IMPLEMENTATION ANALYSIS OF CAMPUS SEXUAL VIOLENCE PREVENTION PROGRAMMING

by

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While institutions of higher education provide opportunities for personal and intellectual transformation, they are also prevalent sites of sexual and intimate partner violence in the United States. The Campus Sexual Violence Elimination (SaVE) Act, passed federally in 2013, "require[s] institutions to provide to incoming students and new employees and describe in their Annual Security Reports primary prevention and awareness programs" (Federal Register, 2014) in order to reduce— and ultimately prevent— sexual violence on college campuses. In this paper, I assess institutional interpretations of the Act's requirement for "primary prevention programs".

After selecting 60 schools across six states and institutional classifications (i.e. public, private, Tribal, Associate, Baccalaureate, Master, Doctoral) and affiliations (i.e. religious affiliation), I used the prevention programming information described in their Annual Security Reports to measure their implementation of primary prevention programming. I measured the range in programming against a set of "promising practices" outlined by the National Association of Student and Personnel

Administrators (NASPA) and the Center for Disease Control and Prevention (CDC) . These practices include: provision of prevention to students and other targeted groups (e.g. staff), appropriate timing (e.g. student and staff orientation) sufficient dosage (more than once), its inclusion of bystander intervention and empowerment, and its facilitation by peers. I recorded the implementation of programming within these categories for each school, and then combined the categories to create an overall "Promising Prevention Index" score. Using statistical analysis, I tested the relationship between each "promising prevention" category, as well as the overall Index, and school characteristics (i.e. State, setting, gender and racial composition, undergraduate population and student-faculty ratio, Carnegie Classification, and religious affiliation).

Through these statistical analyses, I found that the state, proportion of black and latino students, as well as Carnegie Classification of each school affected implementation in specific programming categories, as well as the overall Index score. While I point to disparities in funding tied to these factors as a potential justification for their statistically significant relationship with prevention programming, I recommend further research in this area.

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Introduction

From the 2017 viral revival of Tarana Burke's #MeToo movement, to Christine Blazey Ford's televised testimony in the Senate Judiciary Committee, the pervasiveness of sexual violence in the United States is at the forefront of national consciousness. Well evidenced and remembered, one in five women will experience sexual assault in their lifetime, and one in 71 men will experience the same (Black et al,, 2011; Fisher et al., 2000). The rate of violence for American Indian, Alaska Native, and black women, as well as the rate for those identifying as lesbian, gay, bisexual, queer, and transgender, is considerably higher than for white, heterosexual, cis-gendered men and women (Walters et al., 2013).

Sexual violence, which "includes a continuum of behaviors such as attempted or completed rape, sexual coercion, unwanted contact, and non-contact unwanted experiences like harassment" (Black, et al., 2011) is experienced disproportionately by gender, sexual, and racial identities (Black et al., 2011; Walters et al., 2013). It is also experienced disproportionately by age and context. Most survivors of sexual assault are harmed between the ages of 18 and 24 (Black et al., 2011), making college campuses particularly prevalent site for violence. The most recent Association of American Universities "Climate Survey on Sexual Assault and Sexual Misconduct" provides an up-to-date illustration of the incidence, prevalence, and characteristics of sexual violence on U.S. college campuses. As expected, the survey found significant levels of sexual violence on college and university campuses, with disparities in the prevalence of sexual misconduct among different categories of students (Cantor et al., 2019). According to the study, the overall rate of nonconsensual sexual contact by physical force or inability to consent since the student enrolled is 13%, with undergraduate women and undergraduate transgender, gender queer, and nonconforming students experiencing significantly higher rates of sexual violence than men and graduate students. Considering the high incidence of violence at colleges and universities, campuses have been, and increasingly are, an important— and necessary— sites for prevention policy efforts (McCauley, 2015).

Following increased awareness and alarm in the 1970's and 1980's around sexual violence on college campuses, federal legislation was passed to mandate that institutions address sexual violence (Jessup et al., 2018). Primary among these laws is the Jeanne Clery Disclosure of Campus Security Policy and Campus Crime Statistics (Clery) Act. The Act, passed in 1990 and amended in 2013, requires public and private institutions that receive federal funding to report information about certain crimes, including crimes about sexual violence. As part of their transparent disclosure of crimes, schools must report crimes in an Annual Security Report and maintain a detailed, accessible crime log. Under the law, both the Annual Security Report and crime log must include incidents that occur on, around, and sometimes off campus. Beyond disclosing crimes in an Annual Security Report, the Act also requires schools to issue timely warnings and implement an emergency response system. Underlying the Act is the mandate to protect the confidentiality of survivors (*Clery Act*, n.d.). While response and reporting constitute the foundation of the Clery Act, recent amendments incorporate primary prevention more explicitly into the law's purview.

The most recent amendment made to the Clery Act , which incorporates a mandate for primary prevention campaigns, is the focus of my research. In 2013, Violence Against Women Act (VAWA) updated the Clery Act, expanding the scope of the policy in terms of reporting and response. The VAWA amendment, which itself is called the Campus Sexual Violence Elimination (SaVE) also “require[s] institutions to provide to incoming students and new employees and describe in their Annual Security Reports primary prevention and awareness programs” (Federal Register, 2014). My research will assess the institutional interpretation of the amendment’s requirement for “primary prevention” programs— those which “intend to prevent the development of a disease and the occurrence of injury, and thus, to reduce the incidence in a population” (Goldsteen et al., 2015).

Research Questions

In my thesis, I aim to answer the following questions:

1. How does the implementation of prevention programming mandated by the Campus SaVE Act vary across institutions?

2. What factors could be driving variations in implementation?

3. What recommendations can be made to further push research, policy, and programming in this area?

In answering these questions, I ultimately hope to give researchers, administrators, and policy-makers alike an illustration of institutional implementation of the 2013 VAWA amendments to the Clery Act, an explanation of the factors driving variation in implementation, and recommendations to guide further research and policy.

Literature Review

My intended research contributes to a growing body of work on campus sexual violence prevention and policy.

