

# The Effects of Fraternity Moratoriums on Alcohol Offenses and Sexual Assaults



Michael Topper

Last Updated: 2022-04-11

## Abstract

Fraternalities maintain a presence at over 800 universities in the United States. While there are positive effects of membership such as increased graduation rates and future income, fraternities are also a reliable source of alcohol and partying for undergraduate students. In this paper, I exploit the variation in timing from 44 temporary university-wide halts on all fraternity activity with alcohol (moratoriums) across 37 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 and sexual assault offenses. In particular, I find strong and robust evidence that fraternity moratoriums decrease alcohol violations campus-wide by 26%. This effect is driven by decreases in weekend reports, consistent with the timing of most college partying. Additionally, I find suggestive evidence that moratoriums decrease reports of sexual assault on the weekends. However, while moratoriums clearly impact student behavior when implemented, I do not find evidence of long-term changes once the moratorium is lifted.

# 1 Introduction

Over 800 universities in the United States accommodate fraternities (Hechinger 2017). Many have documented benefits of membership which include higher future income (Mara, Davis, and Schmidt 2018) and significantly more hours spent participating in community service and volunteering (Hayek et al. 2002; Asel, Seifert, and Pascarella 2009). Moreover, according to a Gallup survey in 2021, over 80 percent of fraternity alumni agreed that they would join their fraternity if they were to redo their college experience.

Despite these benefits, membership has been associated with risky behaviors. In particular, at least one hazing-related death has occurred between the years 2000 and 2019<sup>1</sup> and studies have found that fraternity members binge drink and party more frequently than their non-member peers (DeSimone 2007; Routon and Walker 2014). While universities have regularly banned specific misbehaving fraternities from their campuses, the past decade popularized a new policy tool called moratoriums—campus-wide halts on fraternity social events with alcohol—as a way to change member behavior.

This paper is the first to estimate the causal effects of moratoriums on campus-wide police reports of alcohol offenses and sexual assaults. 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 affect student behavior, and thus on-campus crime, is theoretically unclear. On one hand, prohibiting alcohol from fraternity social events may reduce incidences 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

---

<sup>1</sup>This is based on the online repository of hazing deaths from journalist Hank Nuwer. See here: <https://www.hanknuwer.com/hazing-destroying-young-lives/>

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 incidence 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 off-campus where behavior is less regulated. As a result, the net effect of moratoriums is ambiguous.

In this paper, I estimate the causal effect of 44 fraternity moratoriums across 37 universities over a six-year period (2014-2019) on university police reports of alcohol and sexual assault offenses. I use a difference-in-differences identification strategy, leveraging the variation in timing of moratoriums. Intuitively, I compare academic-calendar days (e.g., excluding summer and winter breaks) 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 these data, I find that moratoriums significantly decrease alcohol offenses campus-wide by 26%. This effect is driven by weekends (Fridays-Sundays) when college partying is more frequent and is robust across various specifications, estimation methods, and sensitivity tests. Furthermore, I find suggestive evidence that reports of sexual assaults decrease by 29% on the weekends. Both of these decreases are concentrated only when a moratorium is in place suggesting that there are no persistent effects once a moratorium is lifted.

Importantly, I am not able to directly attribute these decreases to fraternity members themselves. Hence, while a working paper by Raghav and Diette (2021) shows that a larger

percentage of enrolled students in fraternities is associated with an increase in the number of drug-law arrests, the results in this paper cannot claim that the reductions are ascribed to members only. However, similarly to (Liang and Huang 2008), this paper does provide evidence that stronger sanctions on alcohol decreases risky behavior. Hence, this paper more broadly relates to the literature relating to the effects of alcohol on college-aged individuals which include increases in mortality (Carpenter and Dobkin 2009), emergency room visits (Francesconi and James 2019), and crime (Carpenter and Dobkin 2015), in addition to hindering academic performance (Carrell, Hoekstra, and West 2011; Ha and Smith 2019).

Most closely related to this paper is Lindo, Siminski, and Swensen (2018) whom find a large 28% increase in daily reports of rape on days with college football games. This paper differs from this work on several levels. First, while college football games intensify binge drinking and partying behavior, studies have also linked such increases with fraternity membership (DeSimone 2007; Routon and Walker 2014). As such, fraternities are an important component to party culture within universities since fraternities are a reliable source of alcohol for underage students (Armstrong, Hamilton, and Sweeney 2006). Moratoriums therefore represent an understudied policy lever that university officials can use to reduce campus-wide partying, which in-turn, may reduce reports of sexual assaults. Second, since this study focuses on sanctions against university fraternities and uses only university-police crime reports, I am able to more closely link moratoriums with changes in *student* behavior rather than *non-student* behavior—college football attracts a large demographic whom are not necessarily students of the university. Last, as shown in Cunningham and Shah (2018) who study the effects of decriminalizing and criminalizing prostitution on rape, there is reason to anticipate asymmetries in *increases* of partying (football games) and *decreases* in partying (moratoriums). However, the 29% weekend reduction in reports of sexual assault I find is similar to the 28% decrease of Lindo, Siminski, and Swensen (2018).

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 explores the differences in effectiveness between different types of moratoriums. Section 7 analyzes possible mechanisms and implications. Section 8 concludes.

## 2 Fraternities in the US

### 2.1 Fraternity Demographics and Oversight

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 positive outcomes such as increases in graduation rates (Routon and Walker 2014), future income (Mara, Davis, and Schmidt 2018), and social capital formation (Mara, Davis, and Schmidt 2018). On the other hand, membership has been found to decrease GPA (De Donato and Thomas 2017; Even and Smith 2020) and cause members to spend approximately two more hours per-week partying than nonmembers (Routon and Walker 2014) and binge drink on approximately two additional days per-month (DeSimone 2007). Additionally, Even and Smith (2020) find that membership causes students to select into easier courses and complete less course credits. While not causal, there is also 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 which are a type of social fraternity. These fraternities are the most common at universities and differ from professional, academic, or service fraternities. IFC fraternities participate in philanthropy and professional development and 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 restricted by a moratorium in the sample.

Each IFC fraternity chapter<sup>2</sup> 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.<sup>3</sup> This can include the cancellation of new member recruitment, philanthropy activities, tailgates, or third party vendor events, although the breadth of restrictions differ by university. For example, some universities may allow philanthropy events provided no alcohol is present. Moreover, the timing and length of a moratorium varies substantially. Figure 1 shows the start and end dates of each moratorium over time. Moratoriums in the sample can last as few as six calendar-days, or as long as 848 calendar-days.<sup>4</sup> Additionally, moratoriums are generally implemented because of a triggering event (see Figure C1). This event can be a prominent sexual assault allegation, a fraternity-related death (usually due to alcohol poisoning), or an extreme behavior violation.<sup>5</sup> Figure 2 shows the distribution of the triggering events: 19 are triggered by behavior violations, 10 by sexual assaults, nine by a fraternity-related death, and six are unspecified. As alluded to in the introduction, moratoriums are enacted across the US. Figure 3 shows the locations of the 37 universities in the sample (see Section 3 for further details on sample construction). While most universities

---

<sup>2</sup>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.

<sup>3</sup>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.

<sup>4</sup>Note the distinction between calendar-days and academic-calendar days. A calendar day represent the entire calendar, whereas an academic-calendar represents only the fall/spring semesters of the university school year.

<sup>5</sup>A behavior violation is a catchall term for hazing, rule violations, offensive behavior, and other disorderly conduct that results in a moratorium.

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 council.<sup>6</sup> When a moratorium is implemented by the university, the university sets the guidelines that fraternities must abide by during the moratorium. On the other hand, an IFC-implemented moratorium is student-enforced. This means that the IFC council is responsible for producing both the guidelines and oversight of the moratorium. Figure 2 shows that IFC-implemented moratoriums are less frequent (17) than university-implemented moratoriums (27) and Section 6 examines the heterogeneous effects involving this difference in oversight.



### 3 Data


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

#### 3.1 Sample Construction

The 37 universities in the sample have a combined 44 moratoriums in the sample period (2014-2019). These moratoriums represent any moratorium that match the following criteria; first, the moratorium must prohibit alcohol from all fraternity social events campus-wide, and second, the moratorium must be identifiable by Google/Lexis Nexis searches. Appendix Figure C2 shows a list of all universities included with their corresponding moratorium dates. Importantly, these do not represent the universe of fraternity moratoriums that occurred from 2014-2019. In particular, there are six schools that are known to have experienced a moratorium in this time frame, but are excluded due to data issues or their

---

<sup>6</sup>Note that the fraternity's chapter headquarters cannot impose a moratorium. Since chapter headquarters are unique to a fraternity chapter, they only have jurisdiction over one specific fraternity.

definition of a moratorium.<sup>7</sup> While there is a possibility that the sample period experienced more moratoriums from other universities, the documents provided from various fraternity associations and conversations with experts in the field suggest that the sample covers the large majority. Furthermore, each moratorium's start and end dates are 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.<sup>8</sup>

Daily reports of incidences are collected from Daily Crime Logs maintained by the 37 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 Appendix Figure C1 for an example).<sup>9</sup> 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.<sup>10</sup>

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

---

<sup>7</sup>Miami University is excluded due to being unable to verify the end-date of their moratorium. Pennsylvania 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. The University of Vermont is excluded due to issues with the reliability of the data—crimes often are reported to have occurred in large intervals of days (or months) for nearly 40% of the data provided which is not suitable for the daily-level analysis in this paper. There may exist other universities that experienced a moratorium, but may not have had any sort of news coverage—these are also excluded from the sample.

<sup>8</sup>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](https://newscenter.sdsu.edu/sdsu_newscenter/news_story.aspx?sid=75357).

<sup>9</sup>While the date occurred is technically mandated under the Clery Act to include each of these categories, only 32 of the 37 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.

<sup>10</sup>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.



Crime Reporting System (UCR), and the Campus Safety and Security Data (CSS). First, each university police department 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.<sup>11</sup> Hence, only one university is missing data from a complete calendar-year.<sup>12</sup> Second, the Daily Crime Logs contain all daily incidences of alcohol offenses and sexual assaults 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 not all violations of underage drinking at universities result 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,<sup>13</sup> the CSS data is aggregated to the calendar-year which makes the effect of moratoriums difficult to study given their short-lived nature. See Appendix Table C3 for more details on the advantages of the Daily Crime Logs.

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 define the start of a semester, the first day of instruction is used while the finalized grade date is used to denote the end of a semester. Since there are small changes in academic calendars year-to-year, a seven-day window is added to each start and end date of each semester. For instance, if a semester begins on August 20th and ends on December 16th, the sample period will be August 13th to December 23rd.

---

<sup>11</sup>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.

<sup>12</sup>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.

<sup>13</sup>There are important differences between these two sources. The CSS provides data on liquor 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.

## 3.2 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 and sexual assault offenses.<sup>14</sup> For each offense, I use the following definitions for matching the incident descriptions:

- **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.
- **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

---

<sup>14</sup>In particular, I found all unique descriptions of incidences in each Daily Crime Log, and then independently analyzed which descriptions matched to each offense.

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”). Appendix Table C4 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. 

### 3.3 Descriptive Statistics

Table 2 summarizes the characteristics of the 37 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 29,000. Undergraduates are the majority population with 61% 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 primary outcome measures: reports of alcohol offenses and sexual assaults. Each of these outcomes are 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 one-half. Lastly, Panel C describes characteristics of the 44 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 approximately 46 academic-calendar days (approximately 1.5 months).

## 4 Empirical Strategy

### 4.1 Baseline Specification

The goal of this paper is to identify the average causal effect of fraternity moratoriums on alcohol 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 semesters.

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

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

In Equation 1,  $Y_{u,t}$  is an outcome of alcohol 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  $t$ ,  $\gamma_u$  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. The standard errors are clustered by university. In essence, Equation 1 is comparing moratorium days to non-moratorium days within univer-

sities that have experienced, or will experience a moratorium while accounting for expected differences across universities and time.

Including university-specific fixed effects ( $\gamma_u$ ) in the baseline model accounts for systematic differences between a university’s police department, the corresponding student demographic they are policing, and overall fixed differences in incident prevalence. 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, football game-day, and academic year controls. Day of the week controls are included to address day-to-day fluctuations, while semester controls are included to adjust for activities that vary across the year such as fraternity recruitment. Moreover, football game-day controls are included to account for the increases in both alcohol offenses and rapes that college football games cause (Rees and Schnepel 2009; Lindo, Siminski, and Swensen 2018).<sup>15</sup> Lastly, holiday controls<sup>16</sup> 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,  $\beta$ , 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, football game-days, 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

---

<sup>15</sup>Information on football game dates and locations are found using sports-reference.com and espn.com. In total, 34 of the 37 universities in the sample that have football teams resulting in over 2000 football games, 89 of which coincide with a moratorium.

<sup>16</sup>Holiday controls include indicators 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.

for differences between universities’ academic years. For example, university regulations regarding fraternity recruitment or registration of social events may change by academic year. Hence, the preferred specification 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  $\beta$  to be interpreted as a casual effect of fraternity moratoriums, there are three main assumptions that need to be satisfied. The first assumption is that the timing of a fraternity moratorium is as-good-as-random. There are several reasons why this may be plausible. 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 plausible that the timing of these extreme instances are 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. Appendix Table C1 shows a brief description of each triggering event in addition to the date of the triggering event and date of the enacted moratorium. In 13 of


the 15 moratoriums in which the date of the triggering event is available, the moratorium is enacted within three days of the triggering event. While this is only a small subset of the sample due to data availability, this nonetheless provides evidence that students are unlikely changing their behavior in anticipation of a moratorium. Third, according to an online repository of fraternity-related deaths from journalist Hank Nuwer,<sup>17</sup> there were 19 universities that experienced a fraternity-related death but *did not* undergo a moratorium in the sample period which suggests that fraternity members may not expect a moratorium even when experiencing a particularly salient act of misconduct. Last, I estimate a multiple-event event study to ensure that crime incidences are not already trending downward prior to the moratorium. If crimes are trending downward prior to the moratorium, it is plausible that the moratorium is not the true cause of a decrease in crime and crime may decrease regardless. To estimate the event study, I follow 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, the leads and lags 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 and 5 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 more precise point estimates. 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) is chosen to give approx-

---

<sup>17</sup>See <https://www.hanknuwer.com/hazing-deaths/>.

imately a median moratorium length of days (46) before and after the moratorium period. In each figure, there is little suggestive evidence of a downward or upward trend prior to a moratorium. This is reinforced with statistically insignificant F-test showing that the three pre-periods are jointly zero at the five and 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 C2 and C3. Each of these figures fails to show evidence of a decreasing or increasing pre-period trend. Taken together, there is little suggestive evidence that crime was already decreasing prior to a moratorium or that fraternity members and students expect a fraternity moratorium based on a triggering event.


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 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 the time of incident reported changes during moratorium days. 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. In particular, I construct the proportion of offenses that are reported with a lag on a given day for each offense.<sup>18</sup> 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. Table 3 shows the results of this test. In each column, I change the definition of a lag to reflect a difference of one,

---

<sup>18</sup>Only 32 of the 37 universities had data for the date occurred of their incidents. Hence, this test only reflects a subset of the sample.



three, seven, and 14 days between the date occurred and date reported.<sup>19</sup> Panel A shows that alcohol offenses are rarely reported with a lag. Roughly 0.3% of offenses are reported with a one-day lag, and the change during a moratorium is insignificant from zero. This provides evidence that police departments do not appear to undergo significant changes in their reporting behaviors during moratoriums. Similarly, Panel B shows no difference in lagged reporting for sexual assault offenses. While sexual assaults have a higher proportion of reports that are reported with a lag (1.7%), the change during a moratorium is also insignificant from zero. Hence, from the results of this test, there is little evidence to support that students change their propensity to report a sexual assault within a moratorium.

