most frequent (29% reduction) while nonexistent on the weekdays. Moreover, I find weaker evidence of decreases in sexual assaults on the weekends with a 26% reduction from the mean, although only significant at the 10% level. Notably, the moratoriums show no lasting effects; including an indicator for the week before and week after a moratorium shows a significant dip during the moratorium, but immediate returns to previous levels after the moratorium is lifted. These results demonstrate that moratoriums are only effective when in place; despite the motivation that moratoriums allow time for members to reevaluate and change their systematic behavior, the effects do not persist.

One potential caveat to these results is that the decreases of alcohol and sexual assault shown in the Daily Crime Logs are being displaced to potentially riskier areas. For instance, while campus-wide alcohol is decreasing, it may be that fraternity members and other students are substituting their behaviors on-campus to off-campus areas that are less regulated. If this is true, a moratorium may cause more harm than the perceived benefits shown in this paper. Unfortunately, there does not exist a sufficient data source to explore such mechanism directly; the NIBRS data only reliably[23] covers 36% of the sample universities' neighboring

[23] In this case, I consider a data source to be reliable if reporting of crime is consistent in the sample period. NIBRS features only 14 schools that continually report data without large missing periods.

police department and includes alcohol arrests rather than all incidences. Hence, it remains difficult to estimate spillover effects onto nearby areas. As an indirect test, I analyze the CSS data in Appendix A. This data, while similar to the Daily Crime Logs, features all violations of liquor, drug, and sexual assaults that occur in a calendar-year, aggregated to the yearly level. Since the data is aggregated yearly, and moratoriums can last for as few as 6 days, the analysis should be taken only as speculative, not causal. Despite these shortcomings, there is evidence that moratoriums significantly move drinking from fraternity houses to residence halls. Residence halls show a 25% *increase* in alcohol offenses relative to the mean when a proportion of a calendar-year is in a moratorium. This is accompanied by a large 85% *decrease* from the mean in residence hall sexual assaults. These results point to the possibility that moratoriums cause a substitution effect of partying behavior; students substitute drinking from fraternity houses to residence halls. Since residence halls are far more regulated than fraternity houses, problematic alcoholic behavior is stopped (e.g., the increases in alcohol violations) before it can become dangerous to others (e.g., the decreases in sexual assaults).

Taken together, these results support the notion that moratoriums are effective policy procedures in reducing campus-wide alcohol offenses provided that the moratoriums contain at least a month's worth of academic calendar days. However, moratoriums do not substantiate permanent behavior changes. The results show that fraternity and campus behavior returns to prior levels immediately after a moratorium has been lifted. Thus, further research is needed to understand how to permanently change risky behavior rather than temporarily mitigate it. Several universities have completely removed fraternities from their campuses or have implemented restrictions on recruitment strategies in their students' first semester. In particular, Duke University has implemented a deferred recruitment system in which students may not join fraternities until their sophomore year. As of this writing, there are only two studies that evaluate such policy and these papers focused on academic benefits rather than crime (De Donato and Thomas 2017; Even and Smith 2020).

It is important to understand that this paper does not provide evidence advocating for the removal of fraternity life. Within this study, none of the universities removed fraternity life, only restricted it. Hence, this paper does not provide support for national movements such as "Abolish Greek Life." However, this study *does* quantify the effects that fraternities have on university-wide partying behavior. More specifically, this paper is the first to show the causal effect of temporarily restricting alcohol from fraternity social events which significantly reduce alcohol offenses and sexual assaults campus-wide.

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9 Figures

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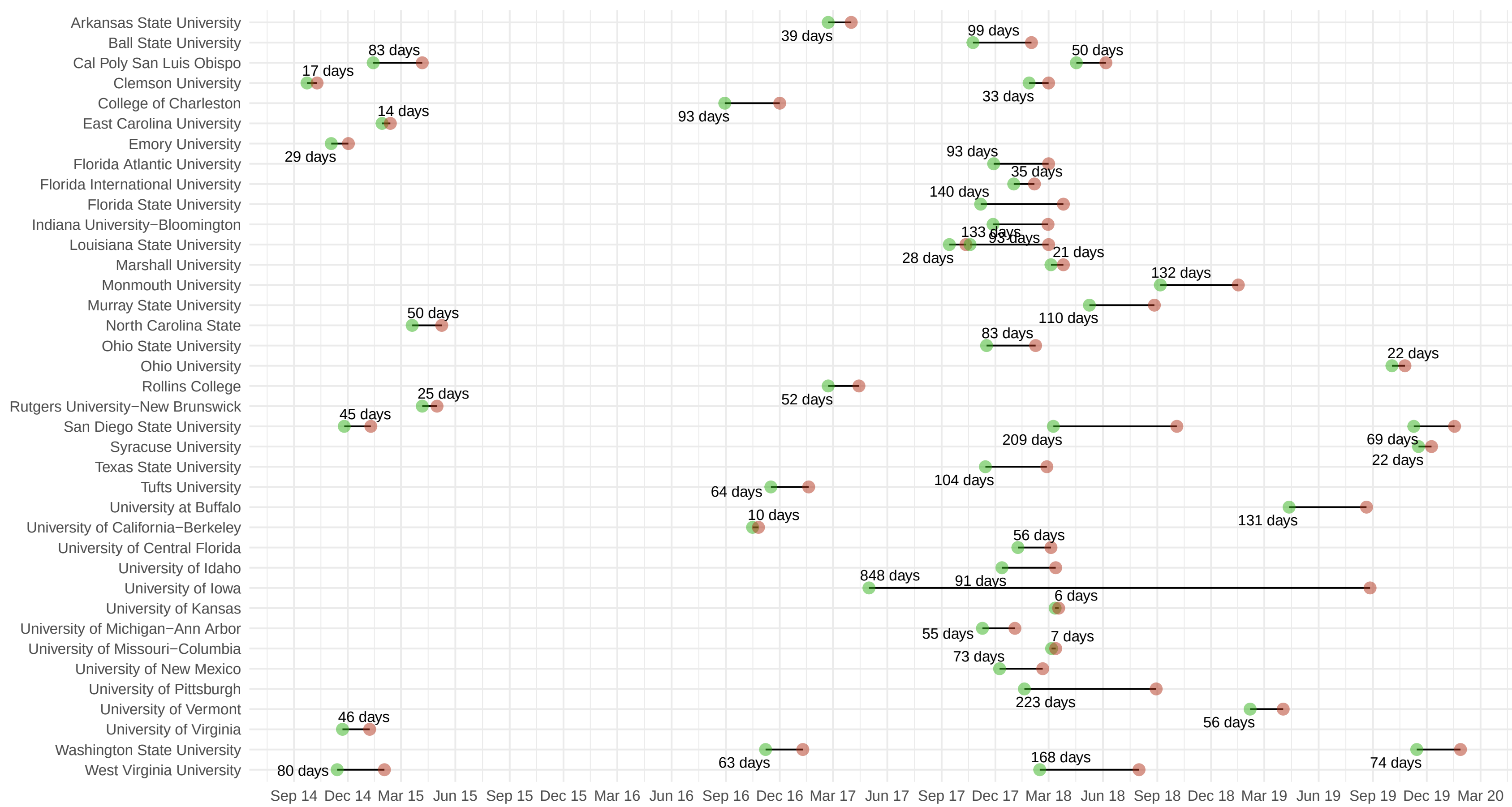


Figure 1: Distribution of Moratoriums Across the Sample Period for all Universities

Notes: The sample period starts in 2014 and ends on the last day of 2019. The lengths of the moratoriums in this graph represent calendar-day lengths, not academic-calendar day lengths. Universities xperience between 1 to 3 moratoriums in the sample period.

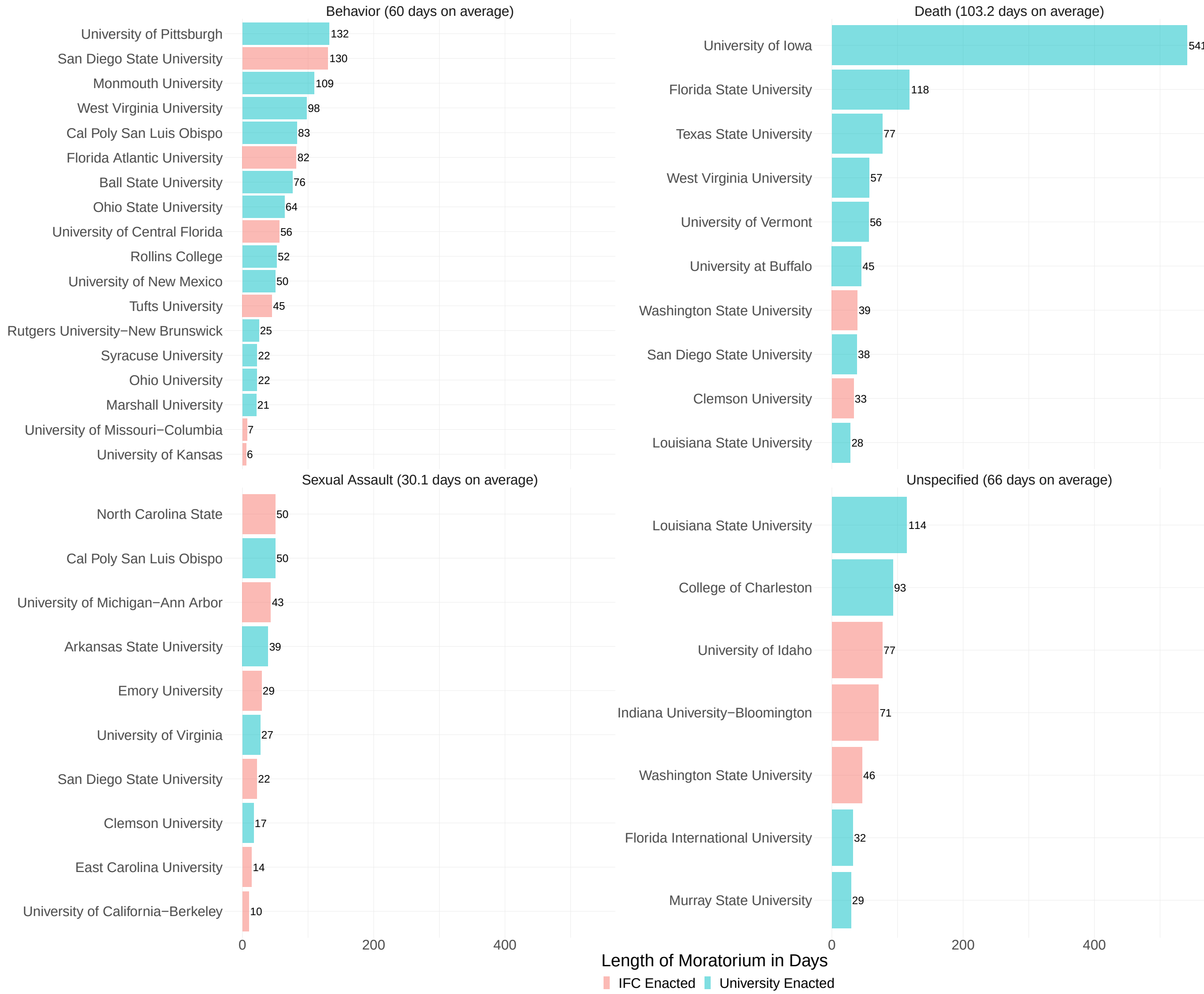


Figure 2: Number of Academic Calendar Days in a Moratorium by Triggering Event

Notes: Lengths of moratoriums represent academic calendar days. Therefore, the lengths of moratoriums differ from Figure 1. Blue shaded regions represent a moratorium that was imposed by the university, while red shaded moratoriums represent moratoriums that were imposed by the IFC. Each of the four categories represents the event that triggered a moratorium. Behavior violations is a catchall term for hazing, rule violations, offensive behavior, and other disorderly conduct. Death relates to a fraternity-related death that triggered a moratorium. Sexual assaults relate to a sexuall assault case that triggered a moratorium. Lastly, the Unspecified category represents all moratoriums in which the moratorium triggering event is unknown or unclearly defined.