Much of the recent literature on sexual violence prevention consists of meta-analyses on strategies for prevention that have passed rigorous effectiveness evaluations. While most meta-analyses agree that very few strategies for sexual violence prevention have proven to be effective in reducing rates of and attitudes towards, sexual violence, particularly within colleges and universities (Degue et al., 2011; Newlands, 2016), some strategies have emerged as promising practices. Researchers agree that the most promising of practices are those that are evidence-based. (Banyard, 2014; Degue et al., 2011; Katz et al, 2013; McCauley et al., 2015). Primary among evidence-based prevention strategies is bystander intervention and empowerment training (Katz et al., 2013; McCauley et al., 2015). A bystander is a “person who is present when an event takes place but isn’t directly involved” (RAINN). Bystander intervention involves stepping into a situation— oftentimes a potentially harmful one— in order to change the outcome. In addition to bystander intervention training, the meta-analyses agree that in-person education workshops— in which educators facilitate training on topics such as healthy sexuality and consent— conducted by trained students or staff produce effective results (Banyard, 2014).

While bystander intervention training conducted through in-person trainings are considered among the most promising practices for campus sexual violence prevention, only three actual programs have passed rigorous evaluation testing (Degue et al., 2011). While proven effective, these programs are not directly aimed at college students. The first of these effective strategies is *Safe Dates* (Foshee & Langwick, 2004), which is a 10-session curriculum focused on consequences of dating violence, gender stereotyping, conflict management skills, and attributions for violence. Another is the *Shifting Boundaries* program (Taylor et al., 2012). This program implements temporary building-based restraining orders, a poster campaign to increase awareness, “hotspot” mapping, and school staff monitoring over a 10 week period. The last statistically significant program found by Degue 2011 is funding associated with the 1994 U.S. Violence Against Women Act. The Act funded programs to improve criminal enforcement, victim advocacy, and state and local capacity, and showed a reduction in annual rape rates (Degue et al., 2011). While researchers, policy-makers, and administrators agree that evidence-based practices are necessary, only a handful of elements (i.e. in person trainings that cover by-stander intervention) and actual programs (i.e. *Safe Dates, Shifting Boundaries,* and funding associated with VAWA) have provided enough evidence to constitute prevention’s promising practices.

Another important area of existing literature is that of evidence-based frameworks for prevention created by government agencies and student affairs associations. Together, these frameworks will be incorporated in my strategy for evaluating the implementation of prevention programming across US schools. Both the Center for Disease Control (CDC) and the National Association of Student Personnel Administrators (NASPA) have recommended guidelines for prevention based on evidence based promising practices.These are included in the CDC’s “Preventing sexual violence on college campuses: Lessons from research and practice” (2014) and in NASPA’s recommended “Culture of Respect: CORE Blueprint” (2018)**.** Both of these reports— though with varying language and prioritization— make clear the components of effective campus sexual violence prevention. These components include: provision educational programs regularly throughout a student's tenure; bystander skills and empowerment opportunities, and provision of targeted programming for specific groups —particularly university faculty and staff— ongoing provision of programming, and appropriately timed programming (Culture of Respect, 2018; CDC, 2014). While the language I use is specific to the CORE Blueprint, the guidelines incorporate evidence found in the aforementioned meta-analyses and in the CDC's publishings. I will ultimately use the CORE Blueprint language in my evaluation of the primary prevention implementation.

In addition to research analyzing evidence for effective sexual violence prevention strategies, there is also significant literature analyzing federal policies that address campus sexual violence and mandates its prevention. Literature in this area primarily addresses the Title IX of the Education Act of 1972, which prohibits sex discrimination within any educational programs receiving financial aid or assistance (Know Your IX, n.d.); and also addresses the aforementioned Clery Act of 1990, amended most recently in 2013. Much of the literature analyzing these policies focuses on the unintended negative consequences of mandatory reporting policies (Driessen, 2019; Perkins et al., 2017). Scholars agree that mandatory reporting policies, those that require victim advocates and faculty members to report disclosure of sexual violence deprive students of an additional confidential resources (Perkins et al., 2017). Scholars also analyze the ambiguity of language regarding mandatory reporting in recent Clery Act amendments, focusing on the varied interpretation and policy development following the Campus SaVE Act, the VAWA amendments to the Clery Act (Royster, 2017). While a vast literature exists on sexual violence prevention, and the federal policies that mandate its implementation on college campuses, explicit analysis of the implementation of primary prevention programs following the 2013 Clery Act amendments is still lacking. By conducting a scan of the implementation on primary prevention programs on a random sample of federally funded institutions, I hope to fill a gap in the extensive literature on campus sexual violence prevention and its policy.

Methods

The first step in my research design was to identify the selection criteria of the schools that I would be researching. The two driving factors in selection were the location and classification of each school. Because I wanted to explore the potential impact of state sexual violence prevention policy on school prevention programming, I decided to focus my research on schools within a select number of randomized states. In order to ensure that the schools were not geographically clustered, I decided to pick states in different regions of the country. Because the nature of my research focuses on school policy, administration, and student affairs, I decided to pick states across the National Association of Student Personnel Administrators (NASPA) programming regions. After using a random value generator with state FIPS codes, I ended up narrowing my research to colleges in California, Idaho, New Mexico, Arkansas, Indiana, and Connecticut. In order to increase my chances of finding patterns in variation of prevention programming across states (and the factors I will mention below), I selected 10 schools in each state— 60 total.

In addition to wanting to explore the impact of state factors on school prevention programming, I also wanted to explore the impact of type of school— that is, the highest degree awarded by schools— on prevention programming. In order to do this, I identified the different types of schools according to the Carnegie Classification system, and then randomly selected schools within those classification. I ended up with between 1-3 Associate, Baccalaureate, Master, and Doctoral schools within each state. Although I included two Tribal colleges in New Mexico, most colleges were scattered evenly across the four previously mentioned categories. Out of the 60 schools on which I conducted research, two schools were designated “Tribal”, 11 schools were designated “Associate”, 12 were designated “Baccalaureate”, 19 were designated “Master”, and 11 were designated “Doctoral”.