The third 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 little reason to act 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 little evidence that there are persistent effects in the week following a moratorium. These results further justify the use of already-treated universities (e.g., universities that have already experienced a moratorium) as a reasonable control group—a common critique of the difference-in-differences estimator with variation in treatment timing (Goodman-Bacon 2021). Given that moratoriums show no lasting effects, an academic-calendar day without a moratorium is a good counterfactual for an academic-calendar day with a moratorium.



## 5 Results

In this section, the causal effects of a fraternity moratorium on alcohol offenses and sexual assaults are estimated using OLS. To reduce potential noise in the estimates, the sample is

---

<sup>19</sup>Literature such as Sahay (2021) use a 3-day lag when applying this test.

restricted to only the academic-calendar days unique to each university.<sup>20</sup> Furthermore, I analyze dynamic effects and perform numerous robustness and sensitivity checks—each resulting in estimates that are consistent with the main findings. Figure 6 serves as a preview of the main results by plotting the distribution of differences between the number of offenses per-25000 enrolled students on moratorium days and non-moratorium days. On average, most universities observe less alcohol offenses and sexual assaults on moratorium days as displayed by the dashed line.

## 5.1 Main Results

Table 4 reports that fraternity moratoriums lead to substantially lower alcohol offenses across university campuses while showing suggestive evidence of decreases in sexual assaults. Column (1) shows the baseline specification from Equation 1. This baseline specification includes day of the week, holiday, semester, football game-day, and academic-year fixed effects. Moreover, columns (2) and (3) 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. Across the three specifications, an average moratorium day exhibits between 26 to 28 percent less alcohol offenses in comparison to an average academic-calendar day as shown in the point estimates. These estimates are statistically significant across each specification, maintaining that moratoriums decrease campus-wide alcohol offenses. Although alcohol offenses are robust, sexual assaults fail to achieve statistical significance across each specification and the magnitude of each effect varies considerably; sexual assaults show a 14-20 percent reduction from the mean across the three specifications. One reason for this discrepancy in magnitude may be that the inclusion of the university by academic year fixed effect (column (2)) 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

---

<sup>20</sup>See the Data section for more details.

university, academic-year, and semester fixed effects (column (3)) only allows for comparisons of moratorium days to non-moratorium days within a particular university’s semester in a particular academic year. While the controls in column (3) are the most flexible, I use the controls in column (2) in all further analysis for two reasons. First, the results in column (2) are the most conservative. Second, 24 of the 44 moratoriums (54%) have moratorium days that span across at least two semesters, while only 6 of 44 (13%) have moratoriums days that span across at least two academic years. Hence, since the specification (3) only compares moratorium days to non-moratorium days within a university-academic-year-semester, there is far less variation than specification (2). In particular, some universities may have very few moratorium days within a university-academic-year-semester in comparison to a university-academic-year. Thus, using column (2) as the preferred specification, only alcohol offenses 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 (2) from Table 4 separated by weekends and weekdays; the column All Days corresponds to the estimates of column (2) from Table 4. During the weekends, alcohol offenses decrease by 28% relative to an average academic-calendar weekend as shown in Panel A. On the other hand, weekdays show no statistically significant decreases. Likewise to alcohol, sexual assaults show larger decreases on the weekend in comparison to weekdays in Panel B. A weekend during a moratorium can expect 29% fewer sexual assaults relative to an average academic-calendar weekend.

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 (2) 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.

## 5.2 Robustness

### 5.2.1 Inclusion of Never-Treated Universities

Given the number of universities in the sample (37), the results shown above can benefit from increased precision—while both alcohol and sexual assault offenses show statistically significant decreases on the weekend, the standard errors can only rule out weekend reductions greater than 41 and 46 percent from the mean with 95% confidence for alcohol offenses and sexual assaults respectively. 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 51 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.<sup>21</sup> Never-treated universities were selected if they were regarded as a Top 50 Greek Life school.<sup>22</sup> However, 17 of these universities were already included in the sample due to experiencing a fraternity moratorium. As such, 14 of remaining 33 Top 50 Greek Life universities were able to provide Daily Crime Logs for the 2014-2019 period. Appendix Table C5 shows the effects of moratoriums when including these never-treated universities. Overall, the results remain similar, with weekend decreases of alcohol of approximately 18 percent reduction from the mean and sexual assault decreases at approximately 26 percent. Although weekend offenses of alcohol may appear slightly less significant, it is noted that the p-value is equal to 0.062—borderline 5% significance. Notably, the standard errors encapsulate the point estimates from the main results in Table 5 and the stability of the estimates and significance instill further confidence in the results of the model.

---

<sup>21</sup>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.

<sup>22</sup>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.

### 5.2.2 Leave-one-out Estimation

Appendix Figures C4 and C5 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, 37 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.

### 5.2.3 Poisson Estimation

Given the non-negative count nature of the offense data and the sensitivity of OLS estimation to outliers, Appendix Tables C6 and C7 show Tables 4 and 5 using poisson estimation in lieu of OLS.<sup>23</sup> The results are consistent with Table 5 as they show a 27 and 32 percent average reduction for alcohol offenses and sexual assaults on the weekends respectively.

### 5.2.4 Robustness to Negative Weights

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’Haultfoeulle 2020; Sun and Abraham 2021; Athey and Imbens 2022). In particular, the parameter of interest (e.g., the coefficient on the treatment 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

---

<sup>23</sup>Despite these advantages of poisson estimation, OLS is the preferred method since the results are more conservative.

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 four types of heterogeneous effects. First, I analyze whether moratoriums are more effective at schools with a reputation for partying and show that moratoriums are more effective in reducing alcohol offenses at party schools than non-party schools. Second, 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. Third, I estimate the required length for a moratorium to show the largest effects. While there is no clear answer to this, the estimates show that moratoriums should last at least a month to exhibit decreases in alcohol offenses. Last, I show that moratoriums are most effective when overseen by the university rather than the fraternity members themselves.

### 6.1 Party Schools

Universities that have a reputation for partying may be more impacted by the restrictions of moratoriums than universities that party less. For example, [Lindo, Siminski, and Swensen \(2018\)](#) find that party schools exhibit two times the increase in reports of rape on football game days than non-party schools. To examine this possibility, I use Niche.com’s Top Party

Schools in America list.<sup>24</sup> The list assigns “party scene” scores based on criteria such as athletic department revenue, fraternity and sorority life statistics, access to bars, and student surveys.<sup>25</sup> Using this list, a university is defined as a party school if it appears in the top 50 rankings. This amounts to 16 of the 37 universities in the sample being classified as a party school.

Table 6 shows that party schools exhibit larger decreases in alcohol offenses than non-party schools. The point estimates in Panel A indicate that moratoriums decrease alcohol offenses on academic-calendar days by approximately 33% from the mean for party schools and 16% for non-party schools. Importantly, only the point estimates for party schools are statistically significant, thus showing that the effects of the moratorium are driven by schools that have a stronger party culture.

## 6.2 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,<sup>26</sup> 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

---

<sup>24</sup>I use niche.com over the Princeton Review since the Princeton Review no longer posts their party school rankings.

<sup>25</sup>For more details on the methodology see: <https://www.niche.com/about/methodology/top-party-schools/>.

<sup>26</sup>Recall that a behavior violation includes hazing, offensive behavior, rule violations, and other disorderly conduct.

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 separately analyze a sample containing the universities that experienced a fraternity-related death and underwent a moratorium with an additional 15 universities that experienced a fraternity-related death in the sample period, but *did not* undergo a moratorium.<sup>27</sup> Hence, these additional universities are those whose students experience the effects of a fraternity-related death, but do not experience a moratorium. If the shock of death is the mechanism which produces decreases in alcohol offenses, then the effects of a moratorium on alcohol offenses should be insignificant when including these universities as a control group. However, with the inclusion of these universities, alcohol offenses maintain similar results—alcohol offenses are still significant at the 10% level. Although the statistical significance is weaker than the main results, this nonetheless signals that the moratorium itself is temporarily 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.<sup>28</sup> 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 (19 universities for 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

---

<sup>27</sup>These universities were found using Hank Nuwer’s repository of hazing-related deaths in the US: <https://www.hanknuwer.com/hazing-deaths/>.

<sup>28</sup>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](https://ira.virginia.edu/sites/ias.virginia.edu/files/University%20of%20Virginia_2015_climate_final_report.pdf)





this claim.

### 6.3 Length of Moratorium

Each moratorium varies in its length. As shown in Table 2, the average length of a moratorium is 64 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 at which length a moratorium will be effective; 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 the 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.

In light of these shortcomings, I analyze the heterogeneous effects of length by binning each moratorium into three percentiles based on length (33rd, 66th, 100th). The three percentiles correspond to [0-32], [33-59], and [60-541] academic-calendar day intervals under a moratorium respectively. Panel A of Table 7 shows that when moratoriums are under 33 days, 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 34% 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.

## 6.4 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 council. In the sample, 27 of the 44 (61%) moratoriums are enacted by a university. While a university-enacted moratorium is overseen by the university, an IFC-enacted moratorium is only overseen by the fraternity members themselves. More specifically, an IFC-enacted moratorium is purely an agreement among fraternity members to restrict their behavior. Hence, there is reason to suspect differences between these two sources of jurisdiction since IFC moratoriums may lack the incentive structure that university moratoriums have. For instance, a university can permanently suspend a fraternity chapter from its campus for failure to abide by moratorium guidelines which may damage the fraternity chapter’s membership and reputation—two components necessary to guarantee longevity of the fraternity. This would give gravity to the university’s enforcement, therefore showing that the moratorium is not strictly political. On the other hand, IFC councils have little incentive to permanently suspend or impose additional sanctions as fraternity chapters rely on each other to create a thriving social life and community. As such, further disciplinary measures by the IFC-council directly affects the council members themselves, thus creating a system that may incentivize IFC council members to look away from any deviations from the guidelines set forth.

In Table 8 alcohol offenses have suggestive evidence of a decline when a university imposes the moratorium as shown in Panel A. Consistent with the main results, the largest effects are on weekends rather than weekdays. The point estimates for sexual assaults are insignificant across both university-imposed and IFC-enacted moratoriums, likely due to the infrequent reporting of sexual assaults. These results show evidence that university-imposed moratoriums are likely more effective than the IFC-enacted moratoriums.

## 7 Discussion

### 7.1 Do Moratoriums Mitigate the Effects of Football Games?

Both [Lindo, Siminski, and Swensen \(2018\)](#) and [Rees and Schnepel \(2009\)](#) show that college football games cause higher instances of rape and alcohol offenses respectively. While football games cause negative outcomes, universities are reluctant to suspend football games—college football is popular among students and alumni in addition to being a major source of revenue. Therefore, finding an effective policy that can mitigate the detrimental effects of football games while maintaining the benefits is important for university administrators. This subsection analyzes whether moratoriums are the policy tool that can accomplish this.

Of the 37 universities in the sample, 34 have football teams. This results in over 2000 football games, 89 of which coincide with a moratorium. Using a similar model as the preferred specification,<sup>29</sup> Figure 9 shows that football game days cause a significant increase in alcohol offenses and sexual assaults. These effects are largest on home games rather than away games which are consistent with [Lindo, Siminski, and Swensen \(2018\)](#) and [Rees and Schnepel \(2009\)](#). Furthermore, Figure 9 also shows the combined effect of a game day that occurs during a moratorium. In each of these estimations, the point estimates remain consistent with the effect of non-moratorium game-days although the point estimates are less precise. This may be caused by a lack of identifying variation—the point estimates are identified by 89 occurrences of game days that coincide with moratoriums. As a robustness check, I broaden the definition of game-days to “ne-weekends” (e.g., Fridays/Saturdays/Sundays in which a football game occurs during one of these days) in Appendix Figure C6. Although this nearly triples the amount of identifying variation,<sup>30</sup> the results remain similar; the point estimates of the effect of game-day weekends with a moratorium are similar to a game-day

---

<sup>29</sup>In this case, I use a model that is nearly identical to the preferred specification although using an indicator variable for whether or not a football game occurred as the explanatory variable. The controls include days of the week, university, holiday, and academic-year by semester—similar to the preferred specification.

<sup>30</sup>Not all game-days occur on a weekend, so the expanding the definition to a game-day weekend does not quite triple the number.

weekend without a moratorium although also less precise. Taken together, it is uncertain whether moratoriums mitigate the effects of game-days. On one hand, these results offer the possibility that fraternities are not an integral component to college partying on game-days—students can substitute away from fraternity parties to other alternatives on game-days. On the other hand, it may be that moratoriums restrict the amount of dangerous partying that occurs during football games and produce a safer environment. Since the estimates are imprecise, it is unclear whether moratoriums can act as an effective policy tool to mitigate alcohol offenses or sexual assaults on football game-days.

## 7.2 Crime Displacement and Substitution of Partying

One potential caveat to these results is that the observed 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, the net effect of a moratorium may be worse than never implementing a moratorium. Unfortunately, there does not exist a perfect data source to explore such mechanism directly; the National Incidence-Based Reporting System (NIBRS) only reliably<sup>31</sup> covers 24% of the sample universities' neighboring police departments and includes alcohol arrests rather than all incidences. Furthermore, the Campus Safety and Security (CSS) data, while possessing all incidences of crime reported on university campuses, is aggregated to the yearly level.

Despite these challenges, I perform two sets of analysis using each of these data sets. First, to identify whether crime incidence is displaced into nearby areas, I use the NIBRS data to compare the reported incidence of crimes at nearby police departments with the crimes reported at university-specific police departments using the Daily Crime Logs. Nearby police departments are defined as police departments that serve the surrounding area, but

---

<sup>31</sup>In this case, I consider a data source to be reliable if reporting of crime is consistent in the sample period. NIBRS features only nine schools that continually report data without large missing periods.

are not affiliated directly with a university.<sup>32</sup> In sum, this amounts to a comparison of a subset of 9 universities from the main sample and their corresponding university/nearby police departments. To harmonize the NIBRS data with the Daily Crime Logs, I define each offense from NIBRS as per-25000 enrolled students at the corresponding university and limit the panel to only academic-calendar days. Both alcohol offenses and sexual assaults are restricted to incidences involving college-aged individuals (e.g., 17-22), although the results are consistent when broadening the definition to include all ages. Moreover, I define sexual assaults in the NIBRS data to include fondling, rape, and sexual assault with an object to align with the definition using the Daily Crime Logs.

Table 9 shows that there is little evidence of heightened alcohol offenses at nearby police departments. In both Panels A and B, alcohol offenses and sexual assaults have a negative point estimate at nearby police departments, although insignificant from the standardized mean. However, the university-specific police departments continue to show large and significant effects of the moratorium for alcohol offenses despite being a small subset of the main sample. This gives confidence to the interpretation that moratoriums are decreasing alcohol offenses on university campuses and students are not taking their risky behaviors off-campus.

