Local Political Context and Pro-Palestinian university encampments

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1 Introduction

The Pro-Palestine encampments in Spring of 2024 were one of the largest student-centric protests of the 21st century so far, with estimates of thousands of students across the country participating in protest encampments, and thousands were arrested (Habeshian 2024). The protests were clearly political, with many encampments focusing their ire on the current Democratic administration's foreign policy regarding Israel and Palestine (Popli 2024). However, not every university had an encampment, and not every encampment had the same level of participation.

Did the political context of a university impact whether its students decided to have an encampment at that university? Existing evidence is mixed, with previous research finding varying levels of support of the impact environmental political factors have on protests (Edwards 2014, 90; Sabine 2006). Additionally, due to the recency of these protests, there is not much literature regarding the pro-Palestine movement's recent student encampments.

I argue that local political context matters in whether an encampment occurred at a university campus. More specifically, that the more Democratic an area, the more likely there will be an encampment that will be larger. This is because broadly, the current Democratic party is more open to protest, seen with large portions of its base supporting the Black Lives Matter Movement, and recent polling data that shows that Democrats are more sympathetic towards Palestinians than Republicans (PEW Research Center 2018; Gallup 2023). This leads to two possible causal mechanisms that I label: the preference mechanism and the punishment mechanism. The preference mechanism claims that greater amounts of partisan allies in an area means there are more potential people that would start or join a protest. Meanwhile, the punishment mechanism asserts that in environments where the partisan makeup of local and regional governments are opposed to certain social movements, those social movements are less likely to generate protests because of the fear of repression by potential protestors.

In order to test my argument, I utilized a mixed methods research design, utilizing both quantitative and qualitative methods to help test my argument. For the quantitative analysis, I ran a hierarchical regression, with data collected from encampments from over 1,200 4-year universities in the U.S. compared with the university's 2020 county voting record. For the qualitative data, interviews were conducted with members of the encampment at UCSD, to identify common patterns in themes and identify true process and motivation.

The quantitative data supports my hypothesis that democratic political contexts made encampments more likely, and also larger. The results provide some evidence that suggests that political context can impact whether social protests occur, especially when the partisan political context is one that is more open towards protest.

This research sits within a gap in the political science field regarding the student-led Pro-Palestine movement. It also works to contribute knowledge of social movements in the specific field of political science. Future research could try to interview encampment participants from other universities, particularly those from red states where the encampments were forcefully ended rapidly, such as in Georgia and Texas. Additionally, more research could be done in understanding the outcomes of the encampments, namely whether they ended in a negotiated agreement or ended by force.

2 Literature Review

2.1 Introduction

There is extensive literature examining social movements, protests, and contentious politics. This literature review will focus on the relationship between political science and social movement literature. It will then analyze the specific theories of social movements as they relate to political opportunities and partisan electoral politics. Third, this review will analyze ideological political beliefs in relation to how likely an individual is to join a protest. Then, this review will look at University demonstrations specifically. Finally, this literature review will discuss the importance of mixed methods design in analyzing social movements from a political science perspective.

This paper covers contemporary events that are extremely contentious. In an attempt to remain as unbiased as possible, the term pro-Palestine will be used to refer to those who participated in or heavily sympathize with the encampments that occurred at university campuses worldwide. While this term does not fully encapsulate a lot of the nuances and even disagreements within the pro-Palestine movement, as Chenoweth et al. in 2024 notes that alternative terms are “even less satisfying characterizations.” For example, Chenoweth et al. finds that generalized categorizations of the pro-Palestinian movement as “anti-Israel” are “empirically incorrect.”

2.2 Resource Mobilization and Political Process Theories

The field of contentious politics, which includes all forms of protest, has been interdisciplinary in nature, with overlap between sociology, political science, anthropology, history, and even social psychology (Tarrow 2021). However, certain research of contentious politics is uniquely suited to the field of political science. In her journal article Kateřina

Vráblíková writes that sociologists use political science concepts for analysis of social movements, which gives a major boon to conducting research on social movements within the political science field (Vráblíková 2017, 5-6).

Historically, there are three analytical approaches to studying social movements: class analysis, role theory, and structural functionalism (Walder 2009, 394-395). What all three approaches share in common is that they try to relate social structures to the character of the social movements; however, they all failed to accurately predict social movements, and as a result, resource mobilization theory became the predominant theory (Walder 2009, 396).

Resource mobilization has its roots in the rational choice theory of the economist Mancur Olson. Traditional theories of why protests occurred relied on the idea that people had grievances and deprivation from their government that naturally spurred them to protest in response. However, Olson challenged this traditional paradigm with his introduction of rational choice theory. Rational choice theory focuses on the fact that the members of a social movement are rational actors, and they have to weigh material costs and benefits when deciding whether to join a protest (Mueller 1992, 3). In fact, this idea that individual activists are rational actors was recently corroborated in a study of the 2020 Black Lives Matter protests by Chenoweth et al. published in 2022. This study found that protestors made a deliberate decision based on potential costs and benefits associated with participating in the protests (Chenoweth et al. 2022, 21 and 27).

Rational choice theory laid the foundations for resource mobilization theory, which focuses on the ability for a movement to gain participation through material and immaterial resources. As a result, many analysts look for factors outside of the social movement that could potentially inhibit or enhance the potential for a social movement to mobilize (Meyer 2004).