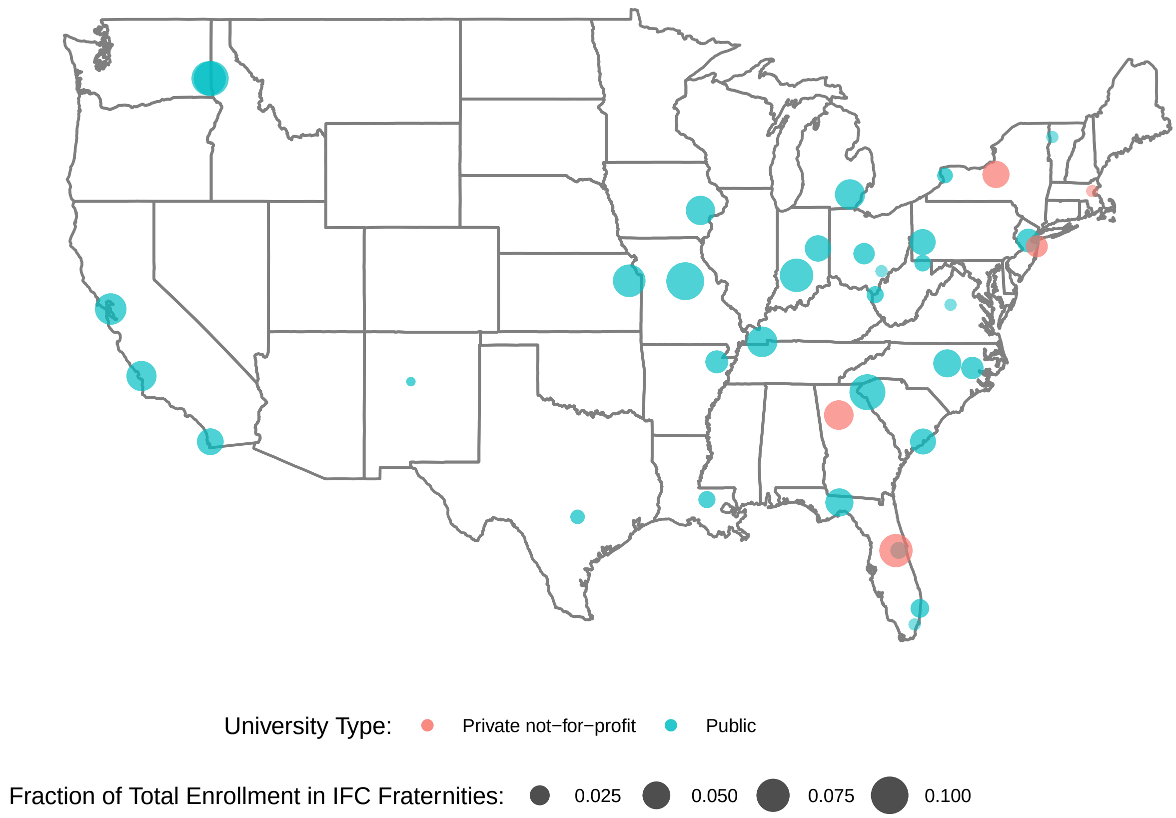


Figure 3: Locations of the Universities Included in the Sample

Notes: The fraction of total enrollment in an IFC fraternity is based on the most recent information available from the university. In the majority of the cases, this resulted in IFC populations from Fall 2019. However, some universities did not disclose this information, and thus this data is not used in the main analysis. In this case, these universities are represented with the smallest size point.

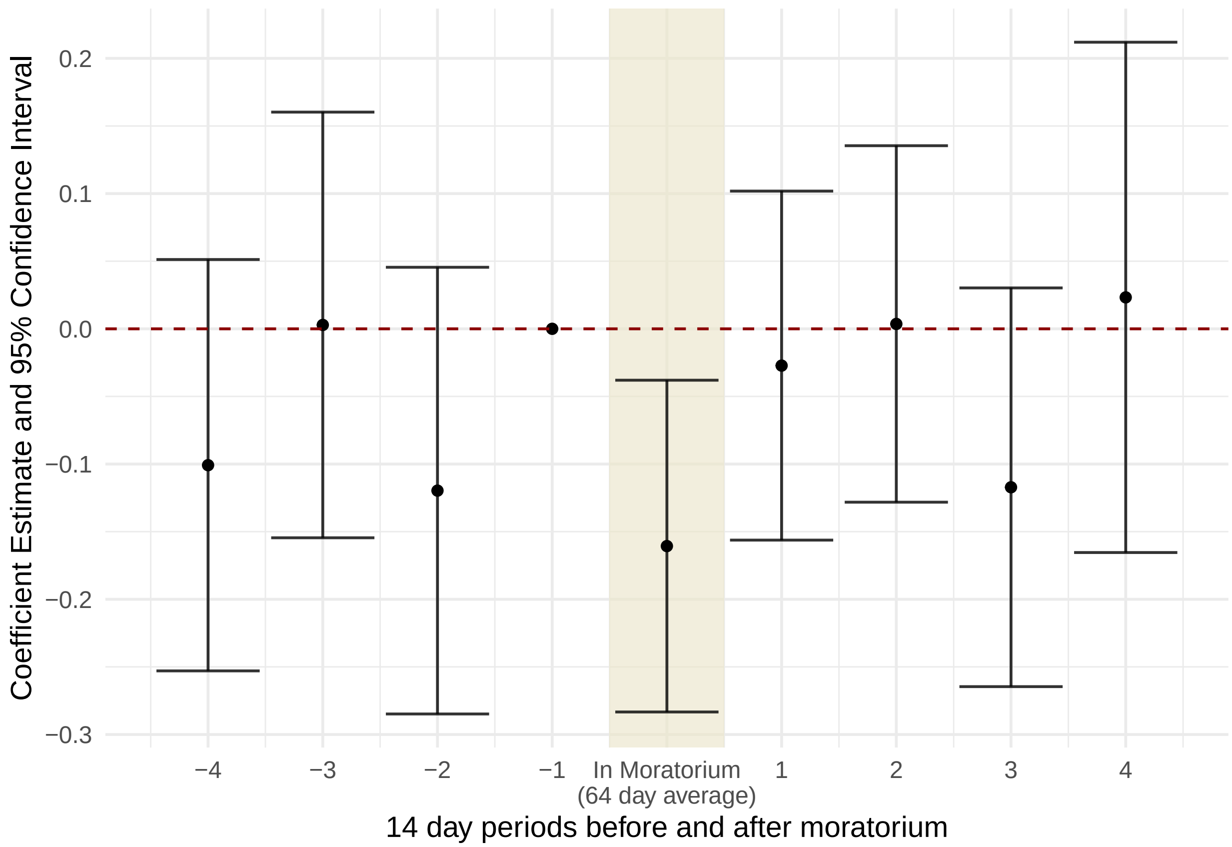


Figure 4: Event Study for Alcohol Offenses

Notes: The shaded area point estimate represents an entire moratorium period for each university. Hence, the shaded area point estimate has varying amounts of days within based on the university. For instance, Arkansas State University had a 39 day moratorium and therefore their shaded area point estimate would be identified by the 39 moratorium days. Point estimates not within the shaded region are 14 day periods. Number of days within a period was chosen to give approximately a median-length (46 days) moratorium on each side of the shaded area. All periods are normalized by the 14-day period before the moratorium. Alcohol offenses are defined as alcohol offenses per-25000 enrolled students. Controls include holiday, spring semester, day of the week and university by academic year. Standard errors clustered by university. All errorbars represent 95% confidence intervals. A joint-hypothesis F-test that each of the leading periods are zero shows that the p-value is 0.39 which is statistically insignificant.

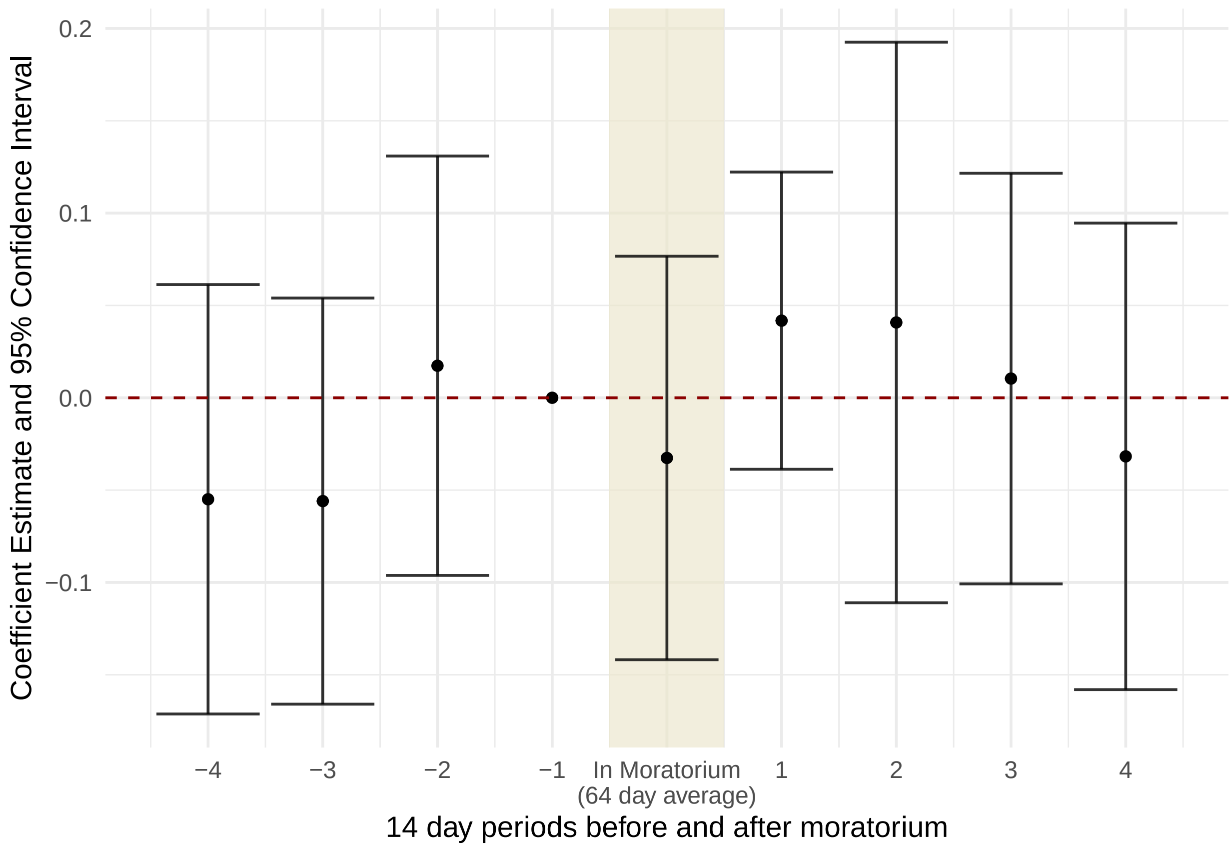


Figure 5: Event Study for Drug Offenses

Notes: The shaded area point estimate represents an entire moratorium period for each university. Hence, the shaded area point estimate has varying amounts of days within based on the university. For instance, Arkansas State University had a 39 day moratorium and therefore their shaded area point estimate would be identified by the 39 moratorium days. Point estimates not within the shaded region are 14 day periods. Number of days within a period was chosen to give approximately a median-length (46 days) moratorium on each side of the shaded area. All periods are normalized by the 14-day period before the moratorium. Drug offenses are defined as drug offenses per-25000 enrolled students. Controls include holiday, spring semester, day of the week and university by academic year. Standard errors clustered by university. All errorbars represent 95% confidence intervals. A joint-hypothesis F-test that each of the leading periods are zero shows that the p-value is 0.55 which is statistically insignificant.

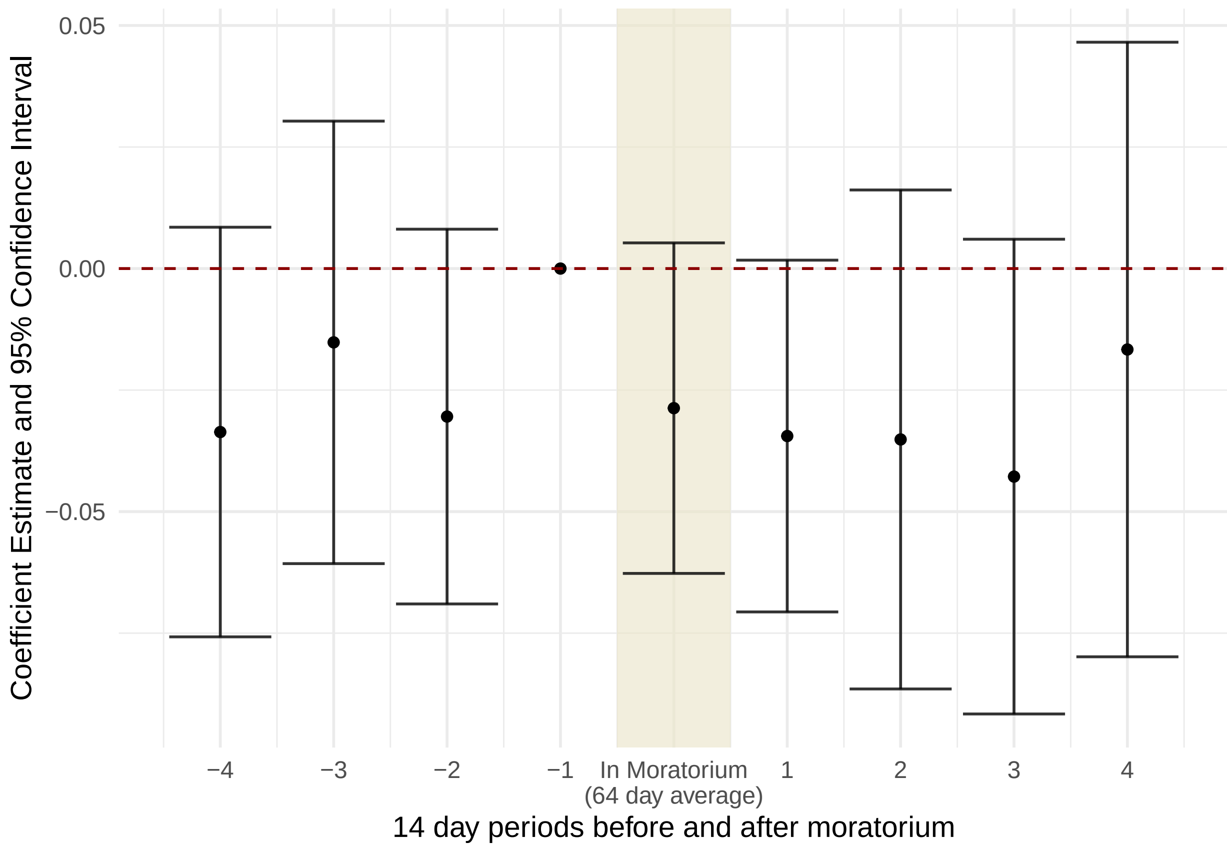


Figure 6: Event Study for Sexual Assault Offenses

Notes: The shaded area point estimate represents an entire moratorium period for each university. Hence, the shaded area point estimate has varying amounts of days within based on the university. For instance, Arkansas State University had a 39 day moratorium and therefore their shaded area point estimate would be identified by the 39 moratorium days. Point estimates not within the shaded region are 14 day periods. Number of days within a period was chosen to give approximately a median-length (46 days) moratorium on each side of the shaded area. All periods are normalized by the 14-day period before the moratorium. Sexual assault offenses are defined as sexual assaults per-25000 enrolled students. Controls include holiday, spring semester, day of the week and university by academic year. Standard errors clustered by university. All errorbars represent 95% confidence intervals. A joint-hypothesis F-test that each of the leading periods are zero shows that the p-value is 0.38 which is statistically insignificant.