As the second set of analysis, I analyze the CSS data to examine if students substitute from partying at fraternity houses to different on-campus locations during moratoriums. The CSS data contains all violations of liquor, drug, and sexual assaults that occur in a calendar-year. The main advantage to using the CSS data is that it delineates between crimes that occur within a residence hall or a different on-campus location. Moreover, the CSS data includes liquor violations that may not have been reported to the police (thus not in the Daily Crime Logs) if they were handled internally by university staff. For instance, if a liquor violation occurred in a residence hall, the Daily Crime Logs will not have record of this if the

---

<sup>32</sup>The neighboring police departments were identified using [Lindo, Siminski, and Swensen \(2018\)](#) public access data files in addition to Jacob Kaplan's NIBRS data tool available here: [https://jacobdkaplan.com/nibrs.html#state=Colorado&agency=Denver%20Police%20Department&category=murder\\_nonnegligent\\_manslaughter&rate=false](https://jacobdkaplan.com/nibrs.html#state=Colorado&agency=Denver%20Police%20Department&category=murder_nonnegligent_manslaughter&rate=false)

citation was handled by university officials. However, the biggest disadvantage to this data is that all incidences are aggregated to the calendar-year level. Since moratoriums can last for as few as six days and can progress through multiple calendar-years, the analysis should be taken only as speculative, not causal. See Appendix B for a more detailed discussion of the CSS data and the corresponding model used.

Despite these shortcomings, there is evidence that moratoriums significantly move drinking from fraternity houses to residence halls. Residence halls show a 28% *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 82% *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 intervened (e.g., the increases in alcohol violations) before it can become dangerous to others (e.g., the decreases in sexual assaults).

## 8 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 offenses and sexual assaults across 37 universities in the US. I construct a novel dataset which includes daily-level incidence reports from each university-specific police department. Using these 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, football game-days, and universities. I find that moratoriums decrease the average reports of alcohol offenses on a given academic calendar day by approximately 26%. This result is most prominent on the weekends when partying is most frequent (28% reduction) while nonexistent on the weekdays. Moreover, I find sugges-

tive evidence of decreases in reports of sexual assaults on the weekends with a 29% reduction from the mean, although only significant at the 10% level. Notably, 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 immediately returns to previous levels after the moratorium is lifted. These results demonstrate that moratoriums are only effective when active; despite the motivation that moratoriums allow time for members to reevaluate and change their systematic behavior, the effects do not persist. Taken together, these results support the notion that moratoriums are only effective in temporarily reducing campus-wide crime.

Given that moratoriums are unable to create permanent changes in student behavior, it is unclear whether they should continue as active policy. On one hand, moratoriums may move college partying behavior to safer areas (residence halls) as speculated in Section 7.2 whereby risky behavior can be intervened more quickly. In addition, moratoriums may alleviate the detrimental health effects that alcohol causes in college students such as hindering academic performance and costly emergency room visits. On the other hand, moratoriums do not change student behavior; while moratoriums have large effects during enforcement, moratoriums are an unproductive policy to systematically reduce college partying behavior. Hence, school administrators should understand that moratoriums are a transient solution and should therefore look for other methods to promote long-term change. Unfortunately, there is a lack of research in such methods. For instance, several universities have implemented restrictions on fraternity 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. Yet, as of this writing, there are only two studies that evaluate such policy and these papers focus on academic benefits rather than crime (De Donato and Thomas 2017; Even and Smith 2020). Moreover, another understudied policy is the barring of specific misbehaving fraternity chapters from universities rather than IFC moratoriums. Although this policy alleviates the criticism that moratori-

ums are punishing even well-behaving fraternities, it is unclear whether this truly propagates behavior change—members of a poor behaving fraternity may choose to substitute to a new fraternity and thereby negatively influence its members.

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 one component: social events with alcohol. Hence, this paper does not provide support for national movements such as “Abolish Greek Life”; recall that prior research has linked membership to beneficial outcomes such as increased income, higher graduation rates, and more hours spent in volunteering and community service. However, this study *does* quantify the effects that fraternities have on university-wide partying behavior. More specifically, this paper is the first to show that restricting fraternity social events with alcohol significantly decreases campus-wide reports of alcohol offenses and sexual assaults.



## 9 References

- Armstrong, Elizabeth A., Laura Hamilton, and Brian Sweeney. 2006. “Sexual Assault on Campus: A Multilevel, Integrative Approach to Party Rape.” *Social Problems* 53 (4): 483–99. <https://doi.org/10.1525/sp.2006.53.4.483>.
- Asel, Ashley, Tricia Seifert, and Ernest Pascarella. 2009. “The Effects of Fraternity/Sorority Membership on College Experiences and Outcomes: A Portrait of Complexity.” *Oracle: The Research Journal of the Association of Fraternity/Sorority Advisors* 4 (2): 1–15. <https://doi.org/https://doi.org/10.25774/2p5f-gt14>.
- Athey, Susan, and Guido W. Imbens. 2022. “Design-Based Analysis in Difference-In-Differences Settings with Staggered Adoption.” *Journal of Econometrics*, Annals issue in Honor of Gary Chamberlain, 226 (1): 62–79. <https://doi.org/10.1016/j.jeconom.2020.10.012>.
- Carpenter, Christopher, and Carlos Dobkin. 2009. “The Effect of Alcohol Consumption on Mortality: Regression Discontinuity Evidence from the Minimum Drinking Age.” *American Economic Journal: Applied Economics* 1 (1): 164–82. <https://doi.org/10.1257/app.1.1.164>.
- . 2015. “The Minimum Legal Drinking Age and Crime.” *The Review of Economics and Statistics* 97 (2): 521–24. [https://doi.org/10.1162/REST\\_a\\_00489](https://doi.org/10.1162/REST_a_00489).
- Carrell, Scott E., Mark Hoekstra, and James E. West. 2011. “Does Drinking Impair College Performance? Evidence from a Regression Discontinuity Approach.” *Journal of Public Economics* 95 (1): 54–62. <https://doi.org/10.1016/j.jpubeco.2010.08.008>.
- Chaisemartin, Clément de, Xavier D’Haultfoeulle, and Antoine Deeb. 2020. “TWOWAYFEWEIGHTS: Stata Module to Estimate the Weights and Measure of Robustness to Treatment Effect Heterogeneity Attached to Two-Way Fixed Effects Regressions.” <https://econpapers.repec.org/software/bocbocode/s458611.htm>.
- Chaisemartin, Clément de, and Xavier D’Haultfoeulle. 2020. “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects.” *American Economic Review* 110 (9):

- 2964–96. <https://doi.org/10.1257/aer.20181169>.
- Cunningham, Scott, and Manisha Shah. 2018. “Decriminalizing Indoor Prostitution: Implications for Sexual Violence and Public Health.” *The Review of Economic Studies* 85 (3): 1683–1715. <https://doi.org/10.1093/restud/rdx065>.
- De Donato, Andrew, and James Thomas. 2017. “The Effects of Greek Affiliation on Academic Performance.” *Economics of Education Review* 57 (April): 41–51. <https://doi.org/10.1016/j.econedurev.2017.01.004>.
- DeSimone, Jeff. 2007. “Fraternity Membership and Binge Drinking.” *Journal of Health Economics* 26 (5): 950–67. <https://doi.org/10.1016/j.jhealeco.2007.01.003>.
- Even, William E., and Austin C. Smith. 2020. “Greek Life, Academics, and Earnings.” *Journal of Human Resources*, March. <https://doi.org/10.3368/jhr.57.3.1018-9814R3>.
- Francesconi, Marco, and Jonathan James. 2019. “Liquid Assets? The Short-Run Liabilities of Binge Drinking.” *The Economic Journal* 129 (621): 2090–2136. <https://doi.org/10.1111/econj.12627>.
- Goodman-Bacon, Andrew. 2021. “Difference-in-Differences with Variation in Treatment Timing.” *Journal of Econometrics*, Themed issue: Treatment Effect 1, 225 (2): 254–77. <https://doi.org/10.1016/j.jeconom.2021.03.014>.
- Ha, Joung Yeob, and Austin C. Smith. 2019. “Legal Access to Alcohol and Academic Performance: Who Is Affected?” *Economics of Education Review* 72: 19–22. <https://doi.org/http://dx.doi.org/10.1016/j.econedurev.2019.05.002>.
- Hayek, J. C., R. M. Carini, P. T. O’Day, and G. D. Kuh. 2002. “Triumph or Tragedy: Comparing Student Engagement Levels of Members of Greek-Letter Organizations and Other Students.” <https://scholarworks.iu.edu/dspace/handle/2022/24308>.
- Hechinger, John. 2017. *True Gentlemen: The Broken Pledge of America’s Fraternities*. 1st ed. Hachette Book Group, Inc.
- Kaplan, Jacob. 2021a. “Jacob Kaplan’s Concatenated Files: National Incident-Based Reporting System (NIBRS) Data, 1991-2019.” Ann Arbor, MI: Inter-university Consortium

- for Political and Social Research. <https://doi.org/10.3886/E118281V4>.
- . 2021b. *National Incident-Based Reporting System (NIBRS) Data: A Practitioner's Guide*. <https://nibrsbook.com/>.
- Liang, Lan, and Jidong Huang. 2008. "Go Out or Stay in? The Effects of Zero Tolerance Laws on Alcohol Use and Drinking and Driving Patterns Among College Students." *Health Economics* 17 (11): 1261–75. <https://doi.org/10.1002/hec.1321>.
- Lindo, Jason M., Peter Siminski, and Isaac D. Swensen. 2018. "College Party Culture and Sexual Assault." *American Economic Journal: Applied Economics* 10 (1): 236–65. <https://doi.org/10.1257/app.20160031>.
- Mara, Jack, Lewis Davis, and Stephen Schmidt. 2018. "Social Animal House: The Economic and Academic Consequences of Fraternity Membership." *Contemporary Economic Policy* 36 (2): 263–76. <https://doi.org/10.1111/coep.12249>.
- Minow, Jacqueline Chevalier, and Christopher J. Einolf. 2009. "Sorority Participation and Sexual Assault Risk." *Violence Against Women* 15 (7): 835–51. <https://doi.org/10.1177/1077801209334472>.
- Raghav, Manu, and Timothy M. Diette. 2021. "Greek Myth or Fact? The Role of Greek Houses in Alcohol and Drug Violations on American Campuses." SSRN Scholarly Paper ID 3908875. Rochester, NY: Social Science Research Network. <https://doi.org/10.2139/ssrn.3908875>.
- Rees, Daniel I., and Kevin T. Schnepel. 2009. "College Football Games and Crime." *Journal of Sports Economics* 10 (1): 68–87. <https://doi.org/10.1177/1527002508327389>.
- Routon, P. Wesley, and Jay K. Walker. 2014. "The Impact of Greek Organization Membership on Collegiate Outcomes: Evidence from a National Survey." *Journal of Behavioral and Experimental Economics* 49 (April): 63–70. <https://doi.org/10.1016/j.socec.2014.02.003>.
- Sahay, Abhilasha. 2021. *The Silenced Women: Can Public Activism Stimulate Reporting of Violence Against Women?* Policy Research Working Papers. The World Bank. <https://doi.org/10.3386/w29042>.

[//doi.org/10.1596/1813-9450-9566](https://doi.org/10.1596/1813-9450-9566).

- Schmidheiny, Kurt, and Sebastian Siegloch. 2020. “On Event Studies and Distributed-Lags in Two-Way Fixed Effects Models: Identification, Equivalence, and Generalization.” *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3571164>.
- Seabrook, Rita C. 2019. “Examining Attitudes Towards Sexual Violence and IPV Prevention Activities Among Fraternity Members with Official and Unofficial Houses.” *Journal of American College Health* 0 (0): 1–6. <https://doi.org/10.1080/07448481.2019.1679153>.
- Sun, Liyang, and Sarah Abraham. 2021. “Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects.” *Journal of Econometrics*, Themed issue: Treatment Effect 1, 225 (2): 175–99. <https://doi.org/10.1016/j.jeconom.2020.09.006>.
- Zimmerman, Paul R., and Bruce L. Benson. 2007. “Alcohol and Rape: An ‘Economics-of-Crime’ Perspective.” *International Review of Law and Economics* 27 (4): 442–73. <https://doi.org/10.1016/j.irle.2007.09.002>.

## 10 Figures

This page is intentionally blank.

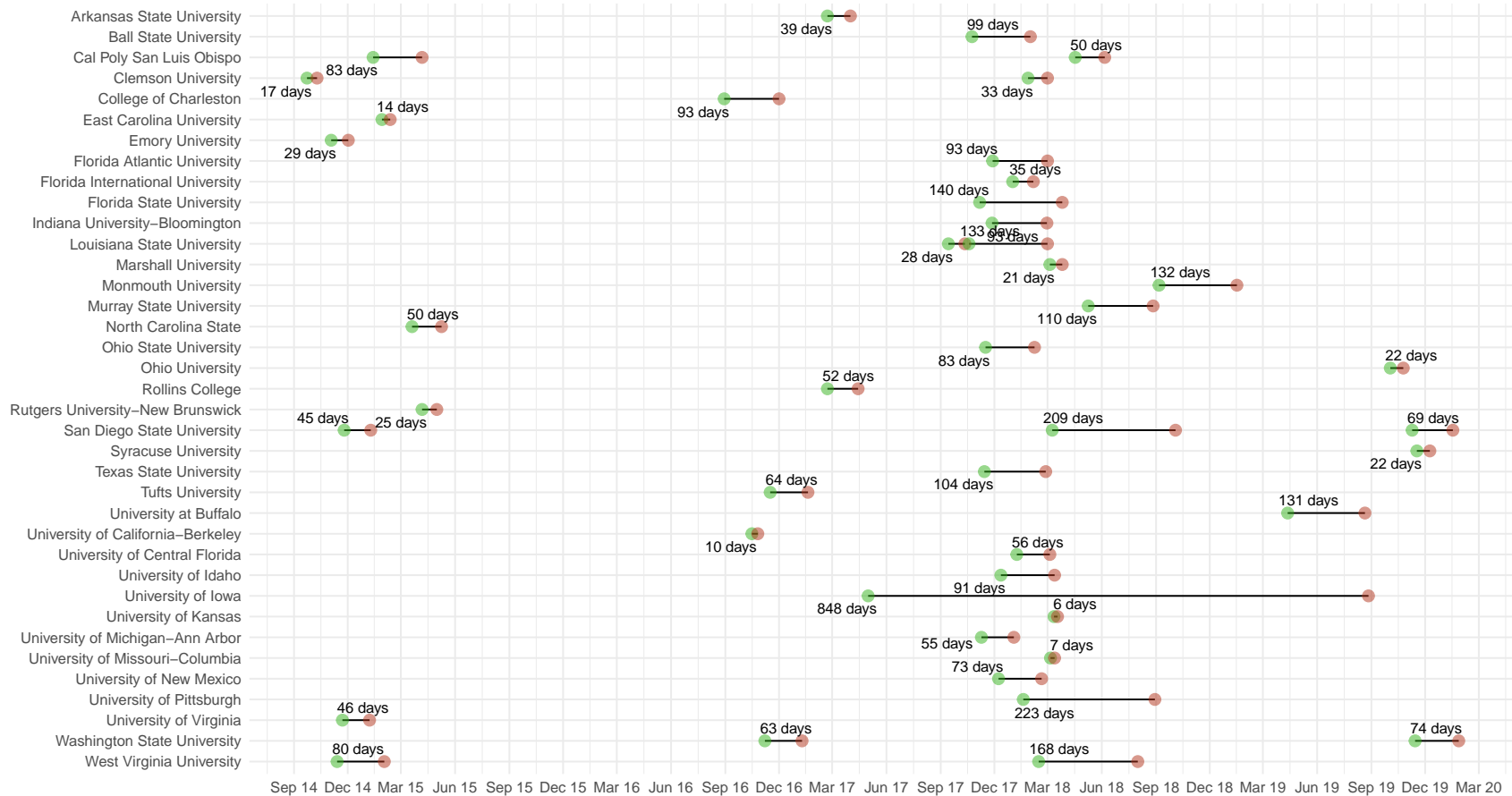


Figure 1: Distribution of Moratoriums Across the Sample Period for all Universities

*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 experience between 1 to 3 moratoriums in the sample period.