More specifically, resource mobilization theory focuses on what resources are available for a movement, how the movement organizes, how the state facilitates or impedes mobilization, and what the outcomes of the protest/social movement are (Mueller 1992, 3-4). For the scope of this paper, the predominant focus will be in determining if the state/local political environment impeded or aided mobilization for these protests, with some attention drawn to the outcomes of the protests as well.

Political process theory is considered an extension of resource mobilization theory, as it not only centers the mobilizing problem as central, but it also assumes there is an internal cost benefit analysis that rational actors make when deciding whether to participate in a form of social movement (Edwards 2014, 79-80). However, political process differs from resource mobilization theory as instead of focusing on internal resources a movement has, political process theory analyzes the political context in relation to protests and social movements (Edwards 2014, 79-80). Moreover, proponents of political process theory assert that the strategies and decisions employed by activists do not occur in a vacuum, and thus that the political context matters in the mobilization and outcome of potential protest (Meyer 2004). Essentially, political process theory asserts that without a favorable political context, then protests will struggle to achieve any desired outcomes. This could be for two reasons. First is the system level explanation, wherein politicians and bureaucrats implement policies that are favorable or repressive towards social movements because of the community support in an area for that social movement. This is what I am calling the punishment mechanism. A non mutually exclusive alternative is that of the community support itself, where more support for perceived partisan allies means that protests have more resources and people willing to join their own movement. This is what I am calling the preference mechanism. While this study does empirically attempt to isolate these two causal mechanisms, they can both be measured by viewing community support for partisan political candidates.

2.3 Political Environment and Opportunities

This paper focuses on analyzing the local political environment of US universities. Political environment and political context are terms in the literature that are generic, with researchers tending to avoid large conceptual definitions in favor of identifying specific variables needed for their specific endeavor (Eisinger 1973, 11-12; Meyer 2004). Nevertheless, the idea of studying a political environment is important, as Eisinger notes that environments can constrain activity and thus deter mobilization (Eisinger 1973, 11-12). Essentially, protests do not occur in a vacuum, and while definitions may vary depending on the specific research question, it is nonetheless important to analyze the role of partisan politics and state actors in mobilization of protests. In fact, previous research has operationalized the political environment to mean the support presidential candidates received within a local area (Huckfeldt 1995, 1026). This legitimizes this studies operationalizing of the political environment on the national scale by focusing on county level data for the 2020 presidential election.

One of the major ways in which political science can uniquely answer puzzles in regards to resource mobilization is by analyzing political opportunities and structures. Traditionally, researchers in political science have defined political opportunities to reflect the 'openness' or 'closedness' of state institutions (Kitschelt 1986, 61). The openness and closedness of an institution often refers to the willingness of governmental forces to crackdown on protest, and the willingness of legislatures to work with activists. It is thus argued that the more open an institution, the more conducive it is to demonstrations and protests (Kitschelt 1986, 61-62). This is because opportunities, policies, and environments that are conducive to protest in political structures shapes the orientations, growth, and success of movements, as seen empirically during the civil rights movement in 1950s and 1960s (Walder 2009, 403). Moreover, it is hypothesized that the state can deter mobilization through threats of violence, however the research is mixed in support of this hypothesis (Sabine 2006, 1). This only adds to the potential knowledge this research could contribute.

There is also debate in current social movement literature regarding whether there is enough attention paid to electoral party politics and political context (Vráblíková 2017, 17). This further allows this thesis to sit within the context of this larger debate and hopefully provide evidence that demonstrates a relationship between politics and social movements. This is especially true considering that only a few studies have been conducted examining the effect that partisanship has on protests (Silver 2023).

Evidence from the Black Lives Matter Protests in 2020 indicate that partisanship influenced support of police repression (Silver 2023). This empirically suggests that there is a possible relationship between partisanship and the responses towards protests dependent on how the protest itself is viewed. This is potentially because the public support and response signals to policymakers what methods and posture towards the protest are politically viable for them to use (Silver 2023). This suggests that if a local political context is strongly opposed to a protest and its aims, then their attitude towards suppression and repression by governmental entities would be more favorable. This would suggest that protests that occur in local contexts with a larger base of partisan opposition would yield fewer protests, and that the ones that materialize would also be smaller. Likewise, in areas with more numerous political allies there would be more and larger protests. However, these ideas often lack rigorous empirical backing due to a lack of current available literature on the relationship between partisanship and protest existence and size. This research thus seeks to understand the relationship between partisanship and whether a protest materializes in the context of the 2024 Spring Pro-Palestine university encampments.

2.4 Leftism and Protests

The left-wing, defined as a broad range of political ideologies that seek to mitigate inequality (occasionally with ties to Marxism and or socialism) is historically associated with a higher propensity to mobilize in favor of protest (Torcal et al. 2016). Moreover, empirical evidence suggests that individuals protest under more right-wing governments than under left-wing governments (Torcal et al. 2016). This is because of two possible reasons, which may not inherently be conflictual. One is that the historical legacy of leftism values protest as this was a common theory of power employed by leftists (Kostelka 2019, 1680). The second explanation is that the ideological objectives of the left naturally align themselves with forms of contentious politics such as protest (Kostelka 2019, 1680-1681).