The next factor I considered in my selection criteria was whether schools were public or private. Although the SaVE Act applies to both public and private colleges alike, I wanted to investigate whether the robustness of prevention programming changed based on this status. The schools on which I did research were nearly half public and private— 29 were public and 31 were private.

The final category that I used to base selection criteria was the religious affiliation of schools. Because many religious schools receive Title IX and certain Campus SaVE exemptions (U.S. Department of Education, 2020), I was curious to find the impact an institution’s religious affiliation would have on its prevention programming. I ensured that at least one school in each state would be religiously affiliated. A total of 15 schools I researched had a religious affiliation.

In order to study both the range in prevention programming of each university, as well as the factors that impact prevention, I collected two types of information for each school. The first was demographic information about each school. In addition to the information that I mentioned above, such as type of school, the religious affiliation, and whether the schools were public or private, I also collected information on the school setting, undergraduate and overall student body size, student-faculty-ratio, and school profit-status. I also collected data on the gender and racial composition of each school. While the race categories that I recorded included: “White”, “Hispanic or Latino”, “Black or African American, Asian, Native Hawaiian or Other Pacific

Islander", "American Indian or Alaska Native", and "Unknown" I combined the last three categories into one both because all three amounted to a small proportion of the racial make-up of the schools I investigated, and because of issues of multicollinearity between "American Indian or Alaska Native" "Tribal" schools, and New Mexico. I collected this data exclusively from the National Center for Education Statistics.

The second type of data that I collected was information directly related to institutional prevention programming. I collected this information from each school's most recent Annual Security Report. As directed in the Campus SaVE Act, schools are mandated to indicate prevention programming within their yearly— Clery Act mandated— Annual Security Report. A link to each institution's Annual Security Report can be found in Appendix 1. As I mentioned previously, I was interested in researching prevention programming through the lens of promising practices recommended by both the CDC and NASPA's aforementioned CORE Blueprint. These components include (most obviously) the provision of educational programming, the requirement that this programming be offered regularly, the appropriate timing of programming, inclusion of bystander intervention and empowerment opportunities, the training of college students by peers, and programming for specific groups, particularly university faculty and staff.

Taking these promising practices into account, I combed through each institution's Annual Security Report and answered a set of questions that I created around the provision of prevention, timing and dosage of programming, inclusion of bystander intervention, and implementation by peers. In order to capture the full range of programming, I inquired about programming that was both offered and mandatory for each school. However, given that mandatory programming ensures that as many students receive prevention skills and information, I employed the mandatory prevention questions in my statistical analysis. The questions I asked, in accordance with the promising prevention categories that I identified, are listed below.

Table 1— Prevention Programming Checklist

Promising Prevention Categories	Questions
Provision of Prevention for Students	• Is primary prevention offered for students? • Is primary prevention mandatory for students?
Provision of Prevention for Staff	• Is primary prevention offered for staff? • Is primary prevention mandatory for staff?
Timing	• Is primary prevention mandatory for students during first year? • Is primary prevention mandatory as part of orientation? • Is bystander intervention mandatory for students first year? • Is bystander intervention mandatory for students as part of orientation? • Is primary prevention for staff mandatory as part of orientation? • Is bystander intervention mandatory for staff as part of orientation?

Dosage	• If provided, is primary prevention offered for students more than once? • If provided, is primary prevention offered for students at least once annually? • If provided, is primary prevention offered for students on an ongoing basis? • Is primary prevention mandatory for students more than first year? • Is primary prevention mandatory for students annually? • If included, is bystander intervention offered for students more than once? • If included, is bystander intervention offered for students at least once annually? • If included, is bystander intervention offered for students on an ongoing basis? • Is primary prevention offered for staff more than once? • Is primary prevention offered for staff on an ongoing basis? • Is primary prevention mandatory for staff more than once? • Is primary prevention mandatory for staff annually? • Is bystander intervention offered for staff more than once? • Is bystander intervention training offered for staff on an ongoing basis? • Is by-stander intervention training mandatory for staff more than once?

Bystander Intervention	• If primary prevention is offered to students, does it include bystander intervention? • Is by-stander intervention training mandatory for students? • If primary prevention is provided to new faculty and staff, does it include by-stander intervention training? • Is by-stander intervention training mandatory for staff?
Peer-Led Education	• Is offered bystander intervention peer-led? • Is mandatory bystander intervention peer-led?

In addition to collecting data on each of the aforementioned categories, I recorded whether or not schools administered online prevention education, in-person education, or as some schools stated in their security reports, in-print education. Because schools that described their programming did not always specify whether trainings are conducted online or in-person, I did not statistically analyze this measure.

After conducting research on a number of schools that indicated little to no programming information, I created “Minimal Information” and “No Information” categories within my survey.

After collecting data on all 60 schools, I coded the data. Because I was planning on eventually creating an index consisting of the addition of “yes” answers within each of the “promising prevention” categories that I listed above, I coded “yes” answers as “1”, and “no” answers as “0”. Initially, with schools that had minimal information on their Annual Security Reports, I coded the missing answers as “.” For schools that had no information, I coded the “No Information” variable as 1, and the rest as “0”. While I maintained this approach while collecting data, when I created the index— which I will discuss further below— I re-coded missing data as “0”.

After coding my responses, I began a threefold analysis process. In order to summarize over 40 dependent variables into more legible and overarching “promising prevention” categories, I combined data that fell into the categories shown in the above table. The resultant categories were: Mandated Student Primary Prevention, Mandated Staff Primary Prevention, Mandatory Orientation Student Programming, Mandatory Student First-Year Programming, Mandatory Staff Orientation Programming, Student Dosage, Staff Dosage, Mandatory Staff Bystander Intervention, Mandatory Student Bystander Intervention and Peer-Led Education. While most of the categories are intuitive, I want to further explain the “Student Dosage” and “Staff Dosage” categories. These were each composed of variables relating to whether primary prevention, and more specifically, bystander intervention programming, were mandated for students more than once or annually. Because there was little difference between the number of schools that mandated programming more than once and that mandated programming annually, I coded “Dosage” variables as “1” if either sub-variable was coded “1”.