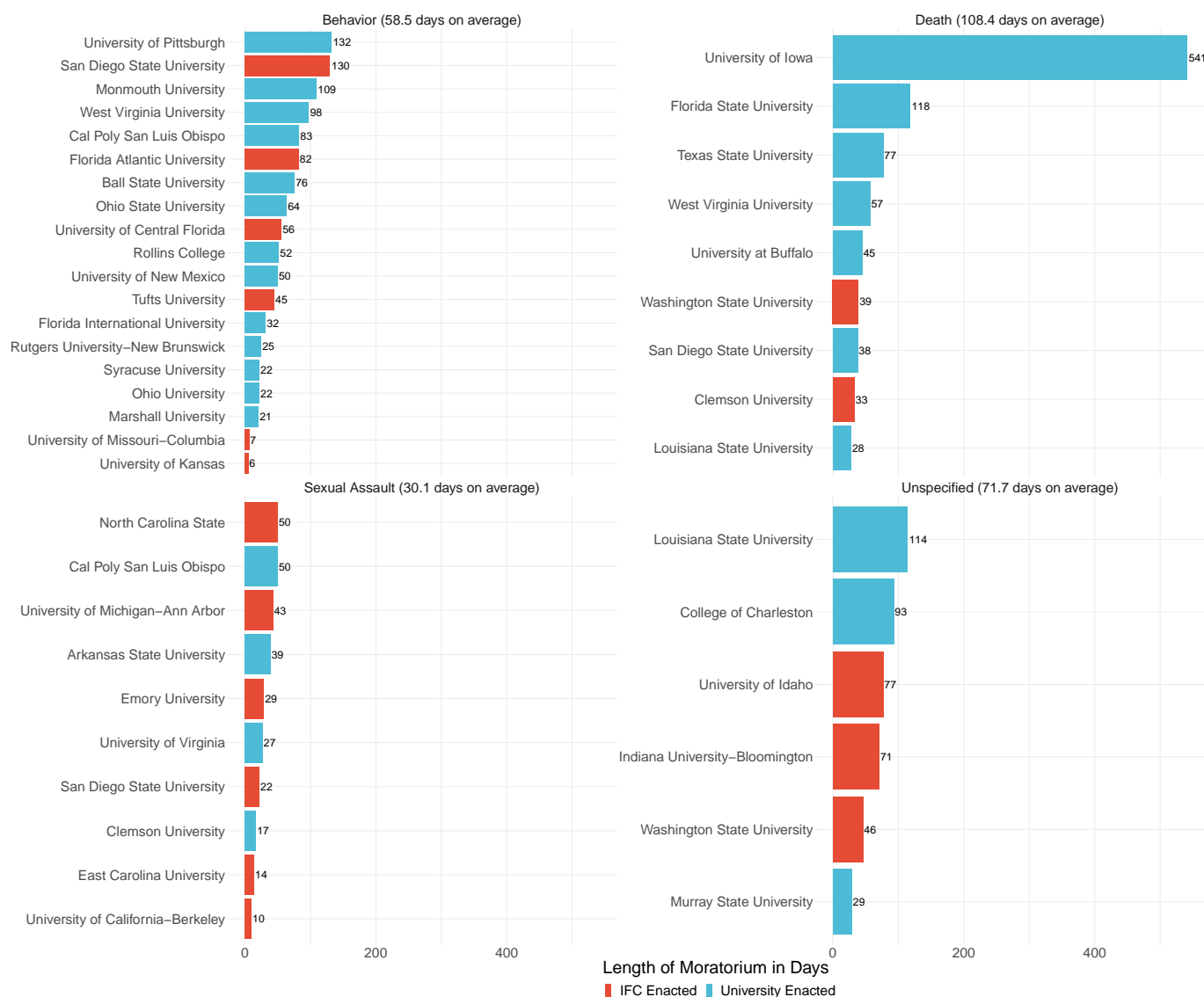


Figure 2: Number of Academic Calendar Days in a Moratorium by Triggering Event

*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 sexual assault case that triggered a moratorium. Lastly, the Unspecified category represents all moratoriums in which the moratorium triggering event is unknown or unclearly defined.

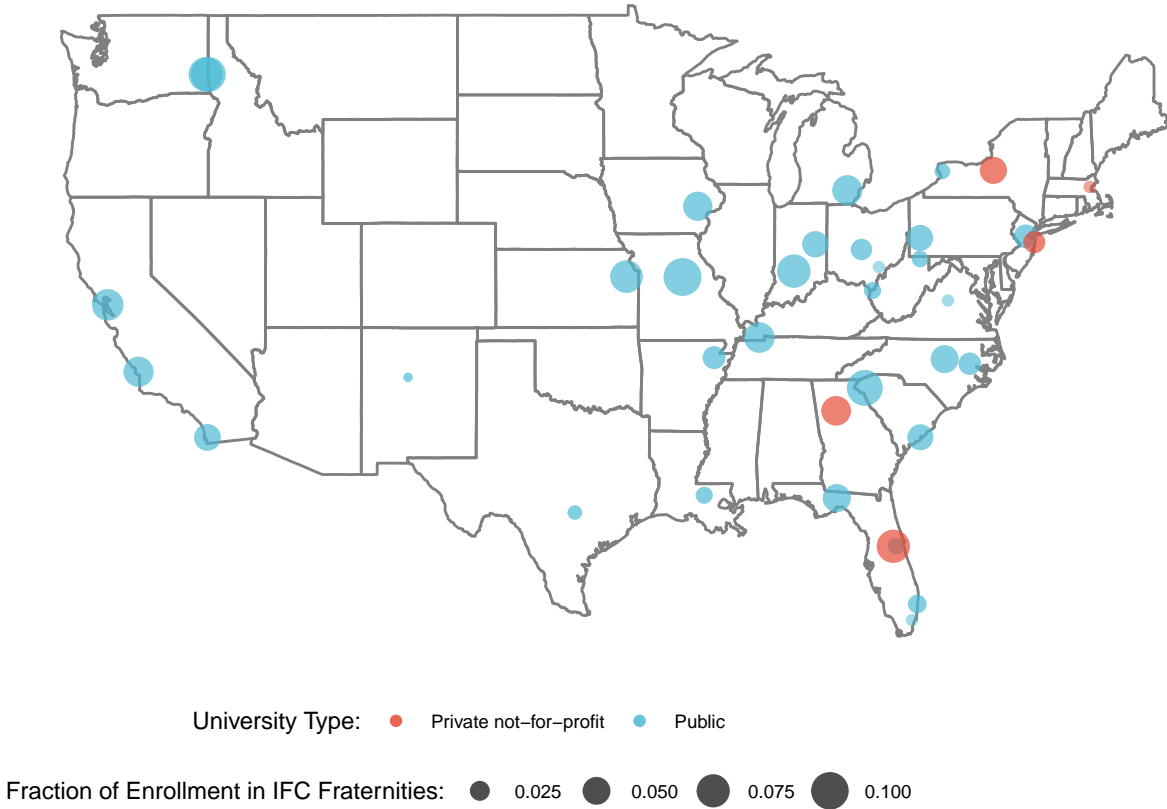


Figure 3: Locations of the Universities Included in the Sample

*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 of missing data, these universities are represented with the smallest size point.



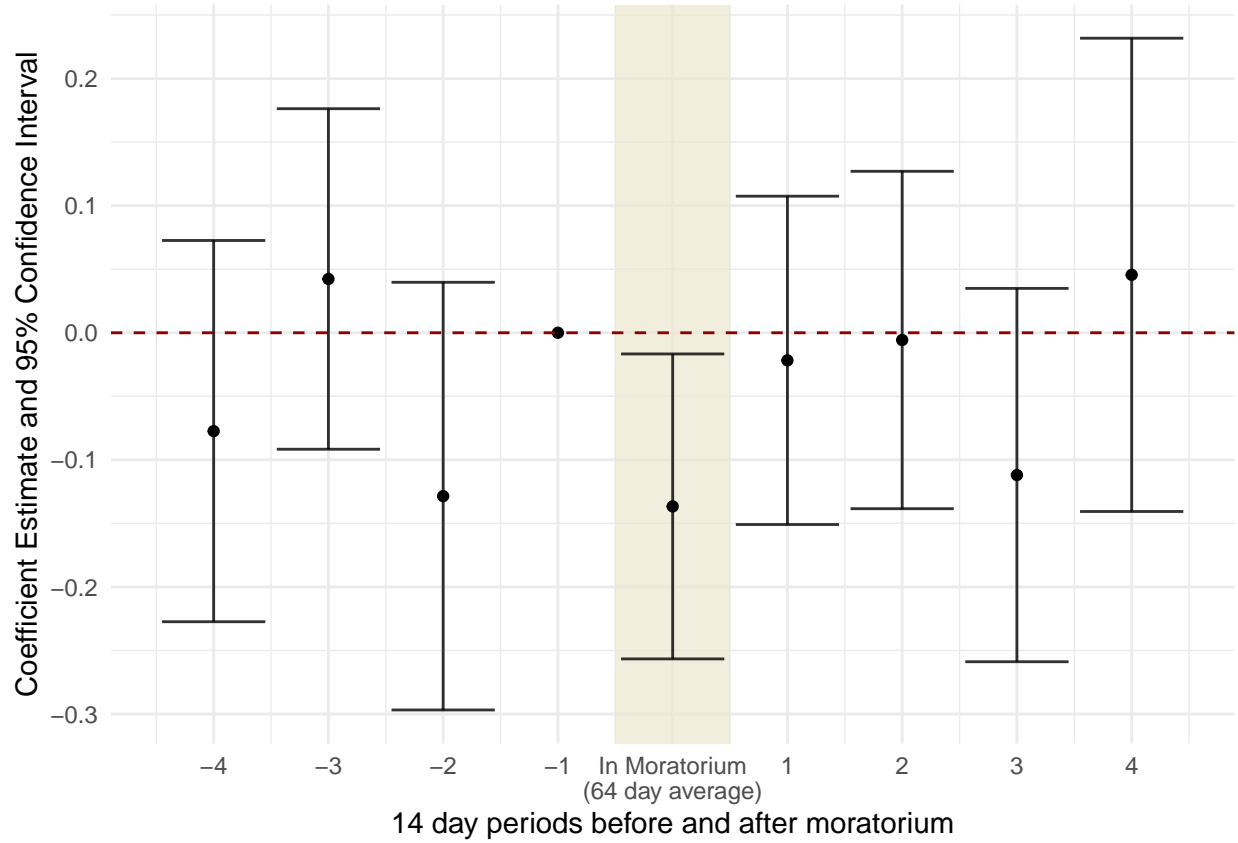


Figure 4: Event Study for Alcohol Offenses

*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, football game-days, 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 0.27 which is statistically insignificant.

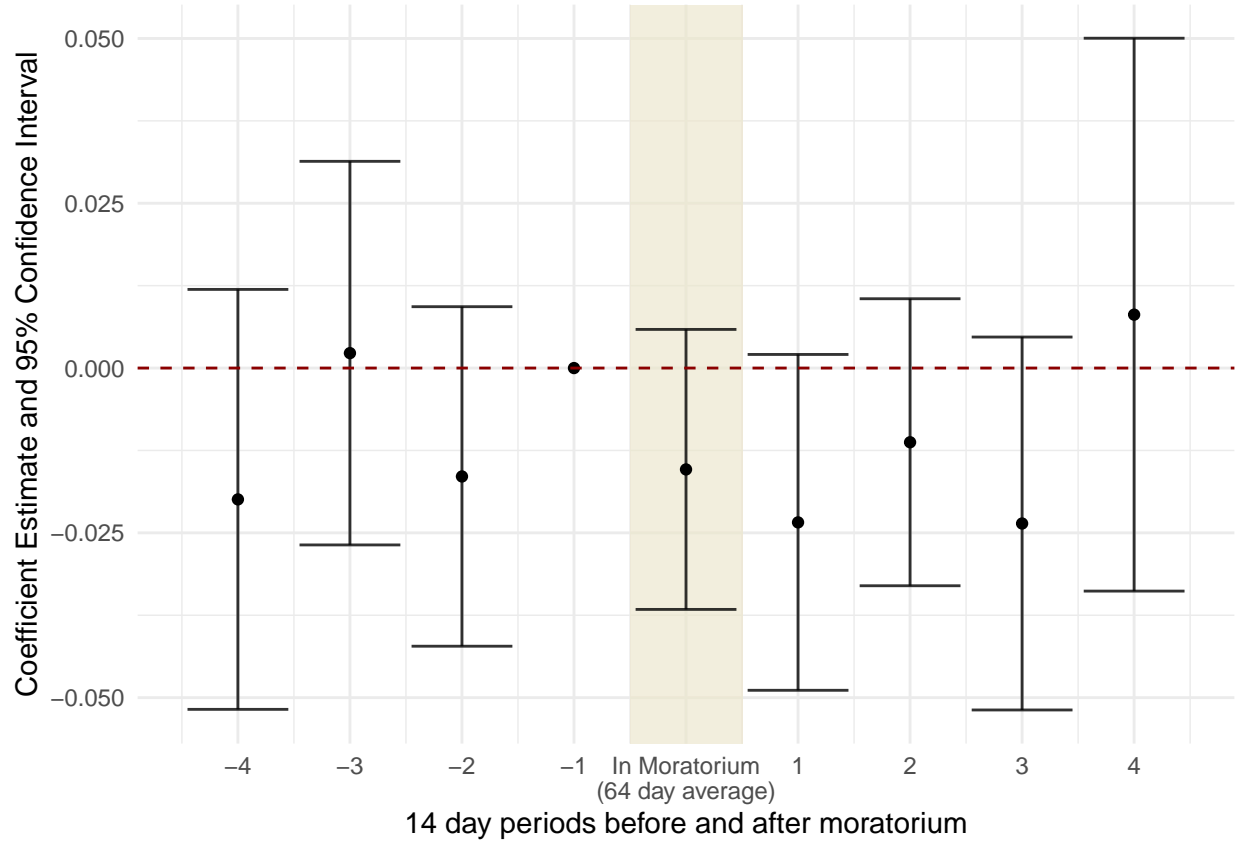


Figure 5: Event Study for Sexual Assault Offenses

*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, football game-day, 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 0.54 which is statistically insignificant.