This situates this research well in trying to understand more local political contexts to determine if this finding remains true with right-wing local political contexts. It thus can be argued that the more left-wing a political environment, the more resources are available to protests, namely in the form of actual participants. This is especially true are there is a growing increase in polarization between the two major political parties in the U.S., with some members of the center-left Democratic party aligning themselves more with the pro-Palestine movement (Rynhold 2020). This occurrence lends further credence to the idea that the more votes the Democratic candidate received, the more successful the mobilization of a pro-Palestine encampment.

In the United States, between the two major parties the Democratic party is considered the party to be more in line with ideological values of the left, with policy proposals typically more centered on some level of economic redistribution and reducing inequality in comparison to Republicans' more laissez faire approach (Zacher 2024). While generalizing, this does put the Democratic party closer as ideological allies to leftism and progressivism than the Republican party. Additionally, contemporary polling data seems to strongly indicate that Democrats tend to be more sympathetic towards Palestine and more critical towards Israel than Republicans (PEW Research 2018; Gallup 2023). This is why I argue that Democrats are more sympathetic and even supportive of the Pro-Palestine Encampments than Republicans, which leads into the hypothesis.

While partisan voting relationships may not perfectly overlap with political ideology, this paper seeks to rectify that throughout its design by utilizing a mixed methods approach and using two cuts of quantitative data.

2.5 University Protests

There is much evidence that supports that tertiary education drives political activism and collective action, making the University a unique environment to analyze the effect of political structures and opportunities on protests (Dahlum and Wig 2021). Dahlum and Wig specifically identify social networks, organizations, opportunity costs, and focal points as factors that university's influence in creating a more conducive environment for protest, yet they also note that the link between tertiary education and mass protest is still poorly understood due to a lack of large-N studies and a focus on political membership operationalized as party membership. This leads to a gap in the literature that this paper can sit within by analyzing the recent pro-Palestine protests that occurred in Spring of 2024.

In trying to understand the size of Pro-Palestine demonstrations, Chenoweth et al. hypothesized that the actual actions of Israel and the U.S. in Gaza lead to the wide-scale pro-Palestine mobilization. However, this ignores the more pragmatic local material political context that impacts not only if a pro-Palestine demonstration occurs, but also its ability to grow in size, which is what this paper seeks to examine. Chenoweth et al. also recognizes that while the terms pro-Israel and pro-Palestine may flatten nuances within both movements, they are still the most accurate terms available.

While historically there is limited research from political science analyzing University protests in The United States, McCarthy et al. analyzed numerous University anti-war protests and demonstrations during the Vietnam war. They identified protest size as the key independent variable in analyzing when police crack down on protests (McCarthy et al. 2007, 278). While the scope of this paper is different, McCarthy et al.'s study does protest size as a relevant variable in studying University protests and also gives possible clues as to why repressive political environments would try and intentionally mitigate the growth of a University protest.

2.6 Importance of Mixed Methods Research Design

As Vráblíková identifies, the lack of quantitative and qualitative mixed methods research has limited the capacity of political science to empirically answer questions as it pertains to social protest (Vráblíková 2017, 24). While the structure of social relations is best studied with quantitative methods, qualitative methods are better to understand actions of individual agents and motivations (Thaler 2017, 60). This lends itself to the scope of this paper, which seeks to understand the relationship between protest size and political context. Quantitatively, this paper will look at a large-N sample and quantitatively analyze relationships between protest size and operationalized quantitative data for political context, while the qualitative side can be used to further isolate causality with political context in directly interacting with organizers and participants of the pro-Palestine demonstrations. This method combines the strengths identified in the literature as noted by Vráblíková and Thaler.

3 Hypotheses

There is one broad overarching hypothesis for this paper, which is as follows: A more partisan democratic political context results in more and larger Pro-Palestine encampments. This overarching hypothesis is consistent with at least two possible mechanisms that I forward. The first I label the preference mechanism, which is that a more democratic context means more democratic voters, whose preferences are more likely to be in support of the pro-Palestine movement and thus start and join in the pro-Palestine encampments. A second mechanism is what I call the punishment mechanism, which asserts that a more democratic context means there is less fear of punishment and repression towards protestors, alleviating significant costs in their decision to join a pro-Palestine encampment.

For the national level data set, the hypothesis is as follows: The universities in counties that voted for Joe Biden in states that voted for Joe Biden in 2020 are more likely to have a Pro-Palestine encampment.

I then hypothesize that among just the universities that had an encampment, those located in counties with a higher vote share for Joe Biden in the 2020 election will have a greater number of participants in said encampments.

The goal of the qualitative data is to get further insight on which causal mechanisms are more at play, and to contextualize the quantitative data. This goal ties back into the broader hypothesis that left-wing politics were more conducive to mobilization of the pro-Palestine encampments.