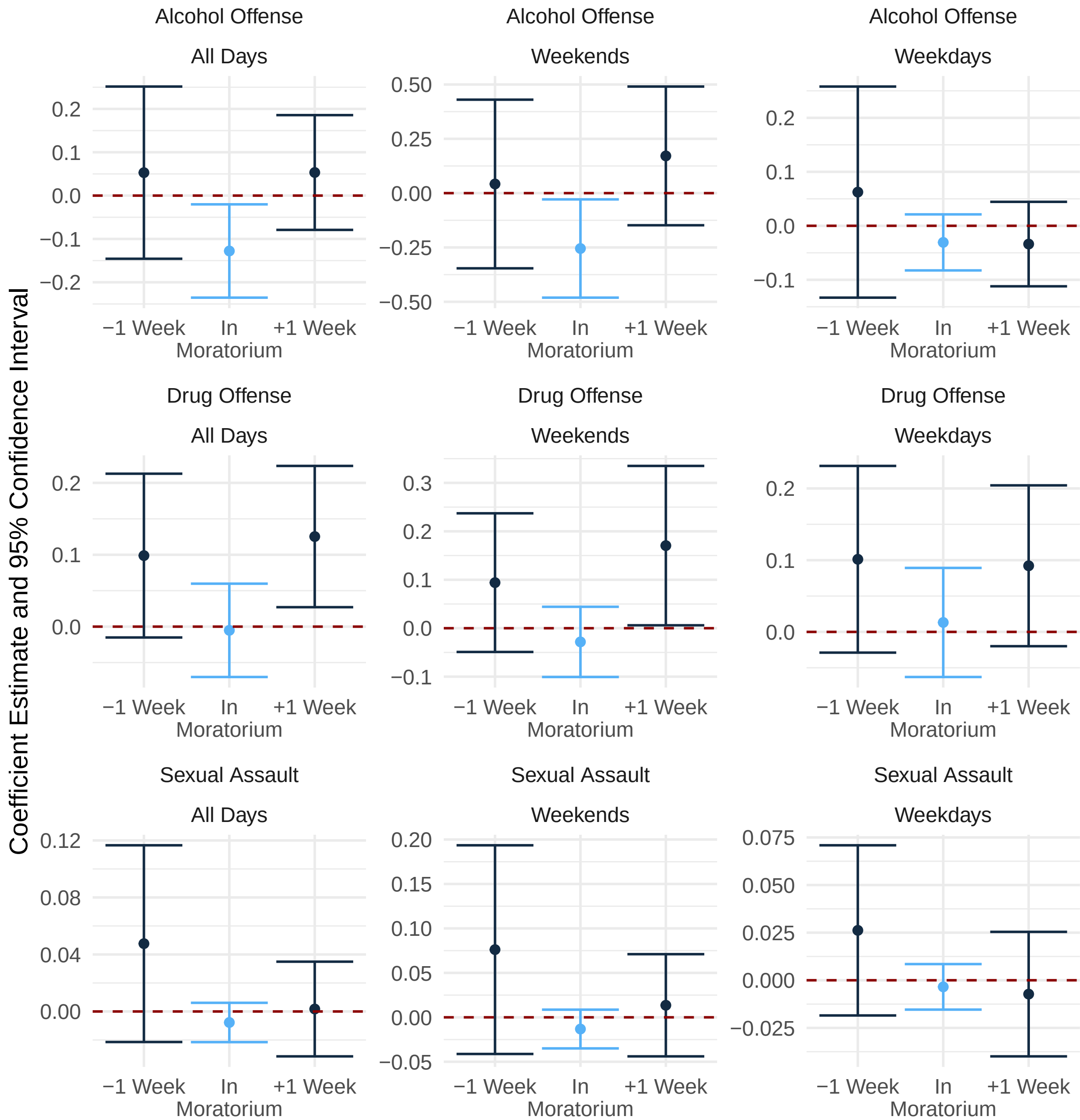


Figure 7: Coefficient Estimates Including a Week Before and Week After Indicator
Notes: The x-axis represents three periods: the week before a moratorium, the moratorium itself, and the week after the moratorium. Indicators for week before and week after are added to specification (3) from Table 4. Controls include holiday, spring semester, day of the week and university by academic year. Standard errors clustered by university. Weekends represent Fridays, Saturdays, and Sundays. Weekdays represent Mondays-Thursdays. Errorbars represent 95% confidence intervals.

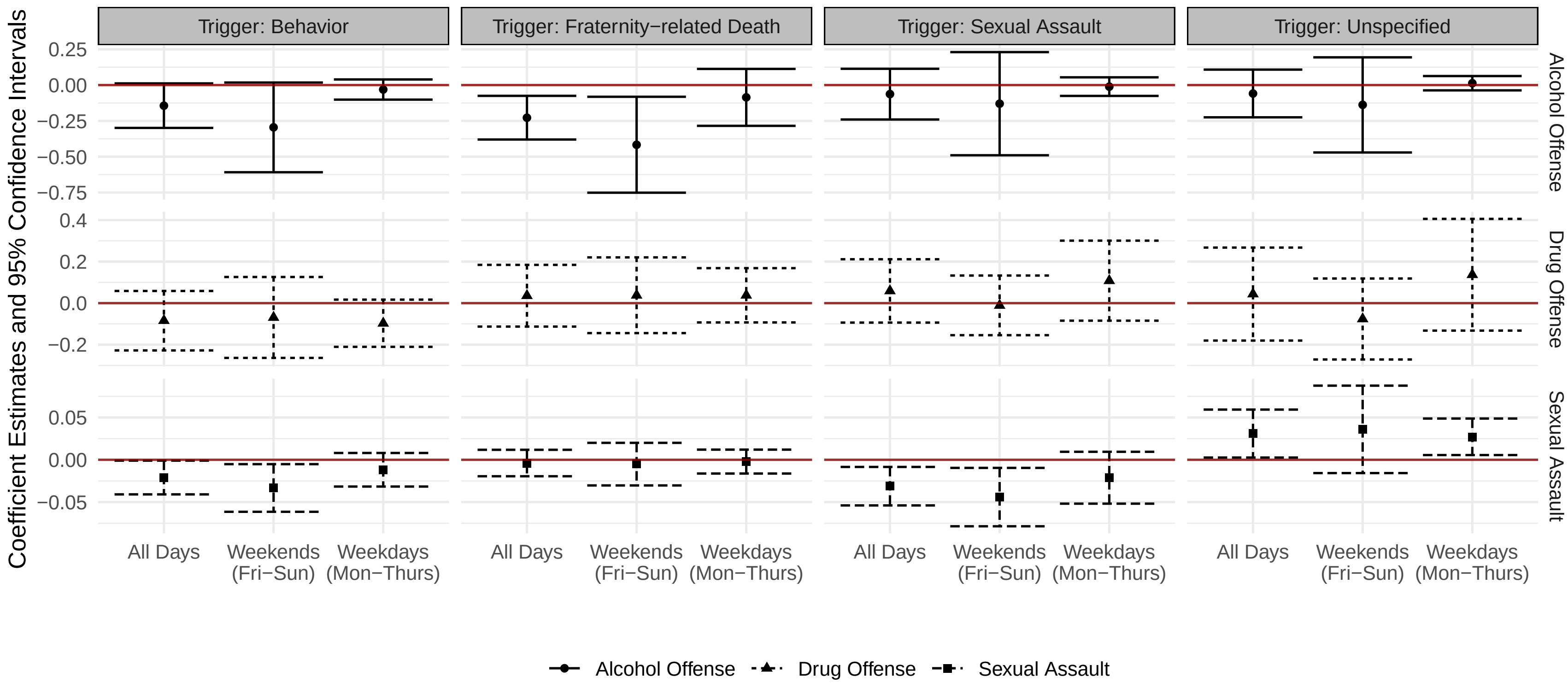


Figure 8: Heterogeneous Effects of Moratoriums by Triggering Event

Notes: The x-axis represents three periods: the entire sample (All Days), weekends only, and weekdays only. Specification (3) from Table 4 is used in estimation. Each of the four categories represents the event that triggered a moratorium. Behavior violations is a catchall term for hazing, rule violations, offensive behavior, and other disorderly conduct. Death relates to a fraternity-related death that triggered a moratorium. Sexual assaults relate to a sexuall assault case that triggered a moratorium. Lastly, the Unspecified category represents all moratoriums in which the moratorium triggering event is unknown or unclear. Controls include holiday, spring semester, day of the week and university by academic year. Standard errors clustered by university. Weekends represent Fridays, Saturdays, and Sundays. Weekdays represent Mondays-Thursdays. Errorbars represent 95% confidence intervals.

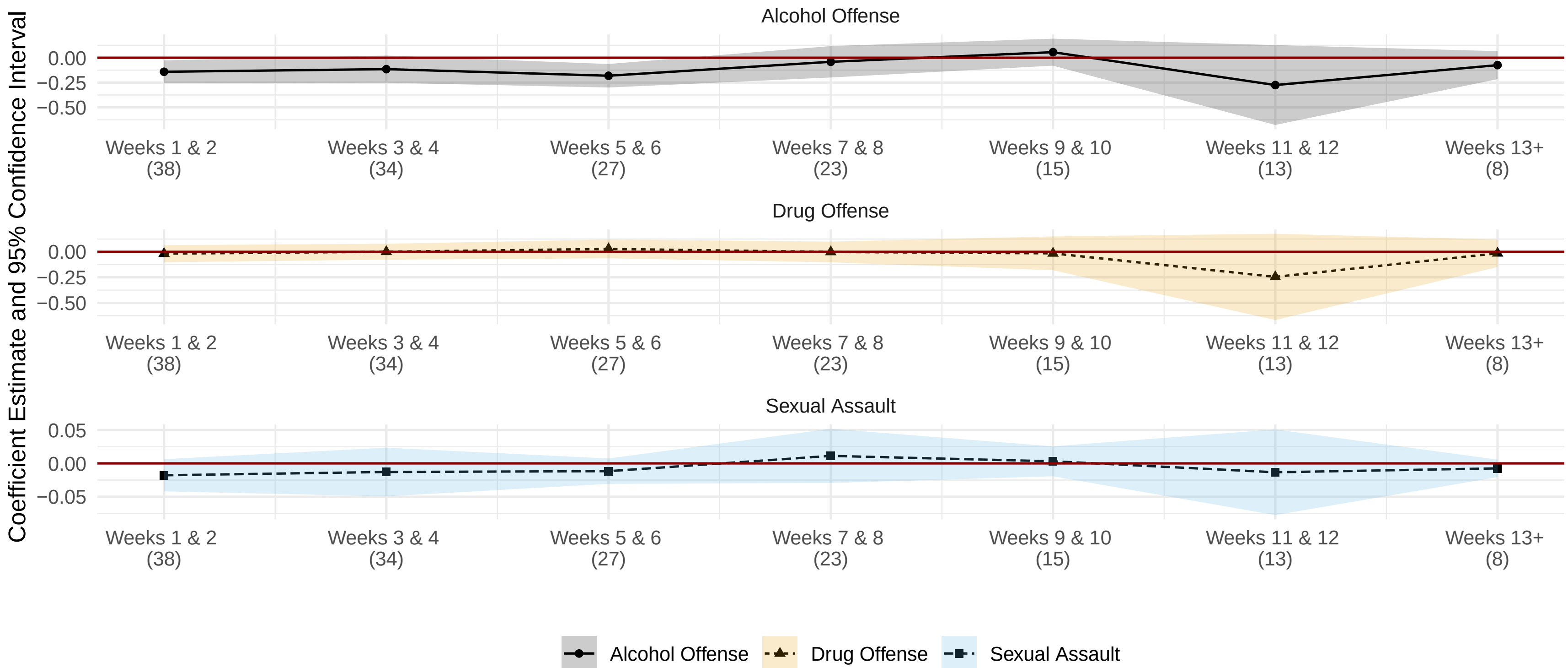


Figure 9: How Moratoriums Effect Offenses by Each Week of the Moratorium

Notes: This figure shows how a moratorium progresses over time. Note that all point estimates shown in this figure are from moratorium days only. Since moratorium lengths differ by university and moratorium universities drop out of the estimates. The number of universities used to identify each coefficient estimate is displayed in parenthesis on the x-axis in addition to the number of weeks within a moratorium. The preffered specification is used which includes day of week, holiday, university by academic calendar, and semester controls. Standard errors are clustered at the university level.