After summarizing my variables into a subset of “promising prevention” categories, I created an “Promising Prevention Index” to even further summarize my data. In order to create this index score, I added up the scores of each of the individual categories. The index originally ranged from 0-10. However, after testing whether the difference between each value was statistically significant, I found that several values did not have statistically significant differences[1]. These values were 2, 3, and, 4— which I coded as 3, and 5 and 6, which I coded as 5.5. In this index, schools that had more programming had a higher index score— the highest being 7—, while schools that had less programming had a lower index score— the lowest being zero. The score provided me with a clear and concrete indicator of prevention programming implementation between schools.

After creating both the Promising Prevention Index as well as its individual components, I used an Ordinary Least Square regression model in order to estimate the relationship between each of the index sub-components (i.e. provision of prevention programming, timing, dosage, bystander-intervention, peer-led education) and school characteristics[2]. These characteristics variables included: the states in which schools were located (i.e. California, Arkansas, Connecticut, Idaho, Indiana, and New Mexico), the setting in which these schools were located (i.e. rural, town, suburb, city), the size of the undergraduate student body, the racial composition (i.e. White, Black, Latino, Asian, and "Other", which as I mentioned previously, was comprised of Native Hawaiian and other Pacific Islander, Native American and Alaska Native, and Unknown), the public or private status, the Carnegie Classification (i.e. Tribal, Associate, Baccalaureate, Master, Doctoral), as well as the religious affiliation of each school. The coefficient estimated in each regression equation provided me insight into the effect and the statistical significance of the effect, that each independent variable, or

1 The lack of statistical significance was found in the cut points of the Ordered Logistic Regression.

2 With a binary dependent variable, these OLS regressions are known as Linear Probability Model estimates. While logistic estimation would generally be preferred with a binary dependent variable, some correlations among independent variables create problems in convergence for logistic equations using maximum likelihood techniques.

school characteristic, had on the interpretation of prevention programming at each school.

To test the relationships between the Promising Prevention Index and the aforementioned school characteristics, I used an Ordered Logistic Regression Model. I used this model because while the dependent variables in the sub-categories were binary categorical variables, the index is an ordinal discrete dependent variable, that is, a variable in which the order of the outcome values matter, but not the spacing between values. In order to test that the difference between one outcome value to the next was significant, I tested the statistical significance of the estimated cut points between the ordinal values[3]. This test indicated that the difference between some scores were not statistically significant. In order to only test the index scores with differences that were statistically significant, I combined the categories that were not significantly different from each other. After combining these categories, I ran the Ordinal Logistic Regression and was able to determine the effect and statistical strength that the independent variables had on individual Index scores.

3 I used the "test _b[/cut1] = _b[/cut2]" function.

Results

In this section, I will first discuss the results first of the descriptive statistical analysis shown in the tables below, and then of the regression analysis that I conducted on the Promising Prevention Index and each of its subcomponents.

Table 2— Descriptive Analysis of **Promising Prevention Practices**

Dep Var: Primary Prevention Students	Dep Var: Primary Prevention Staff	Dep Var: Orientation Prevention for Students	Dep Var: Orientation Prevention for Staff	Dep Var: First-Year Prevention for Students
65	58.33	61.67	41.67	63.33
Dep Var: Dosage Students	Dep Var: Dosage Staff	Dep Var: Bystander Intervention Students	Dep Var: Bystander Intervention Staff	Dep Var: Peer-Led Education
20	33.33	43.33	21.28	6.67

Index Score	*% Scored*
0	20%
1	10%
2, 3, or 4	15%
5 or 6	25%
7	11.67%
8	15%
9	3.33%
10	0

Table 3— Descriptive Analysis of **Promising Prevention Index**

My descriptive analysis of the index sub-components revealed several trends in institutional prevention programming. As evidenced in the above table, I found that across the index sub-components, that schools provided programming more often for students than for staff. The same was true for the timing of prevention education. More schools provided programming for students during orientation— the optimal time for education— than for staff. This trend did not apply to the “Dosage” of prevention education. I found that more schools mandated ongoing programming for staff than for students. As for “Peer-Led Education”, my last index sub-component, I found that a slim proportion—only 6.67% of colleges and universities— implemented peer-led education.

My descriptive analysis of the Promising Prevention Index revealed— apart from the top scores— a mostly even spread across Prevention Index scores. I found that a fifth of schools scored “0”. I found that 25% scored between one and four, and another quarter scored a five or six. The last quarter of schools were spread between seven, eight, and nine, with only 3.33% of schools scoring a nine . None of the schools received 10, the highest Index score.

Primary Prevention for Students

I will now discuss the results of my regression analysis of the Promising Prevention Practices (i.e. Index sub-components). The first of the index components is provision of mandatory primary prevention education. As indicated in Table 4, when I regressed this variable on the aforementioned school characteristics, I found that type of school— its Carnegie classification— has significant impacts on the provision of mandated programming for students. School classification has a varied impact on student programming— both in its degree and significance. As compared to Baccalaureate programs (as well as other school demographics and characteristics), Associate colleges have a 47.3% lower chance of providing mandated primary prevention for students. These results were statistically significant at the 95% confidence level. Also indicated in Table 1, universities classified as “Doctoral” had a coefficient of .318. This means that Doctoral schools are 31.8% more likely to provide mandated prevention programming for students. These results indicate that as compared to Baccalaureate programs, associate colleges have significantly less mandatory programming, while Doctoral schools have significantly more programming.

Targeted Programming: Primary Prevention for Staff

As indicated in Table 5, when I regressed this the “Primary Prevention for Staff " variable on the school demographics and characteristics, I found again that school classification has a statistically significant effect on staff programming. As compared to Baccalaureate programs, Doctoral universities had a coefficient of .436. This coefficient, which was statistically significant at the 95% confidence level, indicated that Doctoral schools are 43.6% more likely to mandate prevention programming for staff than baccalaureate schools.