4 Research Design

The research question for this paper is: How does the local political context of a given university impact the size of a pro-Palestine encampment at the same university? I broadly hypothesize that the more left-wing the local political context, the larger the pro-Palestine encampment. More specifically, I hypothesize that this political context extends to both the state and county level. I thus hypothesize that the greater the vote percentage in a county the more likely a university will have a Pro-Palestine encampment. I also hypothesize that states that are controlled by Democratic governors are also more likely to have an encampment. Additionally, I hypothesize that the greater the vote for Joe Biden the more participants in the Pro-Palestine encampment. As explained in the literature review, there are a few potential causal mechanisms that justify these hypotheses. The first is that being in an environment with more supporters means there are more resources and planning available to execute a protest and more desire to protest this cause in the first place. The second is that being an environment where people are largely supportive or apathetic to the Pro-Palestine protest means that there will be less coercive pressure from governmental and institutional forces that would otherwise work to suppress or mitigate the existence and size of a Pro-Palestine encampment. This punishment mechanism also relies on the state level factors, specifically control over the state government, which connects back to my hypothesis regarding states whose governors are Democrats.

In order to best answer the research question and eliminate possible confounding variables, this research is conducted across three levels in a mixed methods design. Each level or cut of data will become more specifically targeted in its selection in the essence of an inverted pyramid, starting with the most broad large-N analysis and moving into a smaller-N sample with more targeted data collection, and finally ending with a case study with qualitative data.

4.1 National Data Set

The first and broadest cut involves universal data for nearly every single University in the United States. University is defined according to the U.S. Census Bureau is a university engaged in “furnishing academic courses and granting degrees at baccalaureate or graduate levels,” (“North American Industry Classification System”). Additionally, I only included universities that had a recorded population of at least 1,000 people to sharpen the focus of the dataset. This dataset seeks to answer the specific hypothesis that: The greater the average vote percentage that the Democratic candidate for president received in the counties the University resides in, the greater the number of participants in the university’s Pro-Palestine encampment.

I used an exhaustive list of every university according to the North American Industry Classification System (NAICS) from Opensoft. Only schools who had a physical location were selected, as the scope of the research question and hypotheses hinges upon the university occupying a physical space. This gave me a dataset with an N value of 1424.

4.1.2 Independent variable

The independent variable is the local political context, which in this case is operationalized as the partisan voting record in the county that encompasses the university campus in 2020. For this set of data, the local political context is operationalized to refer to the partisan presidential voting record in 2020, where votes for Democratic candidate Joe Biden are understood as liberal/left-wing, while votes for Republican candidate Donald Trump are understood as conservative/right wing. The terms “Blue” and “Red” are operationalized in this paper as shorthand for places that voted more for Biden or Trump respectively.

The raw vote totals for Joe Biden, Donald Trump, and other candidates were recorded for each county in which a university resides based upon each state’s secretary of state office. This was then turned into percentages, yielding the independent variable I labeled Biden Vote percentage, referring to the percent Biden received in a given county. I used the county listed by the NAICS dataset. I then used this raw vote total to create dummy variables. Additionally, counties were coded as 0 if Trump received more votes and as a 1 if Biden received more votes. Once this was done, I then coded each university based on whether it was in a state where Trump received at least a plurality of the vote (coded as a 0) or in a state where Biden received at least a plurality of the vote (coded as a 1). I similarly coded each state depending on if they were governed by a Democrat during the encampment (coded as 1) or not (coded as 0).

By taking this coded data from the state voting record and the county voting record, I could create four dummy variables to understand the differing intersections of this independent variable for further analysis. These dummy variables were entered into a subsequent hierarchical regression.

Table 1: Dummy Variables

Variable Name	Description	False	True
BlueCounty_BluState	County had more votes for Biden, state had more votes for Biden	0	1
BlueCounty_RedState	County had more votes for Biden, state had more votes for Trump	0	1
RedCounty_BluState	County had more votes for Trump, state had more votes for Biden	0	1
RedCounty_RedState	County had more votes for Trump, state had more votes for Trump	0	1
Blue_Governor	Governor at the time of the encampments was a Democrat	0	1

4.1.3 Dependent variable

The dependent variable for this cut of data is the existence of an encampment at a university. The existence of a university's encampment was based on local and student journalism at the university. The existence of the encampment was coded as 0 if there was no encampment, and as a 1 if there was an encampment. This data was collected from an exhaustive list of every encampment on wikipedia that was cross referenced by a report from the Harvard Crowd Counting Consortium to ensure that every single encampment at a university was included in the dataset. I then manually coded each university as either having an encampment or note using the Wikipedia and Harvard Consortium list.

4.1.4 Control Variables

In order to eliminate any possible confounding variables, the following variables were selected as control variables: The university's population according to the NAICS, whether the university was private or public, the county poverty rate, the county education rate (defined as the percentage of adults in the county with a bachelor's degree or higher), the county unemployment rate, and the county's median household income according to data from the USDA.

4.1.5 Method of Analysis

A hierarchical regression model was used in IBM's SPSS software. This regression analysis was used to identify if there were significant relationships between a university having an encampment and the coded voting results used as a proxy for local political context. Descriptive statistics on the presence of encampments were also collected.

A regression analysis was used to identify significant relationships between the size of protest and the partisan breakdown of the presidential election results. Additionally, each state's total vote share was collected via the secretary of state of each state. This was used to reduce possible confounders in understanding if there are differences between states in "blue" areas in largely "red" states, vice versa, and more possible ways to further try and isolate confounders to try and find a causal relationship. This also could provide unique marginal cases for further discussion or analysis.