10 Tables

Table 1: Words and Phrases used to Pattern Match on Offenses of Interest

Outcome	Words to Match
Sexual Assault	sex, rape, fondling, fondle
Alcohol Violations	alcohol, dwi, intox, drink, dui, drunk, liquor, driving under the influence, dip, abcc, underage, dwi, underage, pula, owi, mip, under age, beer, wine, booze, minor in possession, ovi
Drug Offense	drug, narcotic, marijuana, heroin, overdose, cocaine, controlled substance

Note:
Each word to match represents a portion of a word to match on. For example, the word 'sex' will match on 'sexual assault' and 'sex offense' since 'sex' appears in each of these descriptions.
'dwi' is an abbreviation for 'driving while intoxicated'.
'dip' is an abbrevation for 'drunk in public'.
'abcc' is an abbreviation for 'alcohol beverage control comission'.
'pula' is an abbrevation for 'person under legal age'.
'owi' is an abbreviation for 'operating while intoxicated'.
'mip' is an abbreviation for 'minor in possesion'.
'ovi' is an abbreivation for 'operating vehicle intoxicated'.

Table 2: Summary Statistics of the Universities in the Sample.

	Mean	SD	Median	Min	Max
Panel A: University Characteristics					
Total Enrollment	28 683.99	14 455.98	28 664.00	3127.00	69 402.00
Total Undergrad Enrollment	22 142.26	11 859.01	21 921.00	2571.00	59 371.00
Fraction Asian	0.07	0.07	0.04	0.01	0.36
Fraction Black	0.07	0.04	0.06	0.01	0.20
Fraction Hispanic	0.13	0.14	0.07	0.02	0.68
Fraction White	0.62	0.18	0.67	0.08	0.83
Graduation Rate	70.46	13.64	71.00	39.00	95.00
SAT Math 75th Percentile	655.94	68.26	650.00	480.00	790.00
SAT Reading 75th Percentile	641.83	53.72	640.00	490.00	760.00
Fraction Admitted	0.60	0.21	0.62	0.14	0.94
Fraction Private	0.13	0.33	0.00	0.00	1.00
Panel B: Daily Crime Log Offenses					
Alcohol Offense	0.50	1.36	0.00	0.00	40.84
Drug Offense	0.43	0.96	0.00	0.00	25.28
Sexual Assault	0.05	0.32	0.00	0.00	15.99
Panel C: Moratorium Characteristics					
Number of Moratoriums per-University	1.36	0.61	1.00	1	3
Length of Moratoriums	63.89	79.98	46.00	6.00	541.00
Total Number of Universities	*38*				

Note:
Offenses are per-25000 students enrolled per-academic calendar day. Length of moratorium statistics are in academic calendar days. Number of moratoriums refers to number of moratoriums only within the 2014-2019 time period. Some schools may or may not have had moratoriums in periods before or after the time period of analysis. Only a subset of races were chosen, and hence, the sum of the fractions do not sum to 1 in the table. SAT Math 75th Percentile and SAT Reading 75th Percentile correspond to the 75th perctile SAT score for an admitted student. A perfect score is 800, while an average score is approximately 500. Fraction Private refers to the fractin of universities that are private universities.

Table 3: Effect of Moratoriums on Changes in Reporting.

	Reporting Lag			
	More than 1-Day Lag	More than 3-Day Lag	More than 7-Day Lag	More than 14-day Lag
Panel A: Proportion of Alcohol Offenses Reported with Lag				
In Moratorium	0.002	0.000	0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	49425	49425	49425	49425
Mean of Dependent Variable	0.003	0.002	0.001	0.001
Panel B: Proportion of Drug Offenses Reported with Lag				
In Moratorium	-0.001	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	49425	49425	49425	49425
Mean of Dependent Variable	0.002	0.002	0.001	0.001
Panel C: Proportion of Alcohol Offenses Reported with Lag				
In Moratorium	0.000	-0.001	0.000	0.001
	(0.004)	(0.004)	(0.003)	(0.003)
Observations	49425	49425	49425	49425
Mean of Dependent Variable	0.018	0.014	0.011	0.001
Controls for Panels A-C:				
FE: Day of Week	X	X	X	X
FE: Holiday	X	X	X	X
FE: Semester (Spring/Fall)	X	X	X	X
FE: University by Academic Year	X	X	X	X

Note:
Standard errors clustered by university. Panels A-C are OLS regressions of proportions of alcohol, drug offenses, and sexual assaults reported with a reporting lag. A reporting lag is defined as an offense that was reported more than 1 (Column 1), 3 (Column 2), 7 (Column 3), or 14 (Column 4) days after it occurred. Not all universities had information on date occurred (33/38).
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A Appendix

Table 4: Effect of Moratoriums on Alcohol Offenses, Drug Offenses, and Sexual Assaults (OLS).

	(1)	(2)	(3)	(4)
Panel A: Alcohol Offenses				
In Moratorium	0.011	-0.148**	-0.132*	-0.145**
	(0.111)	(0.049)	(0.050)	(0.046)
Observations	56514	56514	56514	56514
Mean of Dependent Variable	0.497	0.497	0.497	0.497
Panel B: Drug Offenses				
In Moratorium	-0.030	-0.076*	-0.014	-0.046
	(0.066)	(0.037)	(0.032)	(0.032)
Observations	56514	56514	56514	56514
Mean of Dependent Variable	0.432	0.432	0.432	0.432
Panel C: Sexual Assaults				
In Moratorium	-0.002	-0.009*	-0.010	-0.007
	(0.007)	(0.004)	(0.006)	(0.006)
Observations	56514	56514	56514	56514
Mean of Dependent Variable	0.055	0.055	0.055	0.055
Controls for Panels A-C:				
FE: Day of Week		X	X	X
FE: Holiday		X	X	X
FE: Semester (Spring/Fall)		X	X	X
FE: University		X		
FE: Academic Year		X		
FE: University by Academic Year			X	
FE: University by Academic Year by Semester				X

Note:
Standard errors are clustered by university and each offense is defined as per-25000 enrolled students. Weekends consist of Fridays, Saturdays, and Sundays. Weekdays consist of Monday through Thursday. Holiday controls include controls for Veterans Day, Thanksgiving, Labor Day, Halloween, and MLK Day. Christmas/New Years/July 4th are not included since these holiday's are not on any university's academic calendar. A moratorium is a temporary halt on fraternity-related activities with alcohol. Specification (3) is the preferred specification due to the flexibility of the fixed effects and the conservativeness of the estimates.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Effect of Moratoriums on Alcohol Offenses, Drug Offenses, and Sexual Assault by Weekend/Weekdays (OLS).

	Days of the Week		
	All Days	Weekends	Weekdays
Panel A: Alcohol Offenses			
In Moratorium	-0.132*	-0.263*	-0.032
	(0.050)	(0.106)	(0.026)
Observations	56514	24244	32270
Mean of Dependent Variable	0.497	0.892	0.201
Panel B: Drug Offenses			
In Moratorium	-0.014	-0.038	0.006
	(0.032)	(0.037)	(0.037)
Observations	56514	24244	32270
Mean of Dependent Variable	0.432	0.495	0.385
Panel C: Sexual Assaults			
In Moratorium	-0.010	-0.017+	-0.004
	(0.006)	(0.010)	(0.006)
Observations	56514	24244	32270
Mean of Dependent Variable	0.055	0.064	0.047
Controls for Panels A-C:			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Semester (Spring/Fall)	X	X	X
FE: University by Academic Year	X	X	X

Note:

Standard errors are clustered by university and each offense is defined as per-25000 enrolled students. The column 'All Days' represents specification (3) from the main results table. Weekends consist of Fridays, Saturdays, and Sundays. Weekdays consist of Monday through Thursday. Holiday controls include controls for Veterans Day, Thanksgiving, Labor Day, Halloween, and MLK Day. Christmas/New Years/July 4th are not included since no university's academic calendar contains them. A moratorium is a temporary halt on fraternity-related activities with alcohol.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Effect of Moratoriums Imposed by the University vs. the IFC

	Days of the Week		
	All Days	Weekends	Weekdays
Panel A: University-Imposed Moratoriums			
Alcohol Offense			
In Moratorium	-0.136*	-0.272*	-0.033
	(0.063)	(0.132)	(0.034)
Observations	56514	24244	32270
Drug Offense			
In Moratorium	-0.052+	-0.063	-0.043
	(0.030)	(0.044)	(0.027)
Observations	56514	24244	32270
Sexual Assault			
In Moratorium	-0.010	-0.018	-0.003
	(0.008)	(0.013)	(0.007)
Observations	56514	24244	32270
Panel B: IFC-Imposed Moratoriums			
Alcohol Offense			
In Moratorium	-0.119	-0.235	-0.031
	(0.086)	(0.176)	(0.027)
Observations	56514	24244	32270
Drug Offense			
In Moratorium	0.094	0.032	0.139
	(0.089)	(0.070)	(0.114)
Observations	56514	24244	32270
Sexual Assault			
In Moratorium	-0.010	-0.015	-0.007
	(0.010)	(0.010)	(0.012)
Observations	56514	24244	32270

Note:
Standard errors clustered by university. Controls follow specification (3) in the main results table with day of week, holiday, semester, and universitiy by academic year fixed effects. Panel A shows the effects of a moratorium when a moratorium is imposed by the university. University-imposed moratoriums represent 28/45 (62%) of the moratoriums. Panel B shows the effects of a moratorium when the IFC council imposes the moratorium. This is a student-lead initiative. IFC-imposed moratoriums represent 17/45 (38%) of the moratoriums in the sample. Weekends represent Fridays through Sundays while Weekdays represent Mondays through Thursdays4
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Effect of Moratoriums by Moratorium Length

	Type of Offense		
	Alcohol Offenses	Drug Offenses	Sexual Assaults
Panel A: Below 33rd Percentile in Length			
In Moratorium	-0.027	0.005	-0.007
	(0.068)	(0.051)	(0.022)
Observations	56514	56514	56514
Panel B: Between 33rd and 66th Percentile in Length			
In Moratorium	-0.161*	0.013	-0.018
	(0.068)	(0.059)	(0.012)
Observations	56514	56514	56514
Panel C: Above 66th Percentile in Length			
In Moratorium	-0.143+	-0.036	-0.005
	(0.072)	(0.073)	(0.006)
Observations	56514	56514	56514

Note:
Standard errors are clustered by university and each offense is defined as per-25000 enrolled students. Each panel represents a subset of moratoriums that were split by three quantiles based on moratorium length: below the 33rd percentile, between the 33rd and 66th percentile, and above the 66th percentile. Controls include day of week, spring semester, holiday, and university by academic year. Holiday controls include controls for Veterans Day, Thanksgiving, Labor Day, Halloween, and MLK Day. Christmas/New Years/July 4th are not included since no university's academic calendar contains them. A moratorium is a temporary halt on fraternity-related activities with alcohol.
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

University	Description of Triggering Event
Arkansas State University-Main Campus	Arrest of a man suspected of raping
Ball State University	Concerns regarding the behavior an
California Polytechnic State University-San Luis Obispo	A report of a sexual assault that all
California Polytechnic State University-San Luis Obispo	Racially insensistive photos surfacin
Clemson University	Alleged sexual assault.
College of Charleston	Decision was made after consulting
East Carolina University	An alleged sexual assault on Jan. 2
Emory University	Report of a sexual assault in a frate
Florida Atlantic University	Tailgating issues involving alcohol.
Florida International University	Growing concerns about the state o
Florida State University	Death of Andrew Coffey.
Indiana University-Bloomington	A university spokesperson said the
Louisiana State University and Agricultural & Mechanical College	Death of Maxwell Gruver.
Louisiana State University and Agricultural & Mechanical College	Unclear.
Marshall University	High-risk behavior in the fraternity
Monmouth University	Troubles within the fraternity syste
Murray State University	The letter implementing the suspen
North Carolina State University at Raleigh	Surfaced newstory of a pledge book
Ohio State University-Main Campus	Proactive step based on the signific
Ohio University-Main Campus	Allegations within the past week of
Rollins College	The temporary suspension was issu
Rutgers University-New Brunswick	Several incidents with alcohol .
San Diego State University	Sexual assault allegations.
San Diego State University	Ongoing concerns related to alcohol
San Diego State University	Death of Dylan Hernandez.
Syracuse University	A string of racist and anti-Semitic i
Texas State University	Death of Matthew Ellis.
Tufts University	Accusations of hazing and discrimin
University at Buffalo	Death of Sebastian Serafin-Bazaan.
University of California-Berkeley	Reports of sexual assault at off-cam
University of Central Florida	Decision was made in light of drink
University of Idaho	A response to the growing national
University of Iowa	Death of Kamil Jackowski.
University of Kansas	Poor behavior among some Greek g
University of Michigan-Ann Arbor	Claims of sexual misconduct cases i
University of Missouri-Columbia	Hazing allegations.
University of New Mexico-Main Campus	With three UNM fraternities alread
University of Pittsburgh-Pittsburgh Campus	A serious alcohol incident involving
University of Vermont	Death of Connor Gage.
University of Virginia-Main Campus	Rolling Stone article describing the
Washington State University	Due to the current negative reputat
Washington State University	Death of Samuel Martinez.
West Virginia University	Death of Nolan Burch

Table A2: Moratorium dates of each university in the sample.