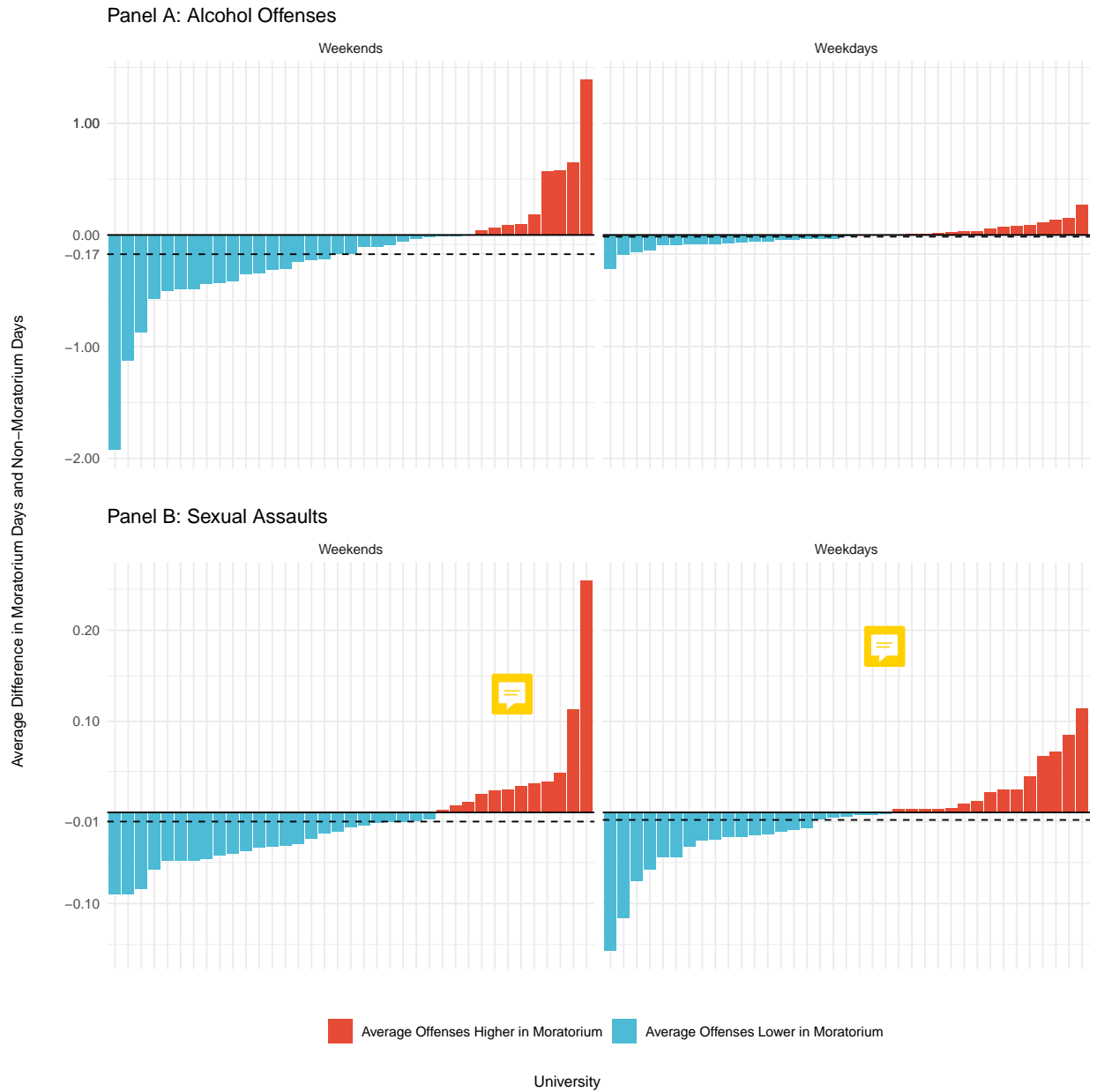


Figure 6: Difference in Average Offenses on Moratorium Days and Non-Moratorium Days  
*Notes:* The y-axis represents the average difference in offenses per-25000 enrolled students on moratorium days and non-moratorium days for each university. Negative y-axis values indicate that average offenses were lower on moratorium days than non-moratorium days. The x-axis denotes a unique university. The solid black line on the y-axis is 0, while the dashed black line denotes the average of the distribution.

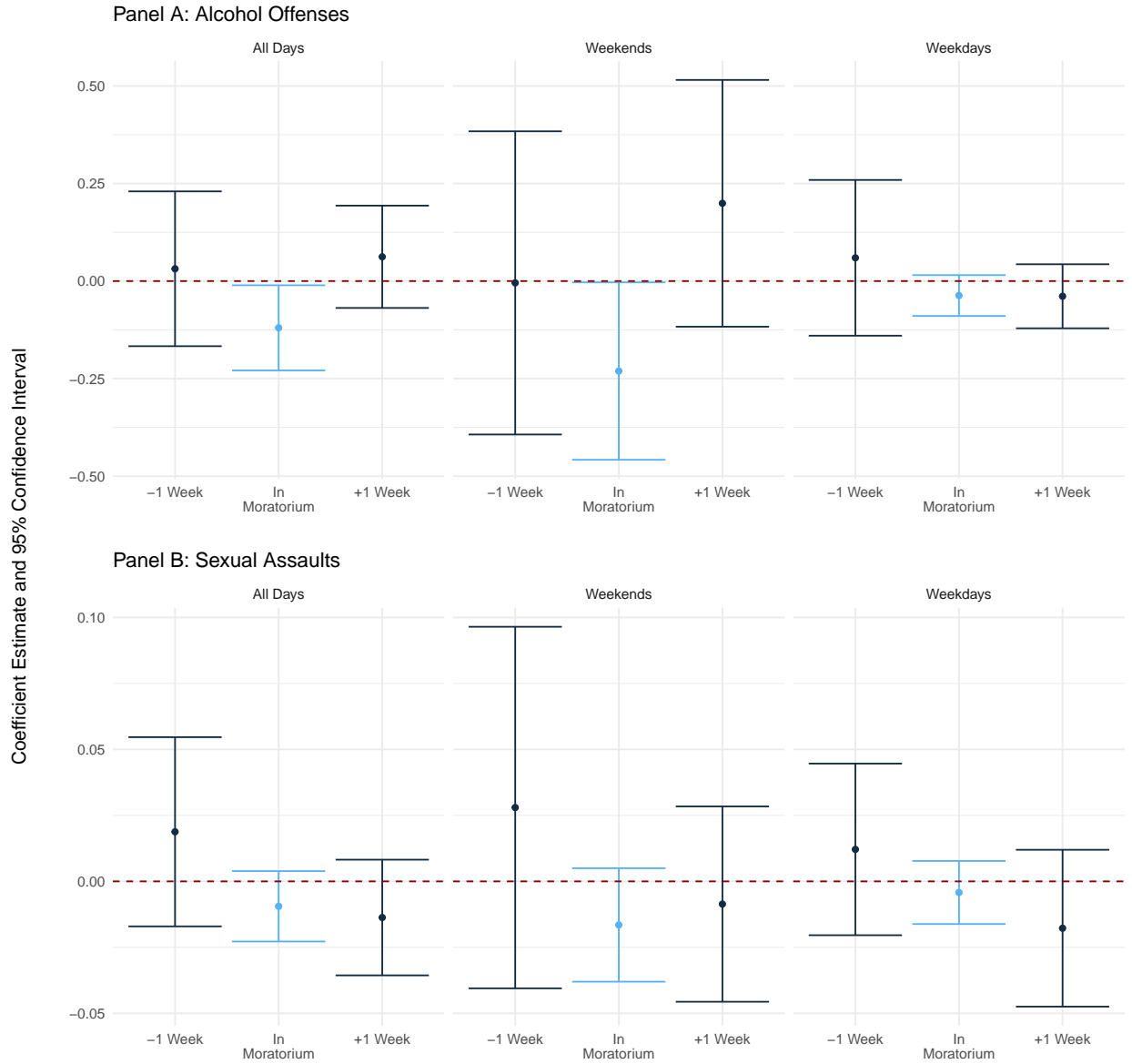


Figure 7: Coefficient Estimates Including a Week Before and Week After Indicator  
*Notes:* The x-axis represents three periods: the week before a moratorium, the moratorium itself, and the week after the moratorium. Indicators for week before and week after are added to specification (2) from Table 4. Controls include holiday, spring semester, day of the week, football game-days, and university-by-academic-year. Standard errors clustered by university. Standard errors are clustered by university. Weekends represent Fridays, Saturdays, and Sundays. Weekdays represent Mondays-Thursdays. Errorbars represent 95% confidence intervals.

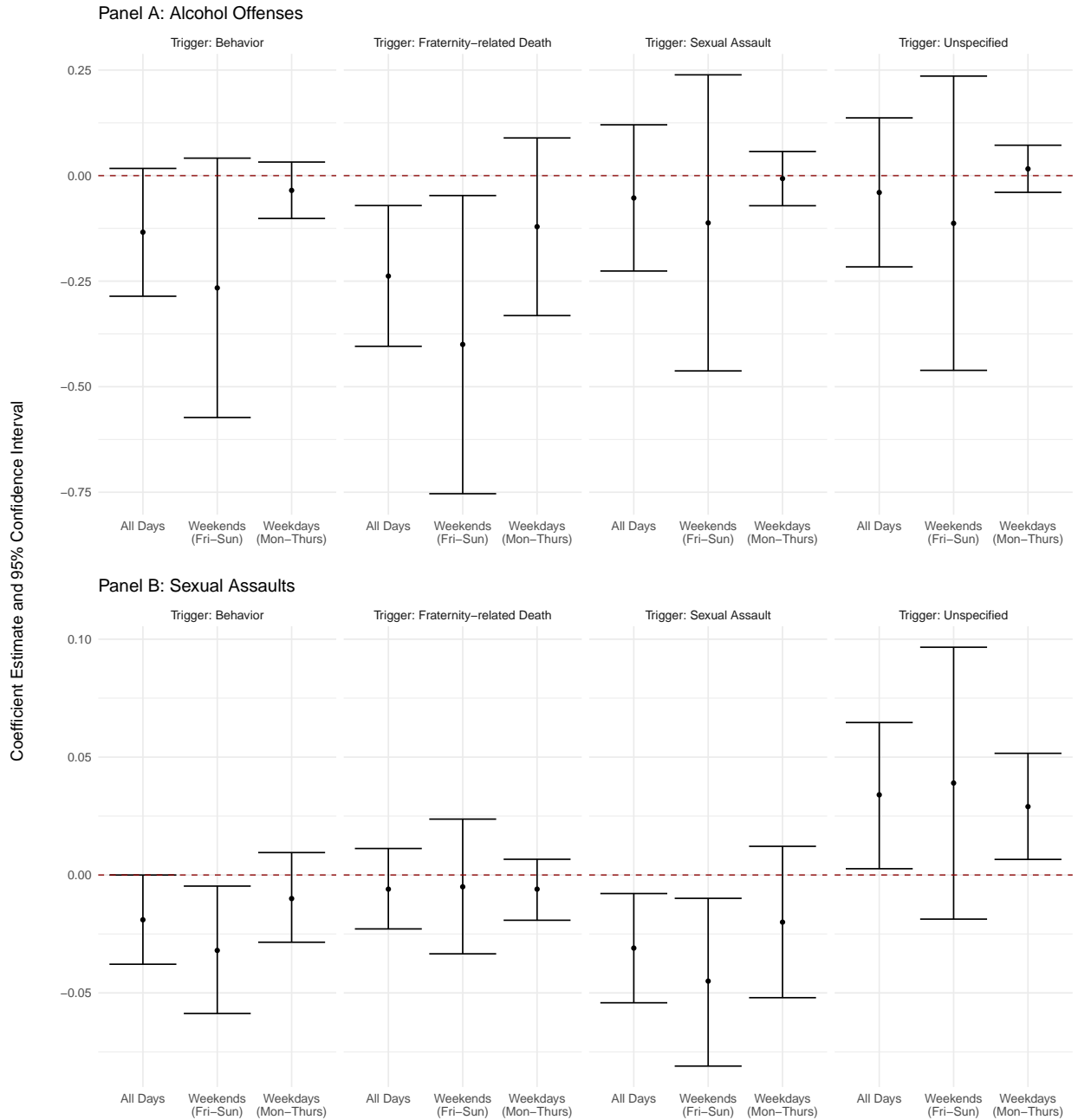


Figure 8: Heterogeneous Effects of Moratoriums by Triggering Event

*Notes:* The x-axis represents three periods: the entire sample (All Days), weekends only, and weekdays only. Specification (2) 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 sexual 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. Error bars represent 95% confidence intervals.

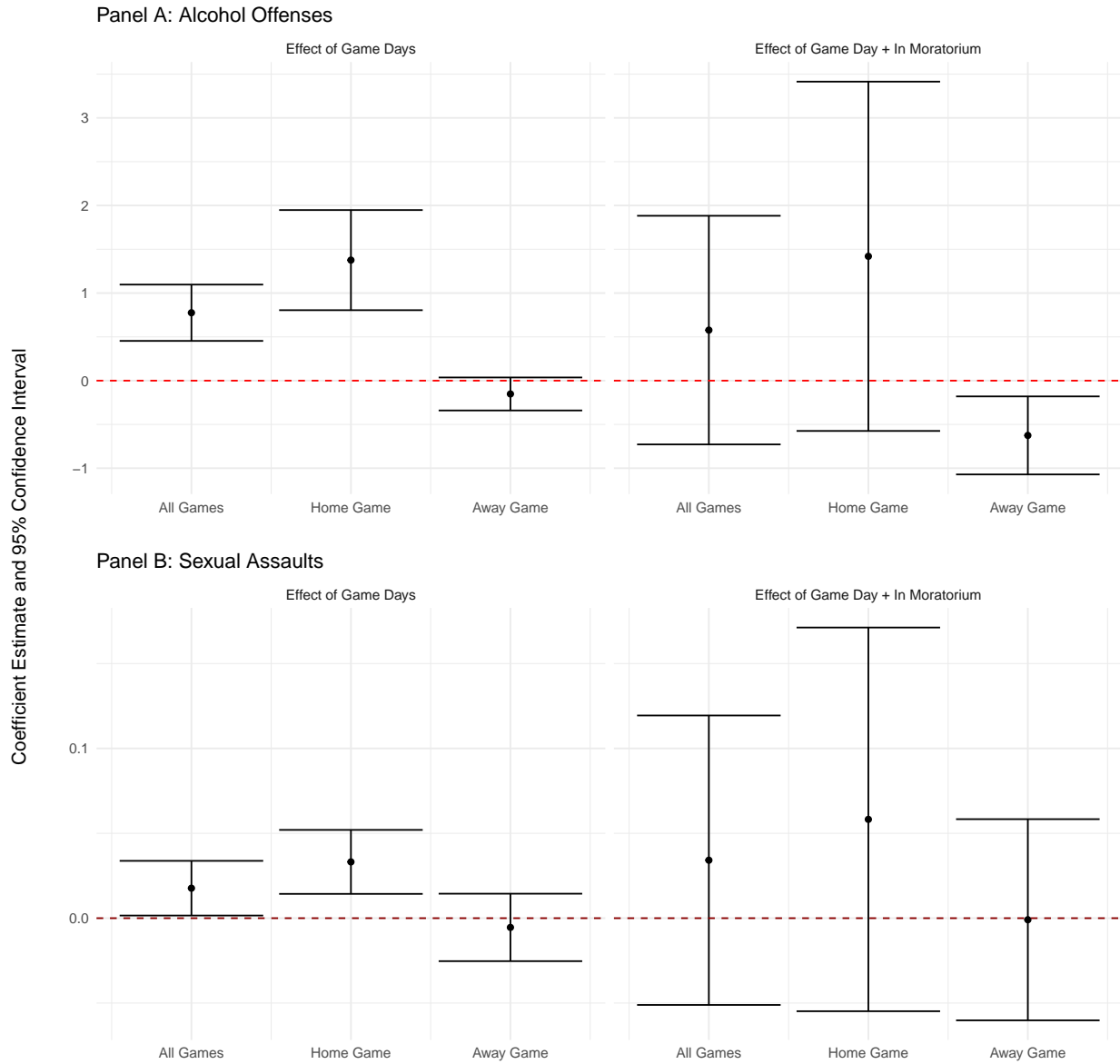


Figure 9: The Effect of Football Game-days and Football Game-days + Moratoriums

*Notes:* Game days include all football games occurring in the sample period. 34 of the 37 universities have football teams and corresponding game days. The y-axis represents coefficient estimates. Errorbars represent 95% confidence intervals. Each panel is split into two effects: the first effect being the effect of only football game days on the outcome per-25000 enrolled students, and the second being the effect of a football game that occurs within a moratorium. All Games includes both home and away games. The effects of game days + moratorium is identified by 89 football games that coincide with moratoriums. Controls include holiday, spring semester, day of the week, and university-by-academic-year. Standard errors are clustered by university.