In the hierarchical regression model, the control variables were inserted into the model first, and then in the second model all of the variables including the independent variables of the Biden vote percentage and coded dummy variables were input into the model. This was done to assess the unique contribution the independent variables have and determine whether they are significant.

4.2 Only University Encampments

I then isolated the data to only include the universities that included an encampment. This was done for several reasons. Isolating the data allows for more in depth and clear analysis of the universities that actually had encampments. By isolating the data to only universities that had an encampment I could manually collect additional information regarding the encampments, including whether the encampment ended peacefully or by force. Additionally, this cut of data allows for an analysis of the size of the protests. Finally, this cut of data also allows for comparison between the large N cut of data and this smaller cut to further interrogate the results and determine their strength in either supporting or rejecting the hypothesis.

4.2.1 Independent Variable

For the encampments only cut of data, the independent variable remains the political context, and is operationalized similarly.

4.2.2 Dependent Variable

For the second cut of data, the dependent variable was the number of participants in an encampment. The information regarding the size of the encampment was recorded by manually going through the student newspapers of each university that had an encampment and reading the articles pertaining to the encampment. If no student newspaper was available, local media was substituted. The information on the size of the encampment was also cross-referenced with the

Harvard Consortium dataset. The size of each encampment was coded according to the same methodology employed by McCarthy et al.'s large-N study of student protests during the anti-Vietnam War protests. The following scheme was used to code the data:

Table 2: Coding Scheme for Number of Protestors

Coded Variable	Numerical estimation of participants (if given)	Adjectives used
1	1-9	Small, few, handful
2	10-24	group
3	25-99	Large gathering
4	100-999	Hundreds, mass, mob
5	1,000+0	thousands

In this scheme, preference was given to any numerical estimations, and adjectives and descriptors were only utilized if there was no estimate available.

Outcome of the encampment was coded either as 0, meaning it ended peacefully (including a negotiation, or a decision from the activists to end the encampment), or 1, meaning the encampment was ended forcefully by police.

4.2.3 Control Variables

The control variables for this cut of data are the same from the large cut of data. This means that the poverty rate, education rate, median household income, university population, and whether the school was private or public were all inputted into separate blocks into the hierarchical regression to control. Additionally, counties were coded as "Blue" if Biden received a plurality of the votes, and states were coded as "Blue" if Biden received a plurality of the votes in the state.

4.2.3 Method of Analysis

A hierarchical regression was used to analyze the data. The dependent variable was the coded amount of participation in an encampment according to the scheme initially used by McCarthy et al.

In the first model, the raw vote totals for Trump, Biden, and other candidates in the county were included, as well as coded variables for whether the county had a plurality of votes for Biden and if the state the university resides in had a plurality of votes for Joe Biden. The second block includes the control variables related to the university like if the university was public or private and the university's population. The third and final block of data looks at county statistics of poverty, the unemployment rate, the median household income, and the level of education (defined as the proportion of adults with a bachelor's degree or higher) from the USDA.

4.3 Qualitative Data

Three interviews were conducted over the phone and each lasted approximately 45 minutes. All interviews were completely anonymous and any identifying information was deleted from any transcription. Interviews were recorded using the Otter.ai software, which meets the Soc Type II requirements for confidentiality and privacy. The interviews followed an interview guide (see Appendix A), however follow up questions were occasionally asked to allow interviewees to expand upon their thought process. All interviewees responded to a pre-interview screening and gave oral consent. Interviewees were selected based on an initial professional connection, and then snowball sampling was employed to find other interviewees who participated in the encampment and would be willing to be anonymously interviewed for this research paper. This process was approved by UCSD's Institutional Review Board.[1]

[1] IRB Protocol Number 811917

This study employs a mixed method design, which has been specifically identified as being particularly suitable for understanding protests in the context of political science (Vráblíková 2017, 24). More specifically the qualitative data will serve as a separated complement, where the responses given by the participants of the encampments will help contextualize and evaluate the conclusions drawn from the quantitative data in the conclusion of this paper. The qualitative data will involve snowball sampling for interviews of members of the UCSD encampment via private contacts I have as the News Editor of the student newspaper The UCSD Guardian. The interviews will try to directly understand the decision making process of organizers and rank and file members of the encampments in participating in the demonstration in the context of the local political context of the university. This qualitative data helps establish causality in tandem with the quantitative data, because while the quantitative data may be more objective in its findings, only the qualitative data can have direct engagement with participants of the encampment and have them describe their own motivations and experiences and directly engage with questions pertaining to the hypothesis. These questions include the specific political opportunities and structures and how they relate towards mobilization of the encampments both from the perspective of organizers and participants. Additionally, by interviewing those with similar personal politics but who did not participate in the encampments it could draw clear lines in seeing if political and institutional barriers deterred certain individuals from protesting. While UCSD was chosen in part because of convenience, it could be a great contrasting case to members of a university in a “red” state in a “red” area in trying to understand if that played a role, in comparison to UCSD which is in a “blue” state in a “blue” city and area.

To interpret the data, key themes and common responses will be tabulated. These common responses and themes will then be discussed in depth in relation to what these potential findings mean in relation to the hypothesis.