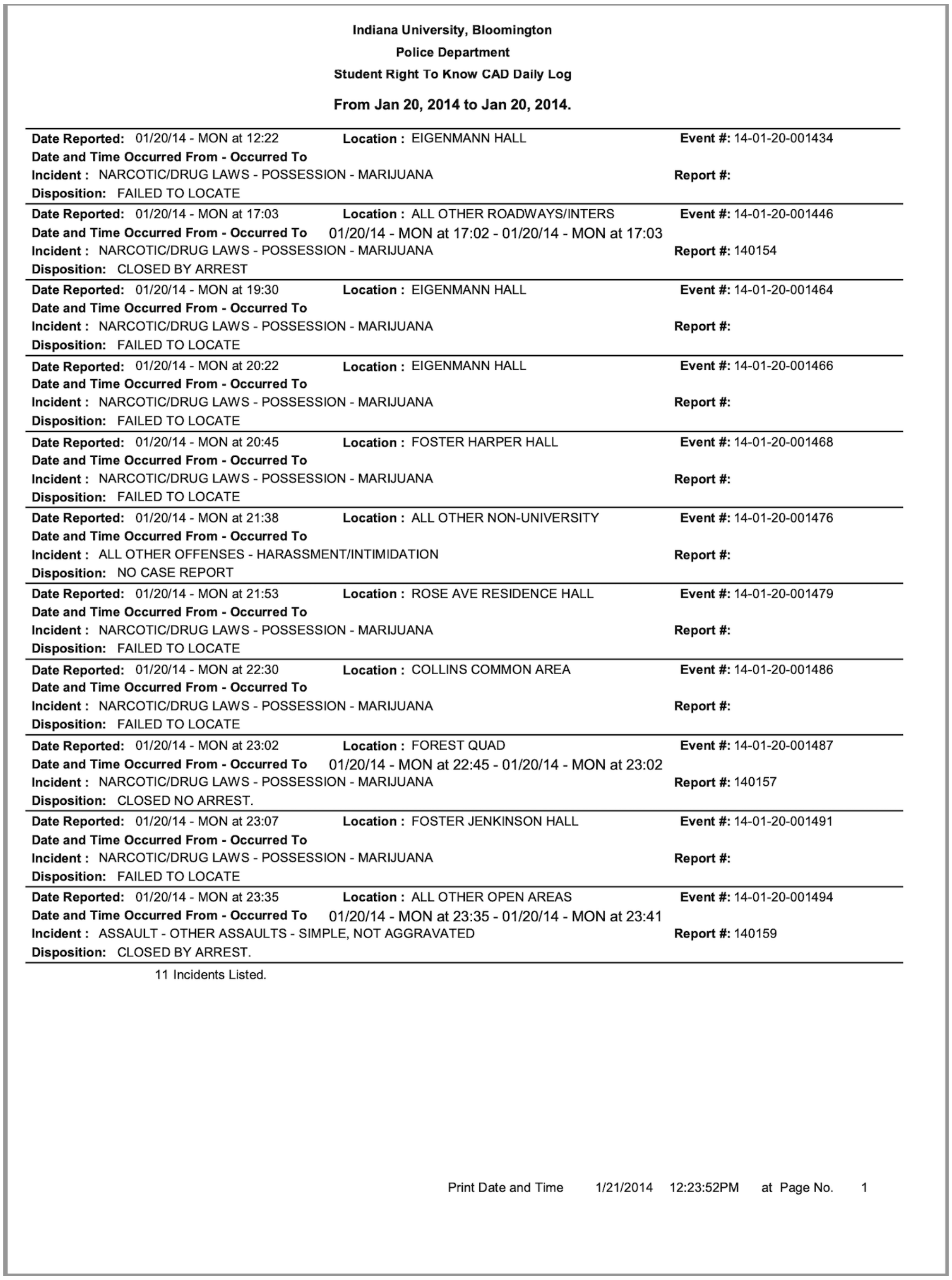
University	Moratorium 1 Start	Moratorium 1 End	Moratorium 2 Start	Moratorium 2 End	Moratorium 3 Start	Moratorium 3 End
Arkansas State University-Main Campus	2017-02-21	2017-04-01	NA	NA	NA	NA
Ball State University	2017-10-24	2018-01-31	NA	NA	NA	NA
California Polytechnic State University-San Luis Obispo	2015-01-13	2015-04-06	2018-04-17	2018-06-06	NA	NA
Clemson University	2014-09-23	2014-10-10	2018-01-27	2018-03-01	NA	NA
College of Charleston	2016-08-30	2016-12-01	NA	NA	NA	NA
East Carolina University	2015-01-28	2015-02-11	NA	NA	NA	NA
Emory University	2014-11-03	2014-12-02	NA	NA	NA	NA
Florida Atlantic University	2017-11-28	2018-03-01	NA	NA	NA	NA
Florida International University	2018-01-01	2018-02-05	NA	NA	NA	NA
Florida State University	2017-11-06	2018-03-26	NA	NA	NA	NA
Indiana University-Bloomington	2017-11-27	2018-02-28	NA	NA	NA	NA
Louisiana State University and Agricultural & Mechanical College	2017-09-14	2017-10-12	2017-10-19	2018-03-01	NA	NA
Marshall University	2018-03-05	2018-03-26	NA	NA	NA	NA
Monmouth University	2018-09-06	2019-01-16	NA	NA	NA	NA
Murray State University	2018-05-09	2018-08-27	NA	NA	NA	NA
North Carolina State University at Raleigh	2015-03-20	2015-05-09	NA	NA	NA	NA
Ohio State University-Main Campus	2017-11-16	2018-02-07	NA	NA	NA	NA
Ohio University-Main Campus	2019-10-03	2019-10-25	NA	NA	NA	NA
Rollins College	2017-02-21	2017-04-14	NA	NA	NA	NA
Rutgers University-New Brunswick	2015-04-06	2015-05-01	NA	NA	NA	NA
San Diego State University	2014-11-25	2015-01-09	2018-03-09	2018-10-04	2019-11-09	2020-01-17
Syracuse University	2019-11-17	2019-12-09	NA	NA	NA	NA
Texas State University	2017-11-14	2018-02-26	NA	NA	NA	NA
Tufts University	2016-11-16	2017-01-19	NA	NA	NA	NA
University at Buffalo	2019-04-12	2019-08-21	NA	NA	NA	NA
University of California-Berkeley	2016-10-16	2016-10-26	NA	NA	NA	NA
University of Central Florida	2018-01-08	2018-03-05	NA	NA	NA	NA
University of Idaho	2017-12-12	2018-03-13	NA	NA	NA	NA
University of Iowa	2017-05-01	2019-08-27	NA	NA	NA	NA
University of Kansas	2018-03-12	2018-03-18	NA	NA	NA	NA
University of Michigan-Ann Arbor	2017-11-09	2018-01-03	NA	NA	NA	NA
University of Missouri-Columbia	2018-03-06	2018-03-13	NA	NA	NA	NA
University of New Mexico-Main Campus	2017-12-08	2018-02-19	NA	NA	NA	NA
University of Pittsburgh-Pittsburgh Campus	2018-01-19	2018-08-30	NA	NA	NA	NA
University of Vermont	2019-02-05	2019-04-02	NA	NA	NA	NA
University of Virginia-Main Campus	2014-11-22	2015-01-07	NA	NA	NA	NA
Washington State University	2016-11-07	2017-01-09	2019-11-14	2020-01-27	NA	NA
West Virginia University	2014-11-13	2015-02-01	2018-02-14	2018-08-01	NA	NA

Note:
Universities can have multiple moratoriums in the sample period. Each moratorium date was verified by either a Fraternity and Sorority Life advisor, a news article, or a Freedom of Information Request. However, the first San Diego State University moratorium end date could not be directly verified by either a fraternity or sorority advisor, news article, or public record request. However, based on the following news article link, I am confident that the moratorium ended before the start of the 2015 semester. Link: https://newscenter.sdsu.edu/sdsu_newscenter/news_story.aspx?sid=75357

Table A3: Comparison of all Relevant Data Sources

	Data Source			
	Daily Crime Logs	Campus Safety and Security	NIBRS	UCR
Source and Requirement:				
Source of Data:	University Police Departments	US Department of Education	FBI	FBI
Reporting Mandate:	By-law	By-law	Voluntary	Voluntary
Aggregation and Consistency				
Level of Aggregation:	Incident-level	Yearly	Incident-level	Monthly
Fraction Reporting Consistently:	1.000	1.000	0.368	0.789
Offenses Reported and Location				
Alcohol Violations:	All Incidences Reported	All Incidences Reported	Arrests Only	None
Sexual Assaults:	All Incidences Reported	All Incidences	All Incidences Reported	Hierarchy Rule
Drug Offenses:	All Incidences Reported	All Incidences Reported	All Incidences Reported	None
Residence Hall Information:	No	Yes	No	No
Analysis in Paper:	Main Analysis	Secondary	Not Used	Not Used

[a] The Daily Crime Logs are used for the main analysis due to the advantages it has over the other sources. NIBRS stands for the National Incidence Based Reporting System. UCR stands for Uniform Crime Reporting Program. The fraction reporting consistency refers to the fraction of the sample university police departments. Hierarchy Rule is where only the most serious crime in an incident is reported. While over 50 percent of UCR data is displayed to be reported consistently, it is actually truly unknown since NAs and 0s are the same.



Indiana University, Bloomington
Police Department
Student Right To Know CAD Daily Log

From Jan 20, 2014 to Jan 20, 2014.

Date Reported: 01/20/14 - MON at 12:22 **Location :** EIGENMANN HALL **Event #:** 14-01-20-001434
Date and Time Occurred From - Occurred To
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:**
Disposition: FAILED TO LOCATE

Date Reported: 01/20/14 - MON at 17:03 **Location :** ALL OTHER ROADWAYS/INTERS **Event #:** 14-01-20-001446
Date and Time Occurred From - Occurred To 01/20/14 - MON at 17:02 - 01/20/14 - MON at 17:03
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:** 140154
Disposition: CLOSED BY ARREST

Date Reported: 01/20/14 - MON at 19:30 **Location :** EIGENMANN HALL **Event #:** 14-01-20-001464
Date and Time Occurred From - Occurred To
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:**
Disposition: FAILED TO LOCATE

Date Reported: 01/20/14 - MON at 20:22 **Location :** EIGENMANN HALL **Event #:** 14-01-20-001466
Date and Time Occurred From - Occurred To
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:**
Disposition: FAILED TO LOCATE

Date Reported: 01/20/14 - MON at 20:45 **Location :** FOSTER HARPER HALL **Event #:** 14-01-20-001468
Date and Time Occurred From - Occurred To
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:**
Disposition: FAILED TO LOCATE

Date Reported: 01/20/14 - MON at 21:38 **Location :** ALL OTHER NON-UNIVERSITY **Event #:** 14-01-20-001476
Date and Time Occurred From - Occurred To
Incident : ALL OTHER OFFENSES - HARASSMENT/INTIMIDATION **Report #:**
Disposition: NO CASE REPORT

Date Reported: 01/20/14 - MON at 21:53 **Location :** ROSE AVE RESIDENCE HALL **Event #:** 14-01-20-001479
Date and Time Occurred From - Occurred To
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:**
Disposition: FAILED TO LOCATE

Date Reported: 01/20/14 - MON at 22:30 **Location :** COLLINS COMMON AREA **Event #:** 14-01-20-001486
Date and Time Occurred From - Occurred To
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:**
Disposition: FAILED TO LOCATE

Date Reported: 01/20/14 - MON at 23:02 **Location :** FOREST QUAD **Event #:** 14-01-20-001487
Date and Time Occurred From - Occurred To 01/20/14 - MON at 22:45 - 01/20/14 - MON at 23:02
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:** 140157
Disposition: CLOSED NO ARREST.

Date Reported: 01/20/14 - MON at 23:07 **Location :** FOSTER JENKINSON HALL **Event #:** 14-01-20-001491
Date and Time Occurred From - Occurred To
Incident : NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA **Report #:**
Disposition: FAILED TO LOCATE

Date Reported: 01/20/14 - MON at 23:35 **Location :** ALL OTHER OPEN AREAS **Event #:** 14-01-20-001494
Date and Time Occurred From - Occurred To 01/20/14 - MON at 23:35 - 01/20/14 - MON at 23:41
Incident : ASSAULT - OTHER ASSAULTS - SIMPLE, NOT AGGRAVATED **Report #:** 140159
Disposition: CLOSED BY ARREST.

11 Incidents Listed.

Print Date and Time 1/21/2014 12:23:52PM at Page No. 1

Figure A1: An Example of a Daily Crime Log

Notes: The main analysis uses data from 38 universities' Daily Crime Logs - each unique in their own respect. All Daily Crime Logs had to be requested from each university and harmonized using pattern matching.