In addition to type of school, I also found for the staff prevention variable that state had a statistically significant impact on provision of mandated programming. Taking California as the base case, universities in Idaho are 67.5% less likely to mandate staff programming than schools in California. These results indicate that the type of school and state in which schools are located have— to varying degrees and significance— statistically significant impacts on mandated staff prevention programming.

Timing

As mentioned previously, the “Timing” category is composed of the mandated provision of student and staff programming during orientation, as well as the mandated provision of primary prevention during a student’s first year. When I regressed these variables related to the timing of prevention education, I again found that school classification had impacts that were statistically significant. As indicated in Table 6, compared to Baccalaureate schools, Associate schools are less likely to provide mandated student programming during orientation, while schools with Masters programs are significantly more likely to provide programming during student orientation. With a coefficient of -.436, Associate colleges are 43.6% less likely than Baccalaureate schools to provide prevention programming for students during orientation. Master's schools on the other hand, had a coefficient of .293, indicating that schools with this classification, as compared to Baccalaureate schools, are 29.3% more likely to mandate student prevention programming during orientation. For mandatory first-year student programming, I found that at the 99% level of confidence, Associate schools are 55.8% less likely than Baccalaureate schools to provide mandated prevention programming during a student's first-year. I also found that Doctoral programs are 34.4% more likely to provide mandated programming during the first year. For staff, I found that Master institutions had a coefficient of .352 while Doctoral institutions had a coefficient of .469 at the 95% level of confidence. While institutions that award Master's degrees are 35.2% more likely to provide programming to staff during orientation, Doctoral programs are 46.9% more likely to provide programming during that period. All of these findings indicate again that school classification has significant but varying effects on the timing of mandated programming.

In addition to finding that school classification has an effect on the timing of mandated prevention programming, I also found that racial demographics of schools significantly impact timing. With regard to orientation programming for students, I found that for every 1% increase in the latino student population of an institution, that the likelihood that mandated programming occurs during orientation falls by 123.2%.

For the first-year category, I found that for every 1% increase in a school's latino student population, the likelihood that training is provided during a student's first year falls by 101.7%. Lastly, for the timing of staff programming, I found that for every 1% proportional increase of black students, the likelihood that mandated prevention occurs during orientation falls by 327.7%. This finding is significant at the 99% confidence level.

Dosage

I did not find any statistically significant correlation between the student and staff dosage of prevention programming and school characteristics.

Bystander Intervention

As indicated in Table 8, when I regressed my student bystander intervention variables and school characteristics, I found significant relationships between the provision of bystander intervention and state, racial composition, and classification of each school. For student-mandated bystander intervention, I found that with a coefficient of -.601 and a level of confidence of 95%, Associate schools are 60.1% less likely than Baccalaureate schools to mandate bystander intervention for students.

Also indicated in Table 8, when I regressed my staff bystander-intervention variables, I found that as compared to Baccalaureate institutions, that doctoral schools are 50.3% more likely to mandate bystander intervention training for staff. This finding was significant at the 95% level of confidence. I also found that in comparison to schools in California, schools located in New Mexico have a 95.9% lower chance of mandating bystander intervention for staff. This finding was statistically significant at the 95% confidence level. Lastly, I found that taking white students as the base case, for every 1% increase in a school's asian student population, the likelihood that training is provided during a student's first year falls by 420.7%. Overall I found — to varying degrees— that school classification, state, and racial composition are significantly correlated.

Peer-Led Prevention

I did not find a statistically significant relationship between peer-led programming and school characteristics.

Promising Prevention Index

Consistent with the results of the above mentioned regressions, the ordered logistic regressions that I ran between the index and school characteristics indicated that school classification, racial make-up, and state have a statistically significant relationship with school promising prevention programming. As indicated in Table 10, schools classified as "Doctoral" have a significantly lower likelihood of having a low Index score, and a significantly higher chance of having a higher score. To elaborate, Doctoral schools have an 11.1% chance of scoring "1", 9.6% chance of scoring a "2", "3", or "4" (recoded as "3", but appears on the table as the second value) , and an 18.8% chance of receiving a "5" or "6" (recoded as 5.5, but appears as the third value on the table). Correspondingly, I found that Doctoral schools have 14.6% chance of scoring an "8" on the Promising Prevention Index. All of these results are significant at the 95% confidence level. These findings indicate that Doctoral universities provide significantly more robust prevention programming than Baccalaureate schools.

In addition to finding that the relationship between the type of school and the Promising Prevention Index is statistically significant, I also found that the proportion of black students at an institution has a statically significant relationship with its Prevention Index score. For every 1% increase in the proportion of black students, the likelihood that institutions score “1” on the Prevention Index increases by 98.5%. Similarly, as the proportion of black students increases, the likelihood that schools score 2, 3, or 4 increases by 77.7%. Correspondingly, as the proportion of black students increases, the likelihood that schools score a “9” decreases by 85.7%. These findings—all statistically significant at the 95% confidence level— indicate that as compared to proportion of white students, the higher the proportion of black students at an institution, the less that sexual violence prevention is provided.

Lastly, the likelihood that schools in New Mexico would have low scores was significantly higher, and the likelihood that schools in New Mexico would have high scores was significantly lower. To further elaborate, for schools in New Mexico, the likelihood scoring a two, three, or four was 12.9%. This likelihood was significant at the 95% confidence level. Correspondingly, the likelihood of a school receiving a 9 (indicated as the seventh value in the table) decreased by 9.85%. This finding is significant at the 95% confidence level. This finding indicates that schools in New Mexico provide significantly less sexual violence programming.

Discussion

In this research project, I originally set out to investigate how the primary prevention has been implemented across colleges and universities in each state following the 2013 Campus SaVE Amendment to the Clery Act. Based on the identified elements of "promising prevention" by NASPA's Core Blueprint, I also set out to identify which school characteristics significantly affect differences in implementation. Based on factors driving disparities in implementation, I also set out to propose ways in which Campus SaVE Act could be more specific in its expectations around "primary prevention" based on aforementioned "promising practices" as well as the provision of resources to institutions that may not be equipped to provide robust programming.