## 11 Tables

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

Outcome	Words to Match
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
Sexual Assault	sex, rape, fondling, fondle

*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 abbreviation for ‘drunk in public’.

‘abcc’ is an abbreviation for ‘alcohol beverage control comission’.


‘pula’ is an abbreviation 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
<b>Panel A: University Characteristics</b>					
Total Enrollment	29 074.92	14 423.12	28 718.00	3127.00	69 402.00
Total Undergrad Enrollment	22 417.97	11 878.10	22 309.00	2571.00	59 371.00
Fraction Asian	0.07	0.08	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	0.61	0.18	0.67	0.08	0.83
Graduation Rate	70.33	13.78	70.00	39.00	95.00
SAT Math 75th Percentile	655.79	69.11	650.00	480.00	790.00
SAT Reading 75th Percentile	641.26	54.25	640.00	490.00	760.00
Fraction Admitted	0.60	0.21	0.61	0.14	0.94
Fraction Private	0.13	0.34	0.00	0.00	1.00
<b>Panel B: Daily Crime Log Offenses</b>					
Alcohol Offense 	0.46	1.23	0.00	0.00	31.68
Sexual Assault	0.05	0.30	0.00	0.00	15.99
<b>Panel C: Moratorium Characteristics</b>					
Number of Moratoriums per-University	1.36	0.61	1.00	1	3
Length of Moratoriums	64.07	80.90	45.50	6.00	541.00
<i>Total Number of Universities</i>	<i>37</i>				

*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 percentile SAT score for an admitted student. A perfect score is 800, while an average score is approximately 500. Fraction Private refers to the fraction 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
<b>Panel A: Proportion of Alcohol Offenses Reported with Lag</b>				
In Moratorium	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002+ (0.001)
Observations	2120	2120	2120	2120
Mean of Dependent Variable	0.003	0.002	0.001	0.001
<b>Panel B: Proportion of Sexual Assaults Reported with Lag</b>				
In Moratorium	0.010 (0.017)	0.010 (0.017)	0.018 (0.024)	0.024 (0.024)
Observations	2120	2120	2120	2120
Mean of Dependent Variable	0.017	0.014	0.011	0.001
<b>Controls for Panels A and B:</b>				
FE: Day of Week	X	X	X	X
FE: Holiday	X	X	X	X
FE: Game Day	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 and B are OLS regressions of proportions of alcohol 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. 32 of the 37 universities have information on date occurred.

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

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

	(1)	(2)	(3)
<b>Panel A: Alcohol Offenses</b>			
In Moratorium	-0.125*	-0.123*	-0.131**
	(0.047)	(0.051)	(0.046)
Observations	55115	55115	55115
Mean of Dependent Variable	0.464	0.464	0.464
<b>Panel B: Sexual Assaults</b>			
In Moratorium	-0.009*	-0.010	-0.007
	(0.004)	(0.006)	(0.006)
Observations	55115	55115	55115
Mean of Dependent Variable	0.049	0.049	0.049
<b>Controls for Panels A-B:</b>			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Game Day	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 (2) 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 and Sexual Assault by Week-end/Weekdays (OLS).

	Days of the Week		
	All Days	Weekends	Weekdays
<b>Panel A: Alcohol Offenses</b>			
In Moratorium	-0.123*	-0.238*	-0.038
	(0.051)	(0.106)	(0.026)
Observations	55115	23643	31472
Mean of Dependent Variable	0.464	0.828	0.190
<b>Panel B: Sexual Assaults</b>			
In Moratorium	-0.010	-0.017+	-0.004
	(0.006)	(0.010)	(0.006)
Observations	55115	23643	31472
Mean of Dependent Variable	0.049	0.058	0.042
<b>Controls for Panels A-B:</b>			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Game Day	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 (2) 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 on Alcohol Offenses and Sexual Assault by Party School (OLS).

	School Type		
	All Schools	Party Schools	Non-Party Schools
<b>Panel A: Alcohol Offenses</b>			
In Moratorium	-0.123*	-0.223*	-0.053
	(0.051)	(0.101)	(0.034)
Observations	55115	23980	31135
Mean of Dependent Variable	0.464	0.658	0.314
<b>Panel B: Sexual Assaults</b>			
In Moratorium	-0.010	-0.008	-0.011
	(0.006)	(0.007)	(0.010)
Observations	55115	23980	31135
Mean of Dependent Variable	0.049	0.045	0.052
<b>Controls for Panels A-B:</b>			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Game Day	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 Schools represents specification (2) from the main results table. A party school classification is determined from niche.com's list of top partying schools. A university in the top 50 is considered a party school which amounts to 16 of the 37 universities. 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 7: Effect of Moratoriums by Moratorium Length

	Type of Offense	
	Alcohol Offenses	Sexual Assaults
<b>Panel A: Below 33rd Percentile in Length</b>		
In Moratorium	-0.020 (0.069)	-0.005 (0.022)
Observations	55115	55115
<b>Panel B: Between 33rd and 66th Percentile in Length</b>		
In Moratorium	-0.158* (0.069)	-0.020 (0.013)
Observations	55115	55115
<b>Panel C: Above 66th Percentile in Length</b>		
In Moratorium	-0.133+ (0.073)	-0.005 (0.006)
Observations	55115	55115

*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, football game-day, 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.

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

Table 8: Effect of Moratoriums Imposed by the University vs. the IFC

		Days of the Week		
		All Days	Weekends	Weekdays
<b>Panel A: University-Enacted Moratoriums</b>				
<i>Alcohol Offense</i>				
In Moratorium	-0.132+	-0.252+	-0.041	
	(0.065)	(0.136)	(0.035)	
Observations	55115	23643	31472	
<i>Sexual Assault</i>				
In Moratorium	-0.010	-0.019	-0.003	
	(0.008)	(0.013)	(0.007)	
Observations	55115	23643	31472	
<b>Panel B: IFC-Enacted Moratoriums</b>				
<i>Alcohol Offense</i>				
In Moratorium	-0.101	-0.197	-0.030	
	(0.082)	(0.166)	(0.026)	
Observations	55115	23643	31472	
<i>Sexual Assault</i>				
In Moratorium	-0.010	-0.014	-0.007	
	(0.010)	(0.010)	(0.012)	
Observations	55115	23643	31472	

*Note:*

Standard errors clustered by university. Controls follow specification (2) in the main results table with day of week, holiday, semester, football game-day, and university 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 27/44 (61%) 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 17/44 (39%) of the moratoriums in the sample. Weekends represent Fridays through Sundays while Weekdays represent Mondays through Thursdays.

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

Table 9: Effect of Moratoriums in Local Police Departments Compared to University Police Departments (OLS)

	Nearby Police Departments			University Police Departments		
	All Days	Weekends	Weekdays	All Days	Weekends	Weekdays
<b>Panel A: Alcohol Offenses</b>						
In Moratorium	-0.156 (0.130)	-0.201 (0.206)	-0.126 (0.114)	-0.320+ (0.141)	-0.714* (0.290)	-0.029 (0.040)
Observations	13764	5898	7866	13743	5889	7854
Mean of Dependent Variable	1.225	1.930	0.696	0.754	1.403	0.267
<b>Panel B: Sexual Assaults</b>						
In Moratorium	-0.025 (0.016)	-0.011 (0.017)	-0.035 (0.021)	-0.003 (0.017)	-0.013 (0.029)	0.004 (0.013)
Observations	13764	5898	7866	13743	5889	7854
Mean of Dependent Variable	0.478	0.522	0.446	0.055	0.071	0.043
<b>Controls for Panels A-B:</b>						
FE: Day of Week	X	X	X	X	X	X
FE: Holiday	X	X	X	X	X	X
FE: Game Day	X	X	X	X	X	X
FE: Semester (Spring/Fall)	X	X	X	X	X	X
FE: Agency by Academic Year	X	X	X			
FE: University by Academic Year				X	X	X

*Note:*

Nearby Police Departments uses the NIBRS data which pertains to police departments that are closest to the university. University Police Departments uses the Daily Crime Log data set in which contains only university-specific police departments. Only 9 local police departments in the NIBRS data consistently report in the sample period. This table represents the comparison of alcohol offenses and sexual assaults per-25000 enrolled students at the nine local police departments and the corresponding nine universities. Standard errors are clustered by agency for NIBRS data and by university for Daily Crime Log data.

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

# Appendix

## A Robustness Under TWFE

In this appendix, I analyze a model that differs from the main specifications shown in Table 4. In particular, specification (1) 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 the models in Table 4 are 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 when utilizing the variation in treatment timing in a difference-in-differences approach (Chaisemartin and D’Haultfoeulle 2020; Sun and Abraham 2021; Goodman-Bacon 2021; Athey and Imbens 2022). In particular, Chaisemartin and D’Haultfoeulle (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’Haultfoeulle, 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  $t$ ,  $\gamma_u$  are university fixed effects,  $\alpha_t$  are day by month by year fixed effects, and  $\epsilon_{ut}$  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, I re-estimate the results in Table 5.

Table A1 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 19% decrease from the mean during a moratorium, and a 25% 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 A1: Effect of Moratoriums on Alcohol Offenses and Sexual Assault by Week-end/Weekdays (No Negative Weights-OLS).

	Days of the Week		
	All Days	Weekends	Weekdays
<b>Panel A: Alcohol Offenses</b>			
In Moratorium	-0.091+ (0.045)	-0.211* (0.097)	-0.004 (0.017)
Observations	55115	23643	31472
Mean of Dependent Variable	0.464	0.828	0.190
<b>Panel B: Sexual Assaults</b>			
In Moratorium	-0.006 (0.005)	-0.008 (0.007)	-0.004 (0.007)
Observations	55115	23643	31472
Mean of Dependent Variable	0.049	0.058	0.042
<b>Controls for Panels A-B:</b>			
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.

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

## B Substitution Effect Using CSS Data

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. 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.

### B.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 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,<sup>33</sup> and on public property.<sup>34</sup> 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

---

<sup>33</sup>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.”

<sup>34</sup>Per the Department of Education, this is 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.”

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:

$$Y_{u,t} = \beta Moratorium_{u,t} + \gamma_u + \lambda_t + \epsilon_{u,t} \quad (B0)$$

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  $30/365$ ),  $\gamma_u$  are university fixed effects,  $\lambda_t$  are calendar-year fixed effects, and  $\epsilon_{u,t}$  is the error term. Intuitively, Equation B0 is comparing fractions of calendar-years with a moratorium to calendar-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 the paper, I am unable to estimate long-run effects in this setting for two reasons. First, including a year lag results in year 2020, the beginning of the COVID-19 pandemic. COVID-19 drastically changed university 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.

Equation B0 is also less flexible than Equation 1, as it does not account for differences in days of the week, football game-days, academic years, semesters, nor does it restrict to academic-calendar days. Therefore, as mentioned, the estimates from this specification should be taken as speculative, not causal.

## B.2 Results

Table B1 shows the comparison of estimating Equation B0 with the Daily Crime Logs aggregated to the calendar-year level<sup>35</sup> with the CSS data. The Daily Crime Logs show somewhat consistent results with those found in Table 4 column (2);<sup>36</sup> daily averages of alcohol offenses decrease by approximately 38% in calendar years with a moratorium and sexual assaults decrease by approximately 30%, although the level of statistical significance is lower for alcohol—likely due to the imprecision of aggregation.

Although the results using aggregated Daily Crime Logs are relatively similar, the CSS data shows that residence halls experience a 28% *increase* in daily alcohol violations when a calendar year experiences a moratorium. Interestingly, this coincides with the 26% *decrease* found in the main results in Table 4, 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 B with the significant *decrease* in sexual assaults (82%). Hence, 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.

---

<sup>35</sup>This aggregation includes all calendar-year days rather than only academic-calendar days that were used in the main analysis.

<sup>36</sup>I consider this specification to have the most similar interpretation to the specification in this Appendix.

Table B1: 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
<b>Panel A: Alcohol Offenses</b>			
In Moratorium	-0.140+	0.297*	0.270*
	(0.077)	(0.118)	(0.125)
Observations	220	222	222
Mean of Dependent Variable	0.359	0.994	0.941
<b>Panel B: Sexual Assaults</b>			
In Moratorium	-0.012	-0.046	-0.033*
	(0.011)	(0.039)	(0.014)
Observations	220	222	222
Mean of Dependent Variable	0.039	0.079	0.040
<b>Controls for Panels A-B:</b>			
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.

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

## C Appendix Figures and Tables

Table C1: Description of the Triggering Events that lead to a Moratorium

University	Description of Triggering Event	Triggering Event Date	Moratorium Start Date	Classification
Arkansas State University-Main Campus	Arrest of a man suspected of raping a 19-year old woman at a party in a fraternity house.	2017-02-10	2017-02-21	Sexual Assault
Ball State University	Concerns regarding the behavior and actions of members of IFC fraternities.		2017-10-24	Behavior
Cal Poly San Luis Obispo	A report of a sexual assault that allegedly took place at a social event hosted by a Greek group.		2015-01-13	Sexual Assault
Cal Poly San Luis Obispo	Racially insensitive photos surfacing on social media featuring fraternity members in both blackface and gang-related images.	2018-04-08	2018-04-17	Behavior
Clemson University	Alleged sexual assault.	2018-01-27	2018-01-29	Sexual Assault
College of Charleston	Decision was made after consulting with student leaders within the community.		2016-08-30	Unspecified
East Carolina University	An alleged sexual assault on Jan. 25 that provoked an ongoing investigation with the Greenville Police Department.	2015-01-25	2015-01-28	Sexual Assault
Emory University	Report of a sexual assault in a fraternity house.	2014-11-02	2014-11-03	Sexual Assault
Florida Atlantic University	Tailgating issues involving alcohol.		2017-11-28	Behavior
Florida International University	Growing concerns about the state of fraternity and sorority life at FIU as well as around the nation.		2018-01-01	Unspecified
Florida State University	Death of Andrew Coffey.	2017-11-03	2017-11-06	Death
Indiana University-Bloomington	A university spokesperson said the decision came in light of the ongoing national conversation about Greek life and its place on college campuses, as well as challenges on IU's Bloomington campus. The decision is not attributable to one particular incident.		2017-11-27	Unspecified
Louisiana State University	Death of Maxwell Gruver.	2017-09-14	2017-09-14	Death
Louisiana State University	Unclear.		2017-10-19	Unspecified
Marshall University	High-risk behavior in the fraternity community.		2018-03-05	Behavior
Monmouth University	Troubles within the fraternity system.		2018-09-06	Behavior
Murray State University	The letter implementing the suspension indicates that "national trends, and our own review...".		2018-08-27	Unspecified
North Carolina State University at Raleigh	Surfaced newstory of a pledge book that featured racially insensitive remarks and rape jokes.	2018-03-20	2018-03-20	Sexual Assault