Table A4: The Top 30 Most Frequently Reported Incidents

Sexual Assault	Alcohol Offense	Drug Offense
(394) rape	(2882) alcohol offense	(3312) drugs
(379) sexual assault	(2311) abcc violation	(2906) drug incident
(301) sex offense	(1272) intoxicated person	(1852) possession of controlled substances
(184) sexual battery	(1216) dui	(1182) possession - marijuana
(144) csa report: rape	(1010) intx-intoxicated person	(1001) narcotics
(114) criminal sexual conduct	(785) buying, consume while underage	(835) drug violation
(88) campus security authority-sex offense	(764) minor in possession	(743) drug violation - vcsa
(77) assist other agency-sex offense	(740) possession/supply alcohol u/21	(729) possession of drugs
(69) sexual abuse 3rd degree	(710) public intox	(680) possession of drug paraphernalia
(62) sex offenses	(702) liquor laws	(605) drug paraphernalia
(56) sex offense - anonymous	(695) driving under the influence	(587) possession of drugparaphernalia
(41) sxof-sex offense	(625) driving under the influence not counted for ucr	(572) controlled substance problem
(38) forcible fondling	(620) public intoxication	(503) drug violation / vcsa
(38) sex crime	(507) mip	(441) possession ofmarijuana
(36) sex offense (except forcible rape or prostitution)	(482) offenses involving underage persons	(338) possession of marijuana and thc
(36) sexual assault using physical force orcoercion; victim does not sustain severepersonal injury	(476) liquor law referral	(331) poss of drug paraphernalia possession marijuana/hash under
(32) 3rd party report sexual abuse 3rd degree	(467) liquor law arrest	(320) drug law referral
(32) forcible sex offense	(456) intoxication	(304) violation of controlled substances
(32) sexual imposition	(435) minors in possession of alcohol	(292) drug-csc sanction only
(31) sex offenses - forcible	(386) liquor laws - illegal possession/consumption	(288) drug law violation
(31) sex offenses sex offenses	(377) intoxicated subjects	(288) medical - medical aid - alcohol/drug
(30) sexual abuse	(349) campus security authority-liquor law violation	(282) narcotic/drug laws - possession - marijuana
(28) anonymous sexual assault	(318) all other offenses (except traffic) liquor laws	(268) possession marijuana, hashish, etc. possession marijuana, hashish, etc.
(27) late reported sexual assault	(288) alcohol violation	(263) possession marijuana, hashish, etc.
(25) sex offense/forcible rape	(288) medical - medical aid - alcohol/drug	(245) smell of marijuana
(23) rape rape	(283) public drunkenness	(242) possession marijuana/hash under poss of drug paraphernalia
(23) rape–rape -report	(251) driving while intoxicated	(242) simple possession of marijuana
(21) anonymous late reported sexual assault	(251) intox person 2	(232) 966 - drug law violation
(21) criminal sexual contact	(237) liquor laws illegal possession/consumption	(211) possession marijuana
(20) sex offenses–sexual battery	(213) mip-alcohol	(203) drug law arrest

Note:
Numbers in parenthesis denote the frequency of offense in the data. These offenses represent the 30 most frequent crimes in each category after the pattern-matching algorithm is applied.

A Robustness Under TWFE

In this appendix, I analyze a model that differs from the main specifications shown in Table 4. In particular, specification (2) in Table 4 uses a two-way fixed-effects (TWFE) design where the group fixed effects are university fixed effects and the time fixed effects are the academic year. While this model is intuitive, recent literature has shown that the OLS estimator $\hat{\beta}$ may not be producing the average treatment effect on the treated when treatment effects are heterogeneous between groups and over time (Chaisemartin and D'Haultfœuille 2020; Sun and Abraham 2021; Goodman-Bacon 2021–differences_2021; Athey and Imbens 2022). In particular, Chaisemartin and D'Haultfœuille (2020) show that the parameter $\hat{\beta}$ on an indicator variable for treatment in a TWFE design is a weighted sum of the average treatment effects on the treated where some of the weights may be negative. While there are a variety of new methods that can mitigate these issues, none of them can accommodate the model used in this paper where universities go in and out of treatment (non-staggered design) and universities are treated multiple times. To circumvent this issue, I estimate a model that contains no negative weights. These weights are calculated using the TwoWayFEWeights package (Chaisemartin, D'Haultfoeuille, and Deeb 2020). The estimated model is the following TWFE specification:

$$Y_{ut} = \beta Moratorium_{ut} + \gamma_u + \alpha_t + \epsilon_{ut}$$

where Y_{ut} is the outcome for university u at time t measured by per-25000 enrolled students per academic-calendar day, $Moratorium_{ut}$ is an indicator equal to one if university u is in a moratorium at time t, γ_u are university fixed effects, α_t are day by month by year fixed effects, and ϵ_{ut} is the error term. Hence, this model compares academic calendar days within a moratorium to the same calendar days without a moratorium while controlling for systematic differences between universities. As mentioned above, there are no negative weights in this specification and therefore sign reversal is impossible. With this advantage,

Table A5: Effect of Moratoriums on Alcohol Offenses, Drug Offenses, and Sexual Assault by Weekend/Weekdays. Never-treated schools included.

	Days of the Week		
	All Days	Weekends	Weekdays
Panel A: Alcohol Offenses			
In Moratorium	-0.121*	-0.240*	-0.031
	(0.051)	(0.107)	(0.026)
Observations	75868	32536	43332
Mean of Dependent Variable	0.638	1.140	0.261
Panel B: Drug Offenses			
In Moratorium	-0.013	-0.039	0.007
	(0.033)	(0.037)	(0.037)
Observations	75868	32536	43332
Mean of Dependent Variable	0.482	0.555	0.428
Panel C: Sexual Assaults			
In Moratorium	-0.010	-0.017+	-0.004
	(0.006)	(0.010)	(0.006)
Observations	75868	32536	43332
Mean of Dependent Variable	0.058	0.068	0.051
Controls for Panels A-C:			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Semester (Spring/Fall)	X	X	X
FE: University by Academic Year	X	X	X

Note:

Standard errors are clustered by university and each offense is defined as per-25000 enrolled students. 14 never-treated schools are included in the sample for additional power. A never-treated schools is defined as a university that does not experience a moratorium in the time period of 2014-2019 and was included on the Top 40 fraternity schools on niche.com. See link here: https://www.niche.com/colleges/search/best-greek-life-colleges/. Weekends consist of Fridays, Saturdays, and Sundays. Weekdays consist of Monday through Thursday. Holiday controls include controls for Veterans Day, Thanksgiving, Labor Day, Halloween, and MLK Day. Christmas/New Years/July 4th are not included since not in panel. A moratorium is a temporary halt on fraternity-related activities with alcohol.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Effect of Moratoriums on Alcohol Offenses, Drug Offenses, and Sexual Assault (Poisson Estimation).

	(1)	(2)	(3)	(4)
Panel A: Alcohol Offenses				
In Moratorium	0.066	-0.237*	-0.324***	-0.360***
	(0.261)	(0.097)	(0.085)	(0.101)
Observations	56514	56514	55550	53820
Mean of Dependent Variable	0.533	0.533	0.533	0.533
Panel B: Drug Offenses				
In Moratorium	-0.027	-0.135*	-0.022	-0.079
	(0.137)	(0.056)	(0.053)	(0.069)
Observations	56514	56514	56026	54794
Mean of Dependent Variable	0.492	0.492	0.492	0.492
Panel C: Sexual Assaults				
In Moratorium	0.057	-0.150*	-0.179+	-0.172
	(0.147)	(0.073)	(0.105)	(0.109)
Observations	56514	56514	54304	51356
Mean of Dependent Variable	0.053	0.053	0.053	0.053
Controls for Panels A-C				
FE: Day of Week		X	X	X
FE: Holiday		X	X	X
FE: Semester (Spring/Fall)		X	X	X
FE: University		X		
FE: Academic Year		X		
FE: University by Academic Year			X	
FE: University by Academic Year by Semester				X

Note:
Standard errors are clustered by university and each offense is defined as a count. Observation values may vary between estimations due to no variation with particular fixed effects specifications. Holiday controls include controls for Veterans Day, Thanksgiving, Labor Day, Halloween, and MLK Day. Christmas/New Years/July 4th are not included since not in panel. A moratorium is a temporary halt on fraternity-related activities with alcohol.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Effect of Moratoriums on Alcohol Offenses, Drug Offenses, and Sexual Assault by Weekend/Weekdays (Poisson Estimation).

	Days of the Week		
	All Days	Weekends	Weekdays
Panel A: Alcohol Offenses			
In Moratorium	-0.324***	-0.358***	-0.221
	(0.085)	(0.091)	(0.160)
Observations	55550	23179	30621
Mean of Dependent Variable	0.497	0.892	0.201
Panel B: Drug Offenses			
In Moratorium	-0.022	-0.073	0.023
	(0.053)	(0.057)	(0.073)
Observations	56026	23731	31713
Mean of Dependent Variable	0.432	0.495	0.385
Panel C: Sexual Assaults			
In Moratorium	-0.179+	-0.338*	-0.021
	(0.105)	(0.138)	(0.129)
Observations	54304	22376	28801
Mean of Dependent Variable	0.055	0.064	0.047
Controls for Panels A-C:			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Semester (Spring/Fall)	X	X	X
FE: University by Academic Year	X	X	X

Note:

Standard errors are clustered by university and each offense is defined as a count. Observation values may vary between estimations due to no variation with particular fixed effects specifications. Weekends consist of Fridays, Saturdays, and Sundays. Weekdays consist of Monday through Thursday. Holiday controls include controls for Veterans Day, Thanksgiving, Labor Day, Halloween, and MLK Day. Christmas/New Years/July 4th are not included since not in panel. A moratorium is a temporary halt on fraternity-related activities with alcohol.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I re-estimate the results in Table 5.

Table B1 shows that the results of the TWFE specification with no negative weights are mostly consistent with the results in Table 5. In Panel A, alcohol offenses exhibit a 21% decrease from the mean during a moratorium, and a 26% decrease on the weekends. Although sexual assaults do not exhibit statistically significant decreases on the weekends, this is potentially due to the loss of identifying variation from the data-intensive controls. However, it is important to note that the coefficient sign remains the same on all of the estimates. Hence, under the identifying assumptions of the model, it is certain that moratoriums decrease alcohol offenses.

Table B1: Effect of Moratoriums on Alcohol Offenses, Drug Offenses, and Sexual Assault by Weekend/Weekdays (No Negative Weights-OLS).

	Days of the Week		
	All Days	Weekends	Weekdays
Panel A: Alcohol Offenses			
In Moratorium	-0.106*	-0.234*	-0.012
	(0.045)	(0.095)	(0.017)
Observations	56514	24244	32270
Mean of Dependent Variable	0.497	0.892	0.201
Panel B: Drug Offenses			
In Moratorium	-0.063+	-0.088*	-0.045
	(0.033)	(0.037)	(0.034)
Observations	56514	24244	32270
Mean of Dependent Variable	0.432	0.495	0.385
Panel C: Sexual Assaults			
In Moratorium	-0.005	-0.006	-0.005
	(0.004)	(0.006)	(0.007)
Observations	56514	24244	32270
Mean of Dependent Variable	0.055	0.064	0.047
Controls for Panels A-C:			
FE: University	X	X	X
FE: Day by Month by Year	X	X	X

Note:
Standard errors are clustered by university and each offense is defined as per-25000 enrolled students. The column 'All Days' represents specification (3) from the main results table. Weekends consist of Fridays, Saturdays, and Sundays. Weekdays consist of Monday through Thursday. A moratorium is a temporary halt on fraternity-related activities with alcohol. The specification used in this table has no negative weights and thus, sign reversal is impossible.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A Appendix C

As discussed previously, while the main results show a significant decrease in daily reports of alcohol offenses and sexual assaults on the weekends, there is concern that these offenses are being substituted to more risky places. To my knowledge, there is no data that can directly address this concern; while the NIBRS data includes incidence-level data, only 36% of the universities in the sample have a nearest-neighbor police department that consistently report crime over the sample period. In addition, the NIBRS data does not include all reports of alcohol offenses, but only alcohol offenses that end in an arrest. Given that university students are unlikely to be arrested for underage drinking, this data would underestimate the true substitution effect (if exists).

In this appendix, I use the CSS Data to indirectly estimate this substitution effect. I compare an aggregation of the Daily Crime Logs to the CSS Data using a model that is less suited for a causal analysis. Hence, the estimates in this appendix should be taken as speculative only.

A.1 CSS Data and Empirical Strategy

I utilize the Campus Safety and Security (CSS) data from the US Department of Education. This data is mandated by the federal government to be updated each calendar year with the yearly totals of liquor, drug, and sexual assault violations that are reported *to any entity* at a university. Hence, this data will not match one-to-one with the Daily Crime Logs as the Daily Crime Logs contain only incidences *reported to or by the university police.* For instance, a residence hall administrator may issue liquor violations to underage students, but handle the issue internally without involving the police. This incident would be counted in the CSS data, but not the Daily Crime Logs. However, one advantage of the CSS data is that it contains counts of offenses that occur on-campus, not-on-campus[24] , and public property.[25] Specifically, I am able to delineate whether offenses occur in student residence halls.

The main issue with the CSS data is that it is aggregated by calendar-year. Given that moratoriums are, on average, short-lived policy, the CSS data is not a preferred source for analysis. For instance, consider Indiana University, a university that experienced a moratorium in November of 2017 that lasted until February of 2018. Since the CSS is aggregated by calendar-year, it is difficult to delineate these effects; 2017 and 2018 only experienced approximately two months worth of moratorium days. To mitigate this issue, I estimate the following difference-in-differences specification:

$$Y_{u,t} = \beta Moratorium_{u,t} + \gamma_u + \lambda t + \epsilon_{u,t} \tag{C0}$$

where $Y_{u,t}$ is the offense of interest defined as offense per-25000 enrolled students per-calendar-day, $Moratorium_{u,t}$ is the *fraction* of calendar-days treated within a year (e.g., a 30-day moratorium would result in 30/365), γ_u are university fixed effects, λt are calendar-year fixed effects, and $\epsilon_{u,t}$ is the error term. Intuitively, Equation C0 is comparing fractions of calendar-years with a moratorium to calendars years without moratoriums while accounting for systematic differences between universities and calendar-years. Standard errors are clustered at the university level.

Unlike the main analysis in Figure 7, I omit a year lead and lag and am therefore unable to estimate long-run effects. I omit these for two reasons. First, including a year lag results in year 2020, the beginning of the COVID-19 pandemic. COVID-19 drastically changed uni-

[24]As defined by the Department of Education, this is "(1) Any building or property owned or controlled by a student organization that is officially recognized by the institution; or (2) Any building or property owned or controlled by an institution that is used in direct support of, or in relation to, the institution's educational purposes, is frequently used by students, and is not within the same reasonably contiguous geographic area of the institution."