After collecting and analyzing data on 60 schools across six states around the provision of primary prevention for students and staff, the timing and frequency of programming, as well as the provision of bystander intervention training and peer-led education, I was able to determine both the range in implementation of prevention programming, as well as factors that significantly affect programming. I was able to determine the range in prevention programming from the Index score that I created from the aforementioned prevention categories. After conducting descriptive analysis on the index score, I found that the robustness of prevention programming was dispersed evenly across each index score. I estimated the impact of the factors contributing to variation through Ordinary Least Squares regression analysis as well as Ordinal Logistic Regression analysis. Through these statistical tests, I found that the significant factors driving variations in the range of prevention programming are type of school, the proportion of black and latino students, as well as the state in which institutions are located.

The first factor that consistently had a statistically significant effect on prevention programming implementation was the Carnegie Classification of each school. I found that across different index subcategories, as well as within the index itself, the higher degree awarded by institution, the higher likelihood of providing more robust prevention programming— and of receiving a higher index score. As compared to Baccalaureate colleges Associate colleges are significantly less likely to mandate primary prevention for students, to provide mandated prevention during a student's first year, and to provide mandated bystander intervention training for students. As compared to Baccalaureate colleges, Doctoral colleges are significantly more likely to mandate prevention education for staff, and significantly more likely to provide this programming during staff orientation. Doctoral colleges are also— to a statistically significant degree— less likely to receive lower index scores, and more likely to receive higher index scores. Ultimately, the higher the degree, the more in line with promising practices are school sexual violence prevention programs.

While the underlying reason for the correlation between degree-type and strength of prevention programming is an area ripe for further research, potential justifications for the disparity in programming between Associates and Doctoral programs could relate to the amount of private and public funding of each university. It is no secret that Associate colleges— funded both federally and by states— receive inadequate funding (Smith, 2019). Meanwhile, the federal government spends billions of dollars on universities in the form of research and development (R&D) grants

(Comen, et., al, 2017). A technical report on the Carnegie Classification system discusses how 80% of federal research and development funding is allocated towards Doctoral universities (2001), some of which accrues to universities as general overhead. This funding complements the influx of funding from private sources, such as “businesses, nonprofits, and universities coffers” (Comen, et., al, 2017). The disparity in funding sources and amounts between Associate and Doctoral colleges could account for the statistically significant disparity in Index scores— and prevention programming — between both types of schools.

Another factor driving differences in prevention to a statistically significant degree is the proportion of minority students— specifically black and latino students— at a given college or university. This conclusion is evidenced by the finding that taking white students as the base case, colleges with higher proportions of black students are less likely to provide mandated primary prevention for staff during staff orientation. This conclusion is ultimately evidenced by the fact that to a statistically significant degree, for every 1% increase in the institutional proportion of black students, the likelihood of receiving a lower prevention score increases and the likelihood of receiving a higher score decreases.

The effect that proportion of minority students has on the implementation of “promising” prevention programming is yet another area for research. A potential reason for the fact that the proportion of minority students has a statistically significant impact on the breadth of programming could be that controlling for the type of school, that students of color attend lower funded institutions. Senator and former presidential candidate Elizabeth Warren stated that “One of the bleak realities we have to acknowledge is that […] as we move to a higher population that is more African American and more Latino, there is less enthusiasm among some parts of the American voting public for investing in those students and communities" (quoted by Smith, 2019). Warren essentially argues that programs that serve minority students— such as already poorly funded colleges— receive diminishing funding because of their high enrollment by black and brown students. The link between attendance of black students at poorly funded institutions could relate to the lack of robust prevention programs at institutions with a higher proportion of black students.

The final factor that I found drives differences to a statistically significant degree— though only in the Promising Prevention Index— is the state of the school, specifically New Mexico. I found that schools located in New Mexico— half of which did not report prevention programming in their Annual Security Report— are significantly more likely to receive lower Index scores. Correspondingly, schools in New Mexico are significantly less likely to receive higher Index scores. Ultimately, schools in New Mexico, as compared to California, provided significantly less prevention programming.

Other than New Mexico, I did not find significant differences in prevention programming across states. This was a surprise to me, as I expected programming patterns to emerge between states. New Mexico's unique impact on prevention programming is another ripe area for future research. Like with both previous findings, the reason for New Mexico's relationship with less extensive programming could lie in New Mexico's higher education funding crisis. For example, budget cuts between 2008 and 2018 to New Mexico's higher education amounted to

30% per student. These post Great Recession budget cuts were the second-worst in the country (Mitchell, et. al., 2018). Severe budget cuts to public universities could account for the disproportionately lower prevention programming within New Mexico’s institutions of higher education.

While funding likely has something to do with the factors driving the range in promising prevention programming, this is a prime field for further research. Future research could look deeper into funding and its relationship not only with sexual violence prevention programming, but also other higher education prevention and health promotion efforts. Future research could also focus on how differences in prevention programming impact campus sexual health and sexual violence indicators. While small but growing body of research exists within the field of higher education sexual violence prevention, better policy and programming depends on future research.