This qualitative data serves as a separated complement to the quantitative data. This means the results of the qualitative data will be interpreted in conjunction with the results of the quantitative data in the conclusion, to hopefully further corroborate the findings of the quantitative data and truly establish a causal relationship of the overarching hypothesis relating political environments to turnout at the pro-Palestine encampments. Even if the quantitative and qualitative data are not in agreement, this still allows for a rich discussion in trying to understand any such discrepancy which will be illuminated in the conclusion.

5 Data Analysis

5.1.1 National Data Frequencies

First, I collected descriptive statistics for the occurrence of encampments from the dataset. The resulting frequencies are found in the table below.

Table 3: Frequency of University Encampments

Description	Frequency
No encampment	1296
Had an encampment	128
Total	1424

Of the 1424 universities collected for the dataset, only 128 universities had an encampment. I then further analyzed the frequencies of the differing independent variables I employed on just the universities with an encampment.

Table 4: Encampment only Political Context Frequencies

Variable	Frequency	Percentage
Blue_County	121	94.5
Blue_State	83	64.8
Blue_Governor	105	82.0
BlueCounty_BlueState	80	62.5
BlueCounty_RedState	41	32.0
RedCounty_BlueState	3	2.3
RedCounty_RedState	4	3.1

These frequencies further qualify my hypothesis, considering that 62.5% of encampments occurred in a blue county that's in a blue state, and that 94.5% of encampments occurred in a blue county. Additionally, what is interesting is that despite 64.8% of encampments occurring in states that voted for Joe Biden, 82% of the encampments occurred in states where the governor is a Democrat. This initially does seem to suggest that it is not so much the grassroots support of a candidate, but rather the partisan makeup of institutions that could potentially be impacting whether a protest occurs. In other words, this evidence seems to favor the punishment mechanism over the preference mechanism.

Additionally, I collected the average for the Biden_County_Vote percentage for just the universities with an encampment, and the average was at 63.5%. This is much higher than Biden's national vote percentage of 51.3%. While on its own insufficient to draw any definitive conclusions, these initial frequency results do seem to give further credence to my hypothesis, as it suggests on average the universities that had encampments occurred in counties where Joe Biden had a lot more votes than he did nationally. This leads into the regression, which allows for a comparison to see if there is a significant relationship between the independent variables of political context and the dependent variable of encampment existence.

5.1.2 National Dataset Hierarchical Regression

The null hypothesis for this cut of data is that there is no significant relationship between the more blue precincts in blue states and the existence of an encampment at a university. The alternative hypothesis is that there is a significant relationship between the blue precincts in blue states and the existence of an encampment at a university. Because dummy variables were used, red precincts in red states were excluded to serve as the reference variable.

The first output from SPSS from the linear regression analysis is the model summary, as seen in the table below.

Table 5: Model Summary of all University Dataset

Model Number	R Squared value
Model 1	0.217
Model 2	0.235

As mentioned in the research design section, the first model includes only the control variables, whereas the second model adds in the independent variables, which includes The Biden County Vote, Blue State, and Blue Governor variables.

The results of the model indicate that there is an increase in the R squared value once the independent variables are introduced. This indicates that the model's accuracy improved with the introduction of the independent variables, which is favorable evidence for my hypothesis.

The next portion of the hierarchical regression is calculating the coefficient and p-values from the hierarchical regression itself.

Table 6: Coefficients and P-Values from all University Dataset Regression

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.152	.061		-2.503	.012
	Poverty	-.002	.003	-.032	-.839	.402
	Education	.003	.001	.104	2.889	.004
	Unemployment	.027	.009	.088	3.031	.002
	Median_Household_Income	-5.018E-8	.000	-.003	-.074	.941
	Private_University	-.009	.016	-.015	-.611	.542
	Uni_Population	8.842E-6	.000	.429	16.508	<.001
2	(Constant)	.016	.069		.233	.816
	Poverty	-.006	.003	-.084	-2.045	.041
	Education	.000	.001	-.009	-.199	.842
	Unemployment	.004	.010	.013	.398	.691
	Median_Household_Income	-1.071E-6	.000	-.070	-1.504	.133
	Private_University	-.014	.015	-.022	-.883	.377
	Uni_Population	8.957E-6	.000	.434	16.872	<.001
	Biden_County_Vote	.002	.001	.126	3.127	.002
	Blue_Governor	.045	.018	.077	2.469	.014
	Blue_State	.028	.020	.048	1.410	.159

The results of both the Blue_Governor and Biden_County_Vote variables are below the critical value of 0.05, meaning that they are significant. Two control variables are also significant, including the poverty variable and the uni_population variables.

The coefficient for Biden_County_Vote is positive. This is favorable for my hypothesis given that the results are significant, because it indicates that encampments are significantly more likely to occur the greater the percentage Biden received in the county. This is similar to the Blue_Governor variable, with the coefficient for this variable also being positive, indicating that states governed by Democrats have universities that are more likely to have an encampment.

University population also has a large impact on encampments. Universities with a larger population means there is a higher base of support for the protest to draw on, which goes back to the idea of resource mobilization impacting protests. This is similar to the poverty variable, which is also significant with a negative coefficient, indicating that the lower the poverty rate the more likely an encampment. The fact that universities in counties with less poverty, and likely more resources, had more encampments further ties back into the general idea of resource mobilization. That said, the results seem much weaker for the control variable of poverty, given that they are not initially significant and only become significant with the addition of the independent variables.