[25]Per the Department of Education, this id defined as "All public property, including thoroughfares, streets, sidewalks, and parking facilities, that is within the campus, or immediately adjacent to and accessible from the campus."

versity activity due to online instruction, and thus, this would not be a good counterfactual. Second, including a year lead (2013) results in possible level-changes in sexual assaults due to the CSS failing to include rapes prior to 2014. Given these limitations, there is no reliable way to estimate long-run effects of moratoriums in this setting.

This equation is less flexible than Equation 1, as it does not account for differences in days of the week, academic years, semesters, nor does it restrict to academic-calendar days. As mentioned, the estimates from this specification should be taken as speculative, not causal.

A.2 Results

Table C1 shows the comparison of estimating Equation C0 with the Daily Crime Logs aggregated to the calendar-year level[26] with the CSS data. The Daily Crime Logs show somewhat consistent results with those found in Table 4 column (2),[27] daily averages of alcohol offenses decrease by approximately 36% in calendar years with a moratorium and sexual assaults decrease by approximately 34%, although the level of statistical significance is lower for alcohol—likely due to the imprecision of aggregation. Drug offenses decrease by 44%, far more than the 17% decrease observed in Table 4—also likely due to imprecision of aggregation.

Although the results using aggregated Daily Crime Logs are relatively similar, the CSS data shows that residence halls experience a 25% *increase* in daily alcohol violations when a calendar year experiences a moratorium. Interestingly, this coincides with the 27% *decrease* found in the main results, suggesting that students substitute their partying away from fraternity houses to their own residence halls. This may be a net-benefit—residence halls are more regulated than fraternity houses and can prevent partying behavior from becoming too risky. This is shown in Panel C with the significant *decrease* in sexual assaults (85%). Hence,

[26] This aggregation includes all calendar-year days rather than only academic-calendar days that were used in the main analysis.

[27] I consider this specification to have the most similar interpretation to the specification in this Appendix.

this is speculative evidence that moratoriums are pushing risky behaviors into *safer* areas that can regulate partying more efficiently. Residence halls are staffed with student employees that patrol the premises for underage drinking or extreme partying behavior. Additionally, residence halls contain an abundance of bystanders. These bystanders likely differ from those at a fraternity house party—some of these bystanders may not be intoxicated (e.g., students that are studying in their homes), and can intervene if they hear/see a potentially risky situation between individuals beginning to coalesce. While there is evidence that moratoriums are pushing risky behavior to less risky areas, it is necessary to point out once more that these estimates are speculative, not causal.

Table C1: Effect of Moratoriums on Alcohol Offenses, Drug Offenses, and Sexual Assaults: Comparison of Daily Crime Logs and Campus Safety and Security (OLS).

	Daily Crime Logs	Campus Safety and Security	
	Full Sample	Full Sample	Residence Halls
Panel A: Alcohol Offenses			
In Moratorium	-0.142+	0.282*	0.249*
	(0.077)	(0.111)	(0.119)
Observations	226	228	228
Mean of Dependent Variable	0.388	1.042	0.979
Panel B: Drug Offenses			
In Moratorium	-0.147**	-0.045	-0.057
	(0.053)	(0.114)	(0.109)
Observations	226	228	228
Mean of Dependent Variable	0.333	0.272	0.228
Panel C: Sexual Assaults			
In Moratorium	-0.015	-0.049	-0.035*
	(0.011)	(0.040)	(0.014)
Observations	226	228	228
Mean of Dependent Variable	0.043	0.081	0.041
Controls for Panels A-C:			
FE: University	X	X	X
FE: Year	X	X	X

Note:
Standard errors are clustered by university and each offense is defined as offense per-25000 enrolled students per-calendar day. Recall that Daily Crime Logs are the primary source of data used in prior analysis. In this model, the 'In Moratorium' treatment variable is defined as a fraction between 0 and 1 where the fraction represents the proportion of calendar-days that experienced a moratorium in a calendar year. Full Samples include the entire Daily Crime Logs/Campus Safety and Security Data (CSS), while Residence Halls is a subset of the CSS. Full Sample in the CSS data contains both off-campus and on-campus reports. CSS data does not necessary need to be reported to the university police and hence, may not show up in the Daily Crime Logs. A moratorium is a temporary halt on fraternity-related activities with alcohol.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

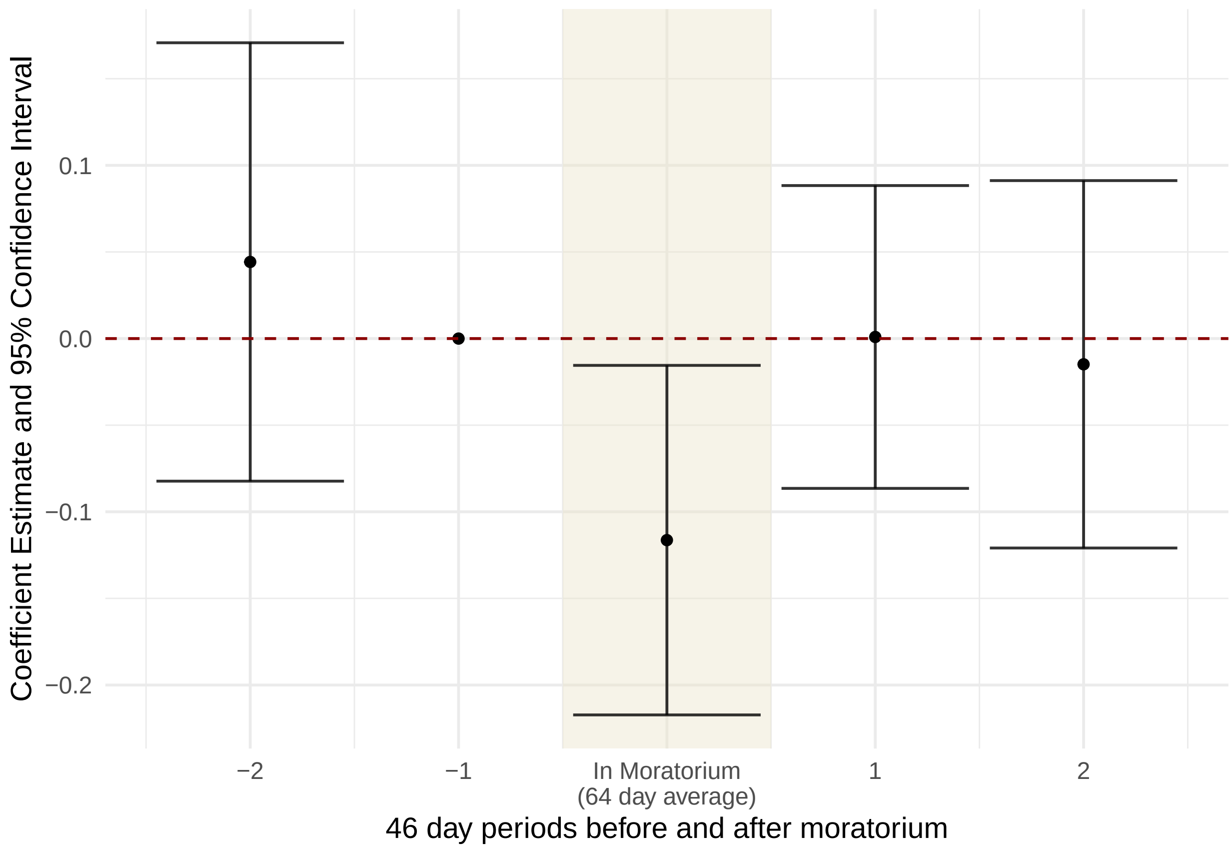


Figure A2: Event Study for Alcohol Offenses

Notes: The shaded area point estimate represents an entire moratorium period for each university. Hence, the shaded area point estimate has varying amounts of days within based on the university. For instance, Arkansas State University had a 39 day moratorium and therefore their shaded area point estimate would be identified by the 39 moratorium days. Point estimates not within the shaded region are 46 day periods. Number of days within a period was chosen to give approximately two median-length (46 days) moratorium on each side of the shaded area. All periods are normalized by the 46-day period before the moratorium. Alcohol offenses are defined as alcohol offenses per-25000 enrolled students. Controls include holiday, spring semester, day of the week and university by academic year. Standard errors clustered by university. All errorbars represent 95% confidence intervals.

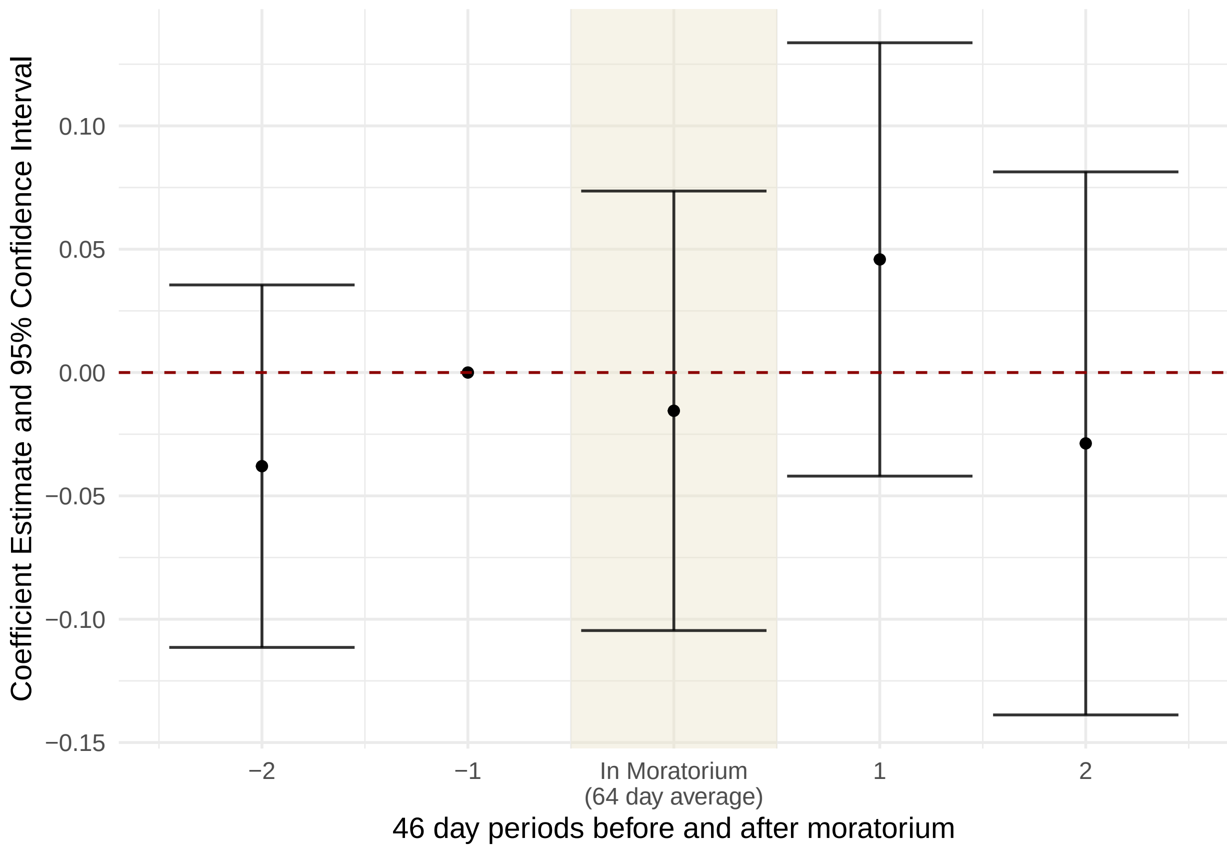


Figure A3: Event Study for Drug Offenses

Notes: The shaded area point estimate represents an entire moratorium period for each university. Hence, the shaded area point estimate has varying amounts of days within based on the university. For instance, Arkansas State University had a 39 day moratorium and therefore their shaded area point estimate would be identified by the 39 moratorium days. Point estimates not within the shaded region are 46 day periods. Number of days within a period was chosen to give approximately two median-length (46 days) moratorium on each side of the shaded area. All periods are normalized by the 46-day period before the moratorium. Drug offenses are defined as drug offenses per-25000 enrolled students. Controls include holiday, spring semester, day of the week and university by academic year. Standard errors clustered by university. All errorbars represent 95% confidence intervals.