Ohio State University-Main Campus	Proactive step based on the significantly high number of investigations this semester, not on the nature of any specific case or cases.		2017-11-16	Behavior
Ohio University-Main Campus	Allegations within the past week of hazing at seven of the fraternities.		2019-10-03	Behavior
Rollins College	The temporary suspension was issued after reviewing a ‘series of student conduct concerns.’		2017-02-21	Behavior
Rutgers University-New Brunswick	Several incidents with alcohol .		2015-04-06	Behavior
San Diego State University	Sexual assault allegations.		2014-11-25	Sexual Assault
San Diego State University	Ongoing concerns related to alcohol.		2018-03-09	Behavior
San Diego State University	Death of Dylan Hernandez.	2019-11-07	2019-11-09	Death
Syracuse University	A string of racist and anti-Semitic incidents.		2019-11-17	Behavior
Texas State University	Death of Matthew Ellis.	2017-11-13	2017-11-14	Death
Tufts University	Accusations of hazing and discrimination.		2016-11-16	Behavior
University at Buffalo	Death of Sebastian Serafin-Bazaan.		2019-04-12	Death
University of California-Berkeley	Reports of sexual assault at off-campus fraternity functions.		2016-10-16	Sexual Assault
University of Central Florida	Decision was made in light of drinking-related controversies.		2018-01-08	Behavior
University of Idaho	A response to the growing national crisis surrounding personal violence like hazing and sexual assault.		2017-12-12	Unspecified
University of Iowa	Death of Kamil Jackowski.	2017-04-30	2017-05-01	Death
University of Kansas	Poor behavior among some Greek groups at the University of Kansas.		2018-03-12	Behavior
University of Michigan-Ann Arbor	Claims of sexual misconduct cases involving fraternity brothers, six incidents of reported hazing, more than 30 hospital transports for students during the weekend of the football game against Michigan State.		2017-11-09	Sexual Assault
University of Missouri-Columbia	Hazing allegations.		2018-03-06	Behavior
University of New Mexico-Main Campus	With three UNM fraternities already in “emergency suspension” following allegations of hazing or alcohol policy violations, administrators have ordered a two-month halt to most social events within the university’s larger Greek system.		2017-12-08	Behavior
University of Pittsburgh	A serious alcohol incident involving members and non-members of one of the fraternities.	2018-01-18	2018-01-19	Behavior
University of Virginia-Main Campus	Rolling Stone article describing the fraternity culture at the school.	2014-11-19	2014-11-22	Sexual Assault



Washington State University	Due to the current negative reputation of the community.		2016-11-07	Unspecified
Washington State University	Death of Samuel Martinez.	2019-11-12	2019-11-14	Death
West Virginia University	Death of Nolan Burch	2014-11-12	2014-11-13	Death
West Virginia University	The result of a Theta Chi brother published a Snapchat video on social media using a racial slur directed at a bartender in a downtown Morgantown club.		2018-02-14	Behavior

*Note:*

Description of the triggering event is summarized based on newsarticles or conversations with Fraternity and Sorority Life staff. The date of the triggering event is shown if provided. The classification of each event is based off of the description and aligns with Figure 2.

Table C2: 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 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 public records 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](https://newscenter.sdsu.edu/sdsu_newscenter/news_story.aspx?sid=75357)

<p align="center"> <b>Indiana University, Bloomington</b>  <b>Police Department</b>  <b>Student Right To Know CAD Daily Log</b>  <b>From Jan 20, 2014 to Jan 20, 2014.</b> </p>		
<b>Date Reported:</b> 01/20/14 - MON at 12:22 <b>Date and Time Occurred From - Occurred To</b> <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> FAILED TO LOCATE	<b>Location :</b> EIGENMANN HALL	<b>Event #:</b> 14-01-20-001434  <b>Report #:</b>
<b>Date Reported:</b> 01/20/14 - MON at 17:03 <b>Date and Time Occurred From - Occurred To</b> 01/20/14 - MON at 17:02 - 01/20/14 - MON at 17:03 <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> CLOSED BY ARREST	<b>Location :</b> ALL OTHER ROADWAYS/INTERS	<b>Event #:</b> 14-01-20-001446  <b>Report #:</b> 140154
<b>Date Reported:</b> 01/20/14 - MON at 19:30 <b>Date and Time Occurred From - Occurred To</b> <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> FAILED TO LOCATE	<b>Location :</b> EIGENMANN HALL	<b>Event #:</b> 14-01-20-001464  <b>Report #:</b>
<b>Date Reported:</b> 01/20/14 - MON at 20:22 <b>Date and Time Occurred From - Occurred To</b> <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> FAILED TO LOCATE	<b>Location :</b> EIGENMANN HALL	<b>Event #:</b> 14-01-20-001466  <b>Report #:</b>
<b>Date Reported:</b> 01/20/14 - MON at 20:45 <b>Date and Time Occurred From - Occurred To</b> <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> FAILED TO LOCATE	<b>Location :</b> FOSTER HARPER HALL	<b>Event #:</b> 14-01-20-001468  <b>Report #:</b>
<b>Date Reported:</b> 01/20/14 - MON at 21:38 <b>Date and Time Occurred From - Occurred To</b> <b>Incident :</b> ALL OTHER OFFENSES - HARASSMENT/INTIMIDATION <b>Disposition:</b> NO CASE REPORT	<b>Location :</b> ALL OTHER NON-UNIVERSITY	<b>Event #:</b> 14-01-20-001476  <b>Report #:</b>
<b>Date Reported:</b> 01/20/14 - MON at 21:53 <b>Date and Time Occurred From - Occurred To</b> <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> FAILED TO LOCATE	<b>Location :</b> ROSE AVE RESIDENCE HALL	<b>Event #:</b> 14-01-20-001479  <b>Report #:</b>
<b>Date Reported:</b> 01/20/14 - MON at 22:30 <b>Date and Time Occurred From - Occurred To</b> <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> FAILED TO LOCATE	<b>Location :</b> COLLINS COMMON AREA	<b>Event #:</b> 14-01-20-001486  <b>Report #:</b>
<b>Date Reported:</b> 01/20/14 - MON at 23:02 <b>Date and Time Occurred From - Occurred To</b> 01/20/14 - MON at 22:45 - 01/20/14 - MON at 23:02 <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> CLOSED NO ARREST.	<b>Location :</b> FOREST QUAD	<b>Event #:</b> 14-01-20-001487  <b>Report #:</b> 140157
<b>Date Reported:</b> 01/20/14 - MON at 23:07 <b>Date and Time Occurred From - Occurred To</b> <b>Incident :</b> NARCOTIC/DRUG LAWS - POSSESSION - MARIJUANA <b>Disposition:</b> FAILED TO LOCATE	<b>Location :</b> FOSTER JENKINSON HALL	<b>Event #:</b> 14-01-20-001491  <b>Report #:</b>
<b>Date Reported:</b> 01/20/14 - MON at 23:35 <b>Date and Time Occurred From - Occurred To</b> 01/20/14 - MON at 23:35 - 01/20/14 - MON at 23:41 <b>Incident :</b> ASSAULT - OTHER ASSAULTS - SIMPLE, NOT AGGRAVATED <b>Disposition:</b> CLOSED BY ARREST.	<b>Location :</b> ALL OTHER OPEN AREAS	<b>Event #:</b> 14-01-20-001494  <b>Report #:</b> 140159
11 Incidents Listed.		
<p align="right"> Print Date and Time    1/21/2014    12:23:52PM    at Page No.    1 </p>		

Figure C1: An Example of a Daily Crime Log

*Notes:* The main analysis uses data from 37 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.

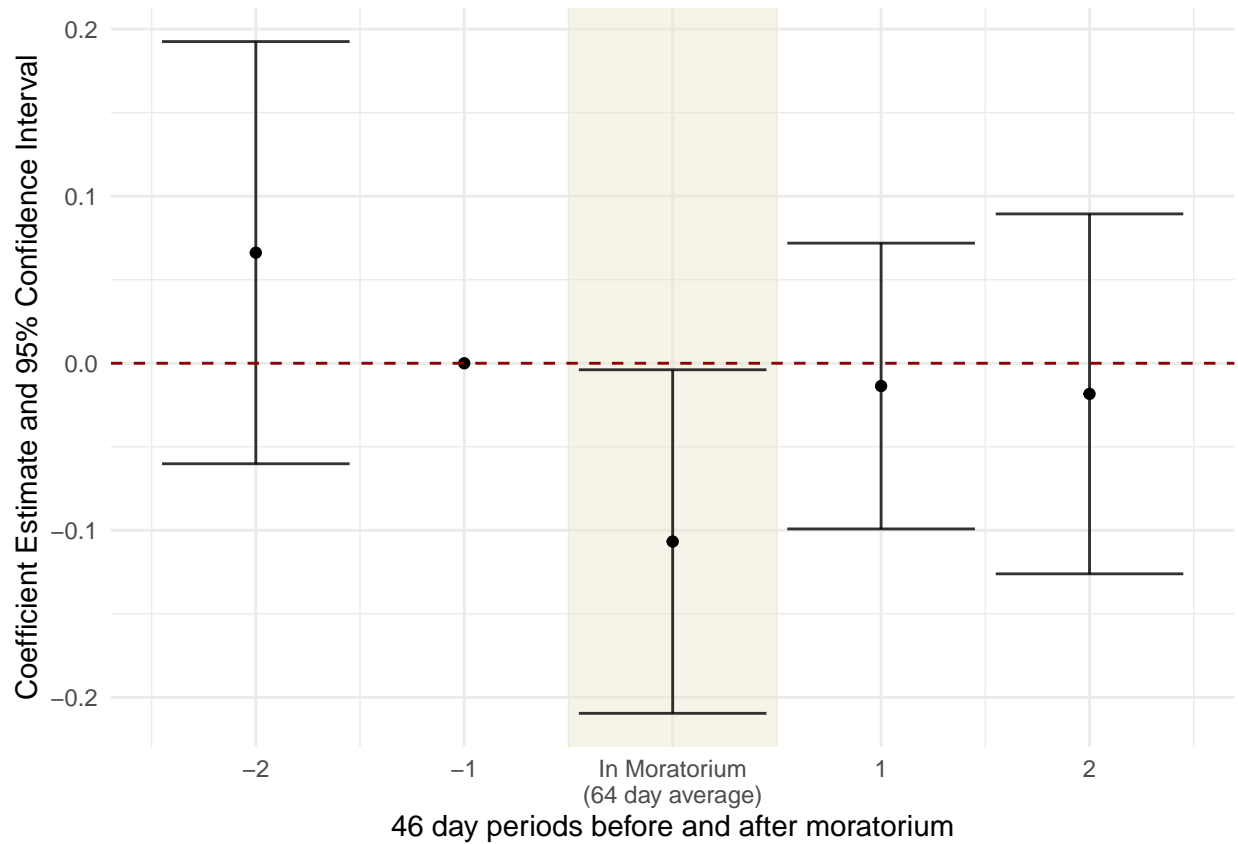


Figure C2: Event Study for Alcohol Offenses

*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, football game-days, and university by academic year. Standard errors clustered by university. All errorbars represent 95% confidence intervals.

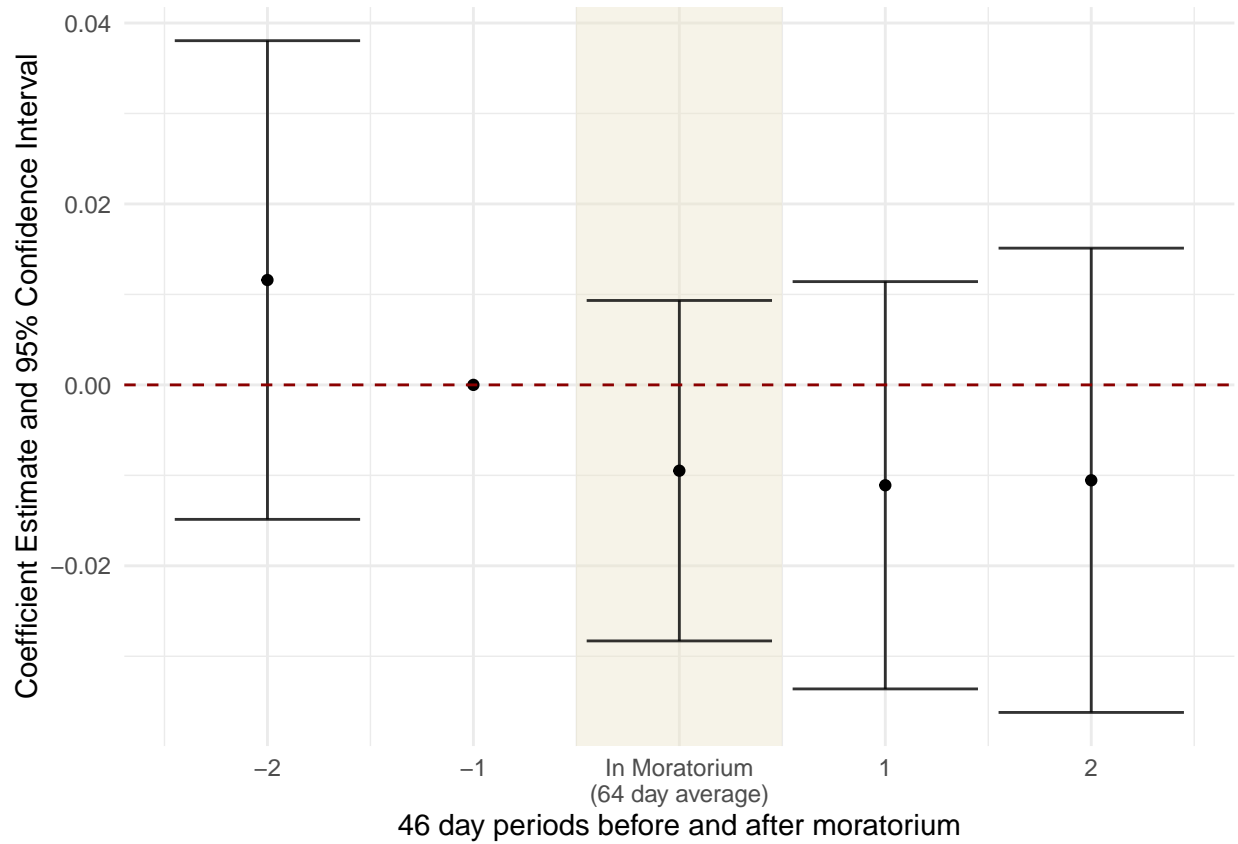


Figure C3: Event Study for Sexual Assault Offenses

*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, football game-days, and university by academic year. Standard errors clustered by university. All errorbars represent 95% confidence intervals.