To further interrogate marginal cases and understand the intersection between state politics and local politics, I ran a separate hierarchical regression, simply swapping out the independent variables for the dummy variables outlined above.

Table 7: Model Summary of all University Dataset with Dummy Variables

Model Number	R Squared Value
Model 1	0.217
Model 2	0.231

The R squared value indicates a similar story to the first version of the hierarchical regression, with the R squared value being slightly smaller with the dummy variables than with the original independent variables. However, this still indicates that the model is improved with these dummy variables.

Table 8: Coefficients and P-Values from all University Dataset with Dummy Variables

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.152	.061		-2.503	.012
	Uni_Population	8.842E-6	.000	.429	16.508	<.001
	Poverty	-.002	.003	-.032	-.839	.402
	Education	.003	.001	.104	2.889	.004
	Unemployment	.027	.009	.088	3.031	.002
	Median_Household_Income	-5.018E-8	.000	-.003	-.074	.941
	Private_University	-.009	.016	-.015	-.611	.542
2	(Constant)	.042	.076		.544	.587
	Uni_Population	8.837E-6	.000	.428	16.556	<.001
	Poverty	-.004	.003	-.061	-1.605	.109
	Education	.001	.001	.044	1.060	.289
	Unemployment	.012	.009	.039	1.259	.208
	Median_Household_Income	-1.068E-6	.000	-.070	-1.480	.139
	Private_University	-.012	.015	-.019	-.765	.445
	BlueCounty_BlueState	.081	.031	.136	2.652	.008
	BlueCounty_RedState	.009	.031	.014	.291	.771
	RedCounty_RedState	-.026	.029	-.043	-.908	.364

These results indicate that in the most Democratic context, of BlueCounty_BlueState the results are significant with a positive coefficient, meaning that the encampments are significantly more likely to occur in the political contexts that are the most democratic. The RedCounty_BlueState variable was excluded as there needed to be a reference for the model. Interestingly, the other two dummy variables included in the model are not significant. This may indicate that only when the context is extremely favorable to a movement, both from the punishment and preference mechanism perspectives, does this materialize in some form of impact on the occurrence of protest.

5.2.1 Encampment Only Hierarchical Regression

128 universities had pro-Palestinian encampments. Once I isolated these universities that had an encampment, I could conduct further regressions on the rate of participation in these encampments based off of the coding scheme outlined in the research design. Similar to the universal dataset, the first model in the regression had all of the control variables, while the second model had the Biden_County vote inputted into the model. As the results show in the table below, the model's accuracy increased from an R square value of 0.184 to 0.271 with the addition of the independent variables.

Table 9: Model Summary of Encampment Only Regression Models

Model Number	R Squared Value
1	0.184
2	0.271

Table 9: Encampments Only Coefficients and P-Values

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.541	.602		2.561	.012
	Uni_Population	8.675E-6	.000	.252	2.725	.007
	Private	.445	.133	.294	3.353	.001
	Median_Household_Income	8.128E-7	.000	.021	.150	.881
	Unemployment	.216	.088	.267	2.466	.015
	Education	.015	.009	.187	1.611	.110
	Poverty	-.016	.027	-.075	-.585	.560
2	(Constant)	1.962	.591		3.320	.001
	Uni_Population	9.546E-6	.000	.277	3.099	.002
	Private	.268	.136	.177	1.970	.051
	Median_Household_Income	-5.370E-6	.000	-.136	-.976	.331
	Unemployment	.104	.090	.128	1.159	.249
	Education	-.003	.010	-.041	-.318	.751
	Poverty	-.051	.030	-.243	-1.701	.092
	Biden_County_Vote	.023	.008	.356	2.796	.006
	BlueGovernor	.374	.181	.191	2.073	.040

This data is highly favorable to my hypothesis as it demonstrates a significant relationship between the percentage of votes received by Joe Biden in a university's county and the number of protestors in an encampment. The only significant variables in the second version of the model are the two independent variables and the university population control variable. Furthermore, the coefficients for both independent variables are positive, which further cements more evidence in support of my hypothesis, as it demonstrates that states with Blue Governors were more likely to have university encampments and universities in counties with a higher percentage of the vote for Biden were more likely to have an encampment.

In sum, the amount of information revealed from the quantitative statistical models likely is enough evidence to reject the null hypothesis across both cuts of data.

5.2.3 Analysis of Force Variable

Although not directly related to the hypothesis, data was also collected on whether encampments ended peacefully or by force. The term force was operationalized to mean any encampment that ended as a result of its physical takedown from those not affiliated with the encampment. The data for force was coded as either a 1 or a 0, with 1 meaning force was used and a 0 meaning no force was used. While the crux of the punishment mechanism relies on perception of risk, it is still useful contextual information to see if these perceptions actually manifested in differing responses dependent on the local political context. Additionally, this analysis opens the door for future research. The resulting frequencies are found below.

Table 10: Frequencies for Force Variable

Description	Frequency
Force used to end encampment	63
No force used to end encampment	65

The resulting frequency information shows that there was a virtual split between encampments that ended peacefully and that authorities forcefully took down the encampment.

The same control variables were inputted into this hierarchical regression as with the encampment only models. The next step was the model summary. The main difference in these models and the models from the encampments only dataset is the force is substituted in for the encampment size variable. The model summary can be found below.