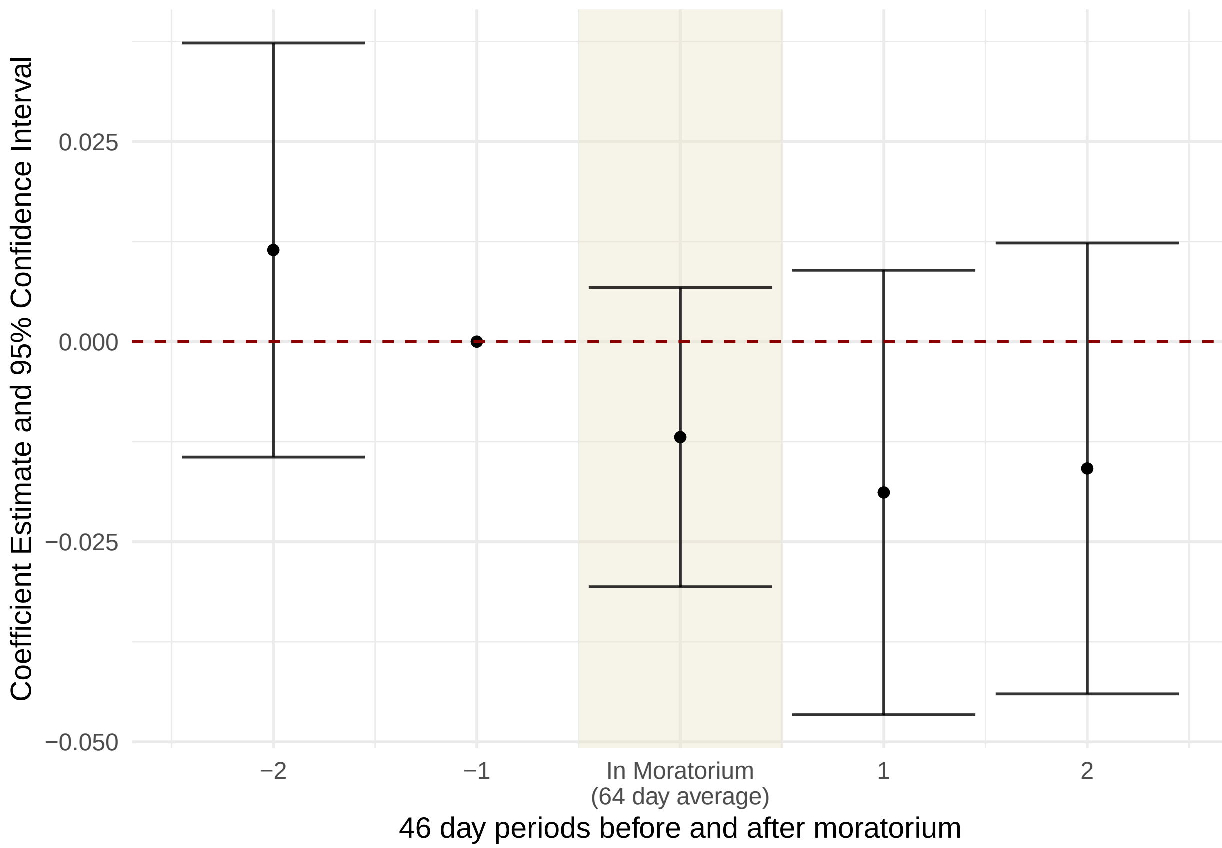


Figure A4: Event Study for Sexual Assault Offenses

Notes: The shaded area point estimate represents an entire moratorium period for each university. Hence, the shaded area point estimate has varying amounts of days within based on the university. For instance, Arkansas State University had a 39 day moratorium and therefore their shaded area point estimate would be identified by the 39 moratorium days. Point estimates not within the shaded region are 46 day periods. Number of days within a period was chosen to give approximately two median-length (46 days) moratorium on each side of the shaded area. All periods are normalized by the 46-day period before the moratorium. Sexual assault offenses are defined as sexual assault offenses per-25000 enrolled students. Controls include holiday, spring semester, day of the week and university by academic year. Standard errors clustered by university. All errorbars represent 95% confidence intervals.

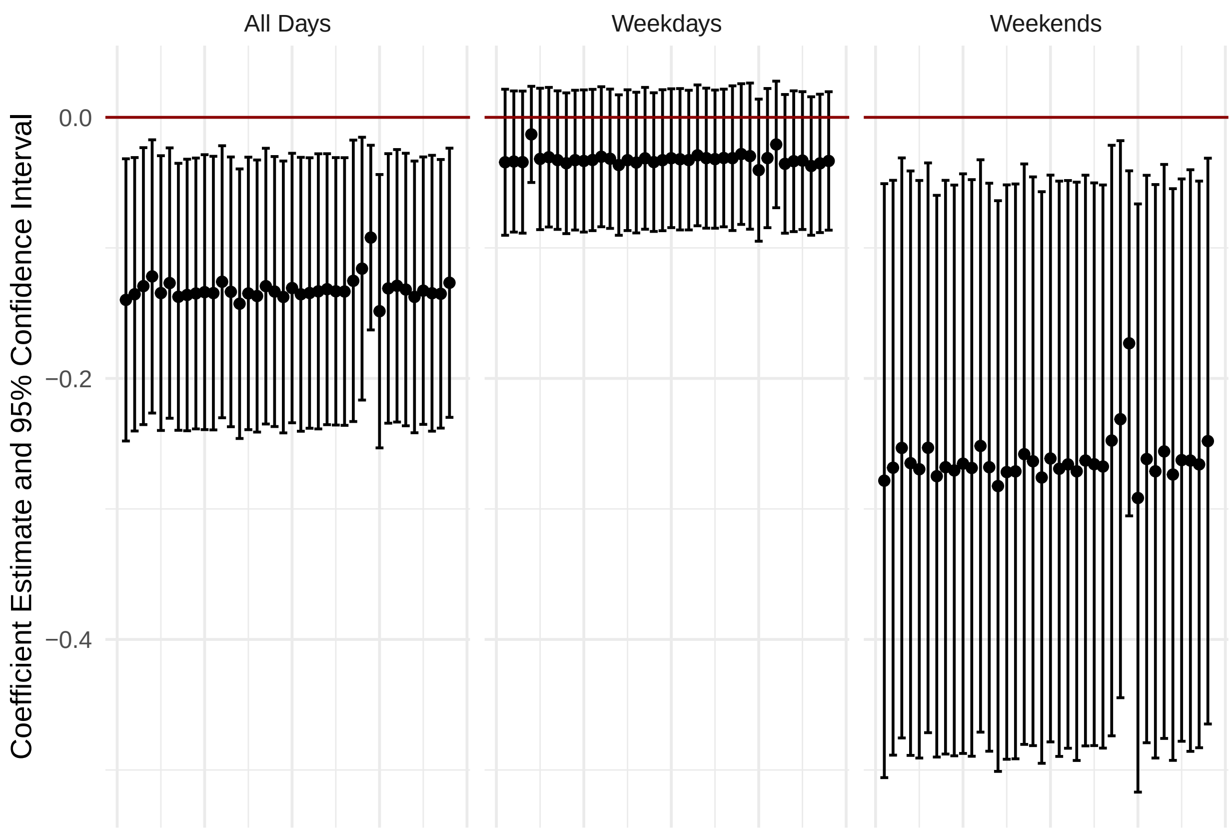


Figure A5: Leave-one-out OLS Regressions of Alcohol Offenses

Notes: Each point represents specification (3) from Table 4 with one university omitted from the sample. Offenses are per-25000 enrolled students. Errorbars represent 95% confidence intervals. Weekends includes only Friday, Saturday, Sunday, while weekdays includes Monday through Thursday.

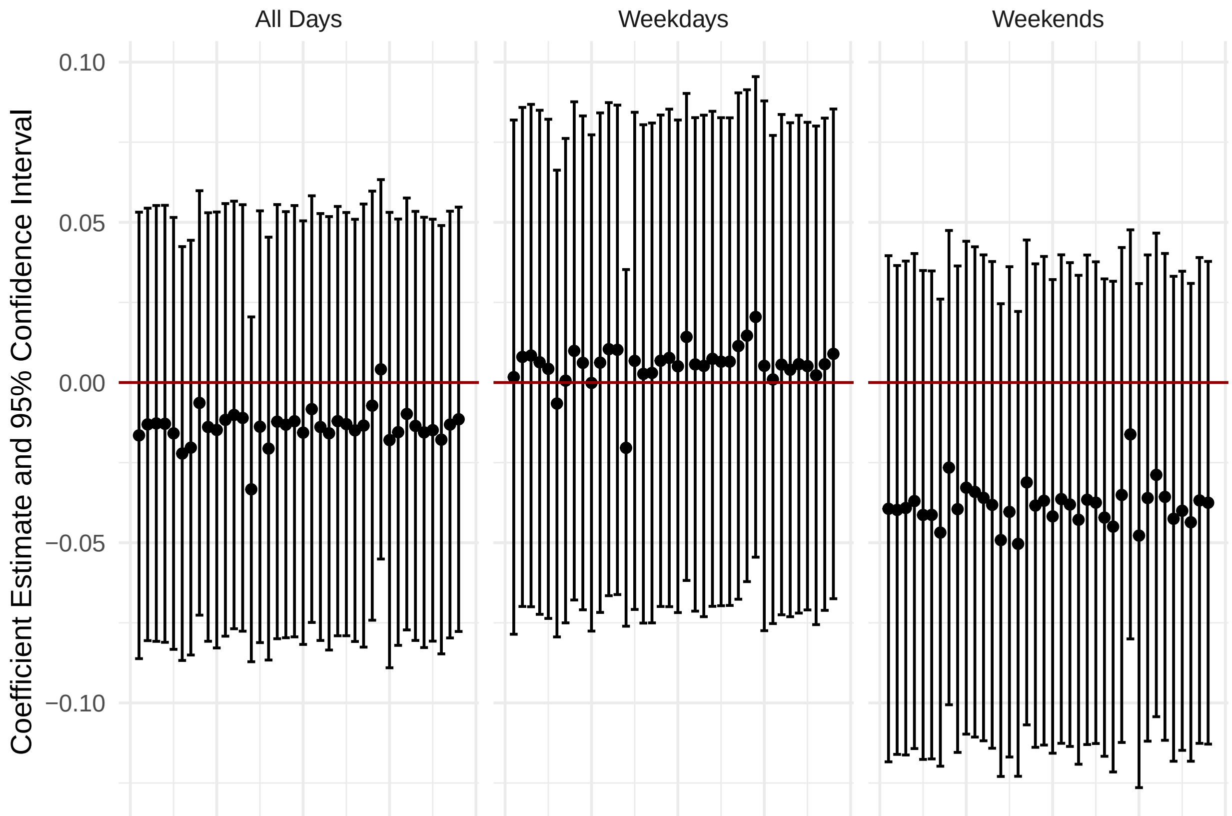


Figure A6: Leave-one-out OLS Regressions of Drug Offenses

Notes: Each point represents specification (3) from Table 4 with one university omitted from the sample. Offenses are per-25000 enrolled students. Errorbars represent 95% confidence intervals. Weekends includes only Friday, Saturday, Sunday, while weekdays includes Monday through Thursday.

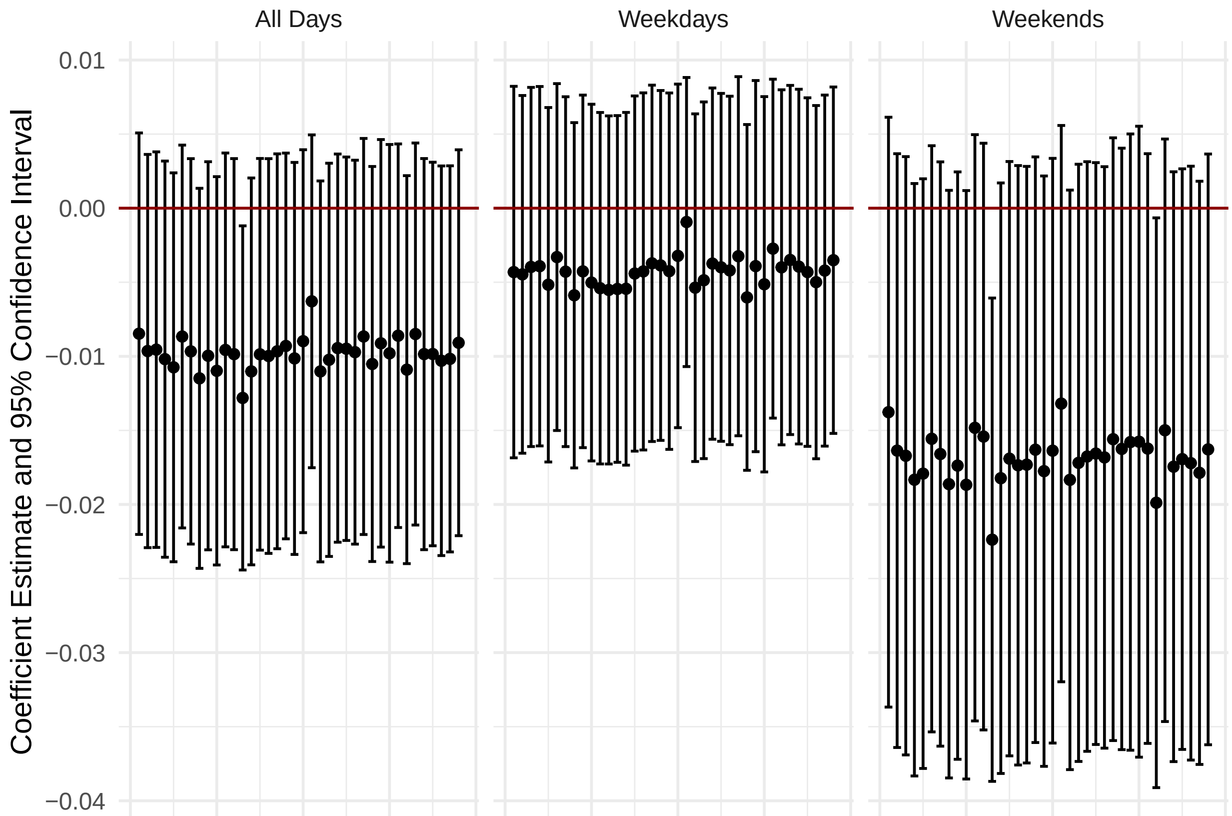


Figure A7: Leave-one-out OLS Regressions of Sexual Assaults

Notes: Each point represents specification (3) from Table 4 with one university omitted from the sample. Offenses are per-25000 enrolled students. Errorbars represent 95% confidence intervals. Weekends includes only Friday, Saturday, Sunday, while weekdays includes Monday through Thursday.