Appendix 1: Links to College and University Annual Security Reports

Albertus Magnus College

Anderson University

Arkansas State University, Beebe

Arkansas Tech University

Boise Bible College

Boise State University

Brigham Young University, Idaho

Brookline College, Albuquerque

California State University, Long Beach

California State University, Monterey Bay

College of the Ouachitas

College of Western Idaho

Concordia University, Irvine

Connecticut College

Gateway Community College

Hanover College

Harding University

Henderson State Univesity

Holy Cross College

Housatonic Community College

Idaho State University

Indiana Institute of Technology

Indiana State University

Indiana University Northwest

Ivy Tech Community College, NorthCentral

John Brown University

Laguna College of Art and Design

La Sierra University

Lewis-Clark State College

Lincoln College of Technology, Indianapolis

Mitchell College

National Park College

Navajo Technical University

New Mexico Highlands University

New Mexico Junior College

New Saint Andrews College

North Idaho College

Northern New Mexico College

Northwest Nazarene University

Occidental College

Sacred Heart University

Scripps College

Southern Arkansas University

Southern Connecticut State University

Southwestern Indian Polytechnic Institute

Southwest University of Visual Arts

Trinity College

University of Arkansas

University of Bridgeport

University of California, Santa Barbara

University of Central Arkansas

University of Evansville

University of Idaho

University of New Mexico

University of Phoenix, New Mexico

University of Redlands

University of Southern Indiana

Vincennes University

Western New Mexico University

West Valley College

Yale University

Appendix 2: Tables Displaying Linear Probability and Ordinal Logic Regression Models

Table 4— Linear Probably Model Explaining: **Primary Prevention for Students**

Variables	*Coefficient*	*Standard Deviation*
Arkansas	-0.335	-0.359
Connecticut	-0.23	-0.31
Idaho	-0.522	-0.324
Indiana	-0.486	-0.338
New Mexico	-0.21	-0.335
City	0.17	-0.136
Undergraduates	3.38E-06	-5.31E-06
Latino	-1.055	-0.634
Black	-0.912	-0.974
Asian	-1.382	-1.741
Other	-0.532	-0.441
Public	0.129	-0.183
Associate	-0.473**	-0.214

Master	0.218	-0.164
Doctoral	0.318*	-0.186
Religious	0.0336	0.0336
Constant	1.102***	-0.377
Observations	60	
R-squared	0.481	

Standard errors in parentheses	**** p<0.01, ** p<0.05, * p<0.1*

Table 5— Linear Probably Model Explaining: **Primary Prevention for Staff**

Variables	*Coefficient*	*Standard Deviation*
Arkansas	-0.285	-0.407
Connecticut	-0.148	-0.352
Idaho	-0.675*	-0.368
Indiana	-0.0867	-0.383
New Mexico	-0.534	-0.38

City	0.143	-0.155
Undergraduates	3.53E-06	-6.03E-06
Latino	-0.174	-0.719
Black	-1.391	-1.105
Asian	-0.181	-1.975
Other	0.203	-0.501
Public	-0.201	-0.208
Associate	0.101	-0.243
Master	0.199	-0.186
Doctoral	0.436**	-0.211
Religious	-0.0556	-0.213
Constant	0.860*	-0.428
Observations	60	
R-squared	0.375	

Standard errors in parentheses	**** p<0.01, ** p<0.05, * p<0.1*

Table 6— Linear Probability Models Explaining Variables Related to **Timing** of Programming

	Dep Var: Orientation Prevention for Students		Dep Var: Orientation Prevention for Staff	
Variables	*Coefficient*	*Standard Deviation*	*Coefficient*	*Standard Deviation*
Arkansas	-0.332	-0.363	0.0622	-0.408
Connecticut	-0.117	-0.314	0.333	-0.353
Idaho	-0.48	-0.328	-0.371	-0.369
Indiana	-0.548	-0.342	0.203	-0.385
New Mexico	-0.187	-0.339	-0.31	-0.381
City	0.111	-0.138	0.0481	-0.155
Undergraduates	4.23E-06	-5.37E-06	2.21E-06	-6.05E-06
Latino	-1.232*	-0.641	-0.298	-0.722
Black	-1.167	-0.985	-3.277***	-1.109
Asian	-0.971	-1.761	-0.397	-1.982
Other	-0.608	-0.447	0.218	-0.503

Public	0.141	-0.185	-0.128	-0.209
Associate	-0.436*	-0.217	0.245	-0.244
Master	0.293*	-0.166	0.352*	-0.187
Doctoral	0.253	-0.188	0.469**	-0.212
Religious	0.0559	-0.19	0.0275	-0.214
Constant	1.085***	-0.382	0.514	-0.43
Observations	60		60	
R-squared	0.489		0.37	

Standard errors in parentheses	**** p<0.01, ** p<0.05, * p<0.1*

Table 7— Linear Probability Models Explaining Variables Related to **Dosage** of Programming

	Dep Var: Prevention Dosage for Students		Dep Var: Prevention Dosage for Staff	
Variables	*Coefficient*	*Standard Deviation*	*Coefficient*	*Standard Deviation*
Arkansas	0.169	-0.365	0.363	-0.455
Connecticu	0.259	-0.315	-0.012	-0.393

t				
Idaho	-0.0345	-0.33	0.0149	-0.412
Indiana	-0.147	-0.344	0.263	-0.428
New Mexico	-0.0214	-0.341	-0.0675	-0.425
City	-0.0731	-0.139	0.218	-0.173
Undergraduates	7.29E-07	-5.40E-06	-4.30E-06	-6.74E-06
Latino	-0.0391	-0.645	0.413	-0.804
Black	-1.068	-0.991	0.317	-1.236
Asian	0.578	-1.771	2.064	-2.209
Other	-0.37	-0.449	0.343	-0.56
Public	0.0515	-0.186	0.314	-0.232
Associate	-0.336	-0.218	-0.255	-0.272
Master	-0.0338	-0.167	-0.178	-0.208
Doctoral	0.0393	-0.189	0.015	-0.236
Religious	0.038	-0.191	0.161	-0.239

	3			
Constant	0.327	-0.384	-0.166	-0.479
Observatio ns	60		60	
R-squared	0.237		0.145	

Standard errors in parentheses	**** p<0.01, ** p<0.05, * p<0.1*

Table 8— Linear Probability Models Explaining Variables Related to Provision of **Bystander Intervention**

	Dep Var: Bystander Intervention for Students		Dep Var: Bystander Intervention for Staff	
Variables	*Coefficient*	*Standard Deviation*	*Coefficient*	*Standard Deviation*
Arkansas	0.0386	-0.38	-0.679	-0.441
Connecticut	0.388	-0.329	-0.308	-0.381
Idaho	-0.0551	-0.344	-0.666	-0.399
Indiana	0.0169	-0.358	-0.393	-0.415
New Mexico	0.0242	-0.355	-0.959**	-0.412