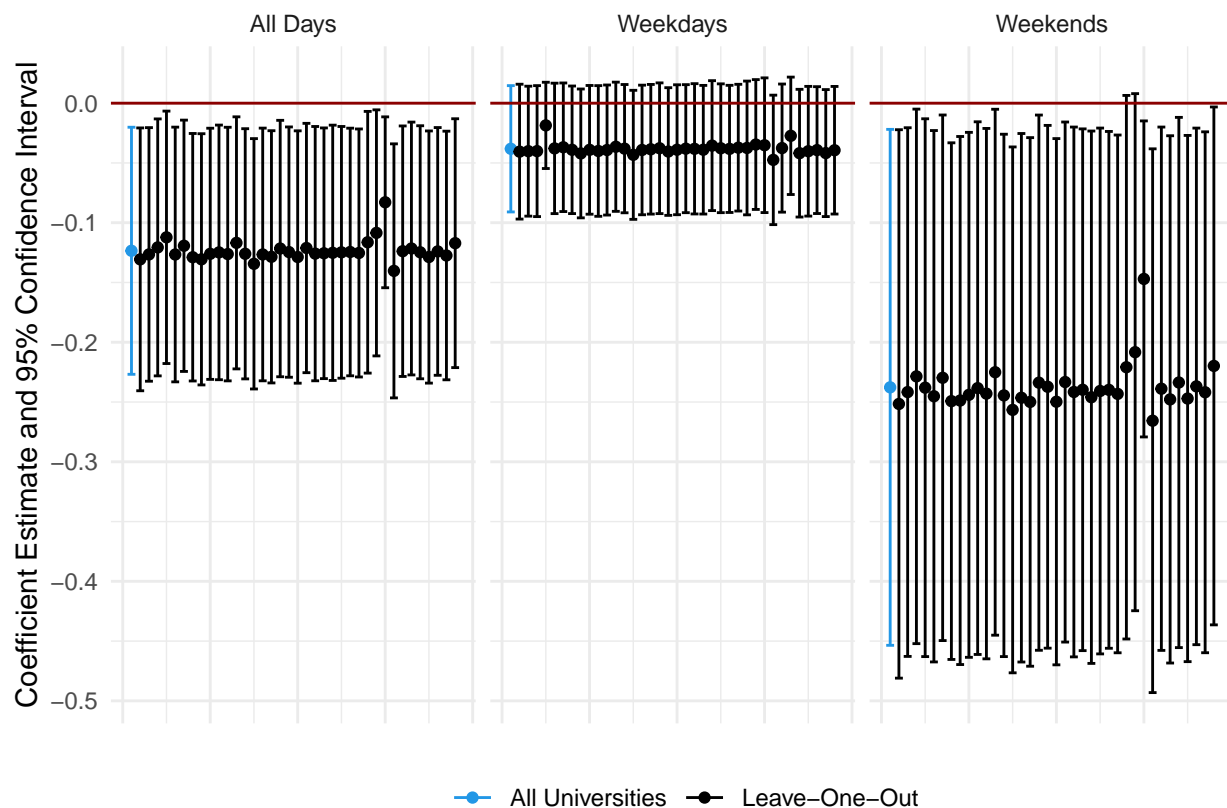


Figure C4: Leave-one-out OLS Regressions of Alcohol Offenses

*Notes:* Each blue point represents the preferred specification (2) from Table 4. Each black point represents specification (2) 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.

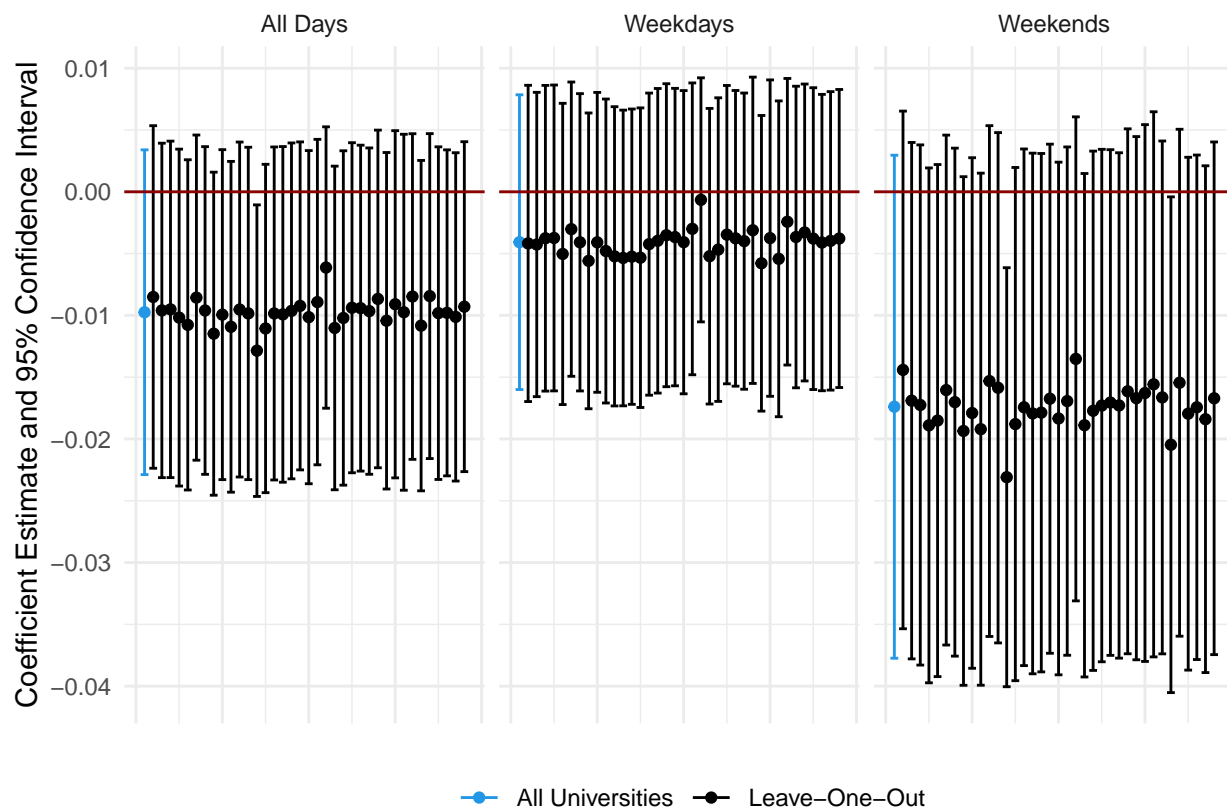


Figure C5: Leave-one-out OLS Regressions of Sexual Assaults

*Notes:* Each blue point represents the preferred specification (2) from Table 4. Each black point represents specification (2) 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.

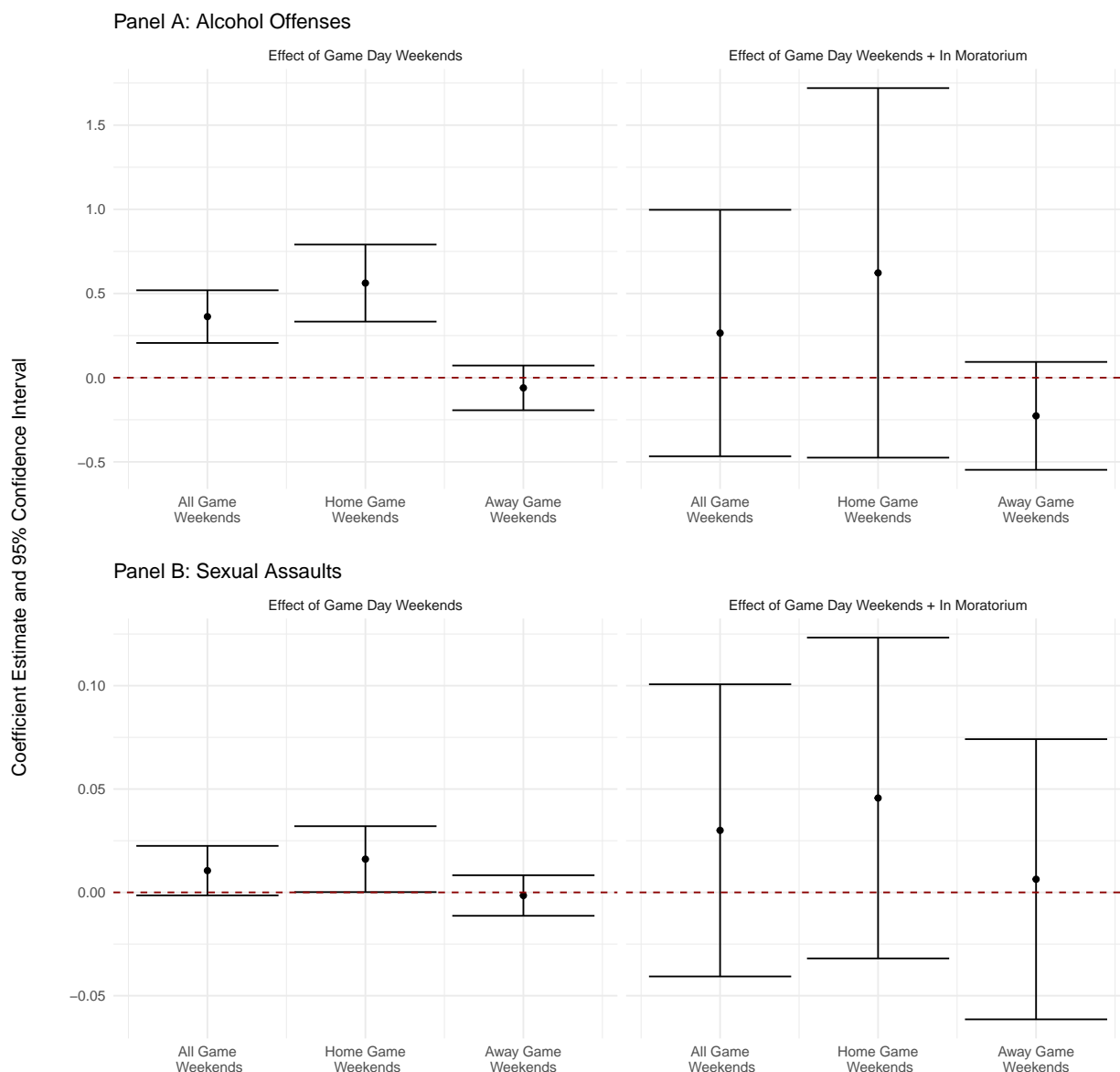


Figure C6: The Effect of Football Game-day Weekends and Football Game-day Weekends + Moratoriums

*Notes:* Game weekends include all football games occurring in the sample period. 34 of the 37 universities have football teams and corresponding game days. The y-axis represents coefficient estimates. Errorbars represent 95% confidence intervals. Each panel is split into two effects: the first effect being the effect of only football game-day weekends on the outcome per-25000 enrolled students, and the second being the effect of a football game-day weekend that occurs within a moratorium. A game-day weekend is defined as a weekend in which a football game occurs. For example, if a game occurs on a Friday, then Saturday and Sunday will be included in the game weekend. Note that weekends are defined as Friday/Saturday/Sunday. "All Game Weekends" includes both home and away games. The effects of game-day weekends + moratorium is identified by 245 football game days that coincide with moratoriums. Controls include holiday, spring semester, day of the week, and university by academic year. Standard errors are clustered by university.

Table C3: Comparison of All Relevant Data Sources

		Data Source		
	Daily Crime Logs	Campus Safety and Security (CSS)	National Incidence-Based Reporting System (NIBRS)	Uniform Crime Reporting System (UCR)
<b>Source and Requirement:</b>				
Source of Data:	University police departments	US Department of Education	FBI	FBI
Reporting Mandate:	By-law	By-law	Voluntary	Voluntary
<b>Aggregation and Consistency:</b>				
Level of Aggregation:	Incident-level	Yearly	Incident-level	Monthly
Fraction Reporting Consistently:	1.00	1.00	0.24	0.78
<b>Offenses Reported and Location:</b>				
Alcohol Violations:	All incidences reported to or by the university police.	All incidences reported to or by any university entity.	Arrests only	None
Sexual Assaults:	All incidences reported	All incidences reported	All incidences reported	Hierarchy rule
Residence Hall Information:	No	Yes	No	No
Analysis in Paper:	Main analysis	Substitution of partying	Spillovers of partying	Not used

*Note:*  
The Daily Crime Logs are used for the main analysis due to the advantages it has over the other sources. The fraction reporting consistently refers row corresponds to the fraction of the sample university police departments. For the NIBRS however, the fraction reported consistently refers to the number of university-specific and corresponding nearby police departments that report consistently. The hierarchy rule is a classification rule by the UCR where only the most serious crime in an incident is reported. While over 50 percent of UCR data is recorded to be reported consistently, the true percentage is difficult to know since NAs and 0s are treated as equivalent in the data.



Table C4: The Top 30 Most Frequently Reported Incident Descriptions

Alcohol Offense	Sexual Assault
alcohol offense (2430)	rape (393)
abcc violation (2311)	sexual assault (324)
intoxicated person (1272)	sex offense (301)
dui (1185)	sexual battery (184)
intx-intoxicated person (1142)	csa report: rape (144)
buying, consume while underage (785)	criminal sexual conduct (114)
minor in possession (764)	campus security authority-sex offense (88)
possession/supply alcohol u/21 (740)	assist other agency-sex offense (77)
public intox (710)	sexual abuse 3rd degree (69)
liquor laws (702)	sex offenses (62)
driving under the influence (694)	sex offense - anonymous (59)
driving under the influence not counted for ucr (625)	sexof-sex offense (41)
public intoxication (620)	sex crime (38)
mip (507)	sex offense (except forcible rape or prostitution) (36)
offenses involving underage persons (482)	sexual assault using physical force or coercion; victim does not sustain severe personal injury (36)
liquor law referral (476)	3rd party report sexual abuse 3rd degree (32)
liquor law arrest (467)	forcible sex offense (32)
minors in possession of alcohol (435)	sexual imposition (32)
liquor laws - illegal possession/consumption (386)	sex offenses - forcible (31)
intoxicated subjects (377)	sex offenses sex offenses (31)
campus security authority-liquor law violation (349)	sexual abuse (30)
all other offenses (except traffic) liquor laws (318)	forcible fondling (29)
medical - medical aid - alcohol/drug (288)	sex offense/forcible rape (25)
alcohol violation (286)	rape rape (23)
public drunkenness (283)	rape-rape -report (23)
driving while intoxicated (251)	criminal sexual contact (21)
intox person 2 (251)	sex offenses-sexual battery (20)
liquor laws illegal possession/consumption (237)	csa report: fondling (18)
mip-alcohol (213)	sex offense - sex offense report (18)
dip (210)	assault/int sex abuse/no injur (17)

*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.

Table C5: Effect of Moratoriums on Alcohol Offenses and Sexual Assault by Week-end/Weekdays. Never-treated schools included. (OLS)

	Days of the Week		
	All Days	Weekends	Weekdays
<b>Panel A: Alcohol Offenses</b>			
In Moratorium	-0.108*	-0.204+	-0.037
	(0.052)	(0.107)	(0.026)
Observations	74469	31935	42534
Mean of Dependent Variable	0.616	1.097	0.254
<b>Panel B: Sexual Assaults</b>			
In Moratorium	-0.010	-0.017+	-0.004
	(0.007)	(0.010)	(0.006)
Observations	74469	31935	42534
Mean of Dependent Variable	0.054	0.063	0.047
<b>Controls for Panels A-B:</b>			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Game Day	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 50 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 C6: Effect of Moratoriums on Alcohol Offenses and Sexual Assault (Poisson Estimation).

	(1)	(2)	(3)
<b>Panel A: Alcohol Offenses</b>			
In Moratorium	-0.216*	-0.305***	-0.328**
	(0.093)	(0.087)	(0.104)
Observations	55115	54151	52541
Mean of Dependent Variable	0.524	0.524	0.524
<b>Panel B: Sexual Assaults</b>			
In Moratorium	-0.164*	-0.199+	-0.187
	(0.076)	(0.110)	(0.117)
Observations	55115	52905	50077
Mean of Dependent Variable	0.051	0.051	0.051
<b>Controls for Panels A-B</b>			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Game Day	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 C7: Effect of Moratoriums on Alcohol Offenses and Sexual Assault by Week-end/Weekdays (Poisson Estimation).

	Days of the Week		
	All Days	Weekends	Weekdays
<b>Panel A: Alcohol Offenses</b>			
In Moratorium	-0.305*** (0.087)	-0.328*** (0.092)	-0.247 (0.161)
Observations	54151	22578	29823
Mean of Dependent Variable	0.464	0.828	0.190
<b>Panel B: Sexual Assaults</b>			
In Moratorium	-0.199+ (0.110)	-0.388** (0.147)	-0.016 (0.141)
Observations	52905	21775	28003
Mean of Dependent Variable	0.049	0.058	0.042
<b>Controls for Panels A-B:</b>			
FE: Day of Week	X	X	X
FE: Holiday	X	X	X
FE: Game Day	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.

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