City	0.038	-0.145	-0.00555	-0.168
Undergraduates	-1.13E-06	-5.63E-06	-9.71E-06	-6.54E-06
Latino	-0.555	-0.672	0.453	-0.78
Black	-1.724	-1.033	-1.381	-1.198
Asian	1.44	-1.846	-4.207*	-2.141
Other	-0.676	-0.468	-0.0817	-0.543
Public	0.21	-0.194	-0.198	-0.225
Associate	-0.601**	-0.227	0.392	-0.263
Master	0.0997	-0.174	0.154	-0.202
Doctoral	0.222	-0.198	0.503**	-0.229
Religious	-0.129	-0.129	-0.0897	-0.231
Constant	0.559	-0.4	1.143**	-0.464
Observations	60		60	
R-squared	0.278		0.459	

Standard errors in parentheses	**** p<0.01, ** p<0.05, * p<0.1*

Table 9— Linear Probably Model Explaining: Inclusion of **Peer-Led Education**

Variables	*Coefficient*	*Standard Deviation*
Arkansas	-0.0122	-0.231
Connecticut	0.0103	-0.2
Idaho	-0.0851	-0.209
Indiana	0.0608	-0.218
New Mexico	-0.181	-0.216
City	0.0231	-0.0879
Undergraduates	-1.68E-06	-3.42E-06
Latino	0.102	-0.408
Black	-0.639	-0.628
Asian	0.484	-1.122
Other	0.131	-0.285
Public	-0.193	-0.118
Associate	0.0451	-0.138

Master	0.00553	-0.106
Doctoral	0.0732	-0.12
Religious	-0.154	-0.121
Constant	0.213	-0.243
Observations	60	

Standard errors in parentheses	**** p<0.01, ** p<0.05, * p<0.1*

Table 10— Ordinal Logistic Regression Model Explaining: **Promising Prevention Index**

	Dep Var: Arkansas		Dep Var: Connecticut		Dep Var: Idaho	
Index Values	*Coefficient*	*Standard Error*	*Coefficient*	*Standard Error*	*Coefficient*	*Standard Error*
1	- 0.0078058	0.1281604	- 0.0994257 *	599248	0.2265323	0.2777061
2	-	0.1034093	-	0.0545234	0.1129176	0.0825294

	0.0062342		0.0869942			
3	-0.0093514	0.1595947	-0.1714818	0.1098712	0.0665152	0.0694128
4	0.0077147	0.1217953	-0.0330818	0.1700178	-0.2158781	0.1997764
5	0.0075924	0.129508	0.1369462 *	0.0792316	-0.098186	0.0670009
6	0.0071675	0.1240209	0.2177333	0.2401676	-0.0819081	0.0541804
7	0.0009168	159002	0.0363039	0.0538453	-0.0099928	0.0103537
	Dep Var: Indiana		Dep Var: New Mexico		Dep Var: City	
Index Values	*Coefficient*	*Standard Error*	*Coefficient*	*Standard Error*	*Coefficient*	*Standard Error*
1	-0.0243638	0.1078582	0.3428503	0.3268462	-0.0264145	0.0533789
2	-0.0199514	0.0911437	0.1284609 **	0.0579135	-0.020755	0.0421503
3	-0.0317936	0.1574434	0.0386104	0.1077679	-0.0301174	0.0606915
4	0.0217448	0.0777772	-0.2813384	0.1756071	0.0267475	0.0558116
5	0.0257945	0.1289328	-0.1179955 *	0.0629446	0.0246133	0.0487639

6	0.025282	0.1333534	-0.0985316**	0.049987	0.0229965	0.0464161
7	0.0032874	0.0175756	-0.0120561	0.0113043	0.0029296	0.0064992
	Dep Var: Undergraduates		Dep Var: Latino		Dep Var: Black	
Index Values	*Coefficient*	*Standard Error*	*Coefficient*	*Standard Error*	*Coefficient*	*Standard Error*
1	1.80E-05	1.96E-06	0.0731615	0.2532761	0.9845961**	0.4430563
2	9.29E-07	1.57E-06	0.057705	0.2021032	0.776585**	0.392053
3	1.35E-06	2.27E-06	0.08408	0.2926594	1.131535*	0.621656
4	-1.20E-06	2.08E-06	-0.0746926	0.2622815	-1.005201	0.6516605
5	-1.10E-06	1.83E-06	-0.0684482	0.2367048	-0.9211652*	0.4872085
6	-1.03E-06	1.71E-06	-0.0637069	0.2222337	-0.857358**	0.3997626
7	-1.30E-07	2.38E-07	-0.0080988	0.0289698	-0.1089922	0.0907571
	Dep Var: Asian		Dep Var: Other		Dep Var: Public	
Index	*Coefficient*	*Standard*	*Coefficient*	*Standard*	*Coefficient*	*Standard*

Values		*Error*		*Error*		*Error*
1	-0.1623062	0.6562945	0.0979932	0.178699	-0.0337247	0.0682394
2	-0.1280165	0.5175403	0.0772906	0.1453593	-0.0263649	0.0541112
3	-0.1865284	0.75011	0.1126175	0.2071802	-0.0379245	0.0747871
4	0.1657028	0.6688517	-0.1000439	0.190838	0.0341871	0.0699275
5	0.1518499	0.6115208	-0.0916802	0.1676671	0.0310928	0.0622244
6	0.1413316	0.5753911	-0.0853297	0.1564495	0.0290352	0.0585485
7	0.0179669	0.0723161	-0.0108476	0.0216263	0.003699	0.0080625
	Dep Var: Religious Affiliation					
Index Values	*Coefficient*	*Standard Error*				
1	0.0309383	0.0811494				
2	0.0234128	0.0587302				
3	0.031193	0.0718904				
4	-	0.0915682				

	0.0333706					
5	- 0.0258829	0.0611156				
6	- 0.0233586	0.0529077				
7	-0.002932	0.0068667				

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