Table 11: Model Summary for Force Variable Regression

Model	R Square value
1	0.040
2	0.085

Similar to the previous findings, the regression model has a larger R square value with the addition of the independent variables. This indicates that the control variables could be exerting more of an impact on whether force was used than the partisanship.

Table 12: Coefficients and P-values for Force Variable

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.135	.758		-.178	.859
	Uni_Population	3.183E-6	.000	.135	.842	.404
	Private	-.042	.169	-.038	-.250	.804
	Median_Household_Income	2.301E-6	.000	.086	.344	.732
	Unemployment	.028	.101	.057	.278	.782
	Education	.001	.012	.029	.124	.902
	Poverty	.016	.035	.098	.457	.650
2	(Constant)	-1.006	1.077		-.934	.355
	Uni_Population	3.240E-6	.000	.137	.777	.442
	Private	.007	.194	.007	.039	.969
	Median_Household_Income	6.805E-6	.000	.254	.845	.403
	Unemployment	.007	.123	.013	.053	.958
	Education	-.002	.017	-.038	-.119	.906
	Poverty	.034	.042	.213	.818	.418
	Biden_County_Vote	-.005	.013	-.101	-.389	.699
	BlueGovernor	.290	.257	.231	1.128	.265
	BlueCounty_BlueState	.493	.609	.488	.810	.422
	BlueCounty_RedState	.717	.643	.706	1.115	.271
	Blue_State	.003	.191	.003	.016	.987

Interestingly, no variable has a significant relationship with the usage of force in taking down the encampment. This does seem to suggest that in terms of the operationalized definition of force, both Democratic and Republican political contexts were just as likely to have an encampment end peacefully or with force.

This opens many avenues for future research. It could be that there is some missing variable that could cause the difference in whether a university responds with force or not. These responses could also be influenced by the individual actors making the decisions on how to respond to the encampments, such as the university administration's makeup.

5.3 Qualitative Data

The results of the quantitative data lead perfectly into the necessity of the qualitative data. Without it, it would be extremely difficult to identify any potential causal relationships, especially given that university population and the blue political context both have statistically significant relationships with the existence and size of the encampments. Thus, the qualitative data can help to parse through whether the local political context is impacting people's decisions to join and protest. Moreover, one of the key goals of the qualitative data is to try and identify which causal mechanisms are likely in play.

After conducting the three interviews, I went through each transcript and coded the information based upon similar and divergent themes brought up in the interviews. The coded information is found below.

Table 14: Themes discussed in qualitative interviews

Coded Theme	Number of Interviews this theme appeared in
Main fear of participating was fear of repression	3
Would not participate in a hypothetical encampment in a “red” state	2
Felt less fear of repression because they live in a “blue” state	1
Explicitly identified some level of ideological congruence with the Democrats	2
Considered the protest to be very left-wing	2
Joined protest because of personal and political beliefs that align with movement	3
Identified themselves as left-wing on the political spectrum	3
Identified the student body at UCSD as generally center-left	3
Felt like the university was influenced by political pressures in its response to the encampment	3

Overall, the results from the three interviews provide further evidence in favor of my hypothesis that the local political context does impact protest ability. Additionally, it gives further insight into which of the two outlined causal mechanisms are having a greater impact. Over the course of the three interviews, the interviewees will be labeled as interviewee 1, 2, and 3 respectively.

All three interviewees described personal moral beliefs and convictions as the motivator for them joining the encampments. Interviewee 1 described these convictions as such: “All my life I wanted to do something to help Palestine.” This belief that joining the encampments would help people in Palestine and Gaza was present in all three interviews.

While all of the interviewees described differing levels of complaint towards the Democratic party, it was evident that in comparison to the Republican party the Democratic party was at least perceived to be more sympathetic towards the pro-Palestinian movement. However, this higher level of perceived sympathy is nuanced, as interviewee 3 put it: “Democrats are definitely more supportive of the Pro-Palestinian movement. But I also think that Democrats, especially more moderate Democrats haven’t been very supportive and kind of have been similar to Republicans in a lot of ways.” This articulation is relevant to my hypothesis because the crux of the punishment and preference mechanisms relies upon the idea that the perceptions of risk and support by the encampment members are in some way impacted by the partisan makeup of their university. Even though all interviewees had complaints about the Democratic party, the fact that there was a recognition, particularly by interviewee 3, that the Democratic party is closer to the pro-Palestinian movement’s ideals is important because it validates my hypothesis that Democratic political contexts are more likely to have more encampments that are larger in size.

In all the interviews, the interviewee identified the perceived risk of arrest or state force/repression as their primary cost when deciding whether to participate in the movement, and all three said that their main motivation in joining the protest relied on personal and political moral convictions that made them compelled to join the movement. This supports that the rational choice theory is in play, as the participants weighed the risk of being punished against the benefit of participating in a movement that they care about. The fact that two of the interviewees explicitly said that they would not participate in the movement if it took place in a “red” state is perhaps the most direct and clear piece of evidence in support of my hypothesis, because two of the participants in the interviews directly acknowledged that the risks would be more significant and likely in a “red” state to the extent that they would not join a hypothetical encampment in the first place. This seems to further the punishment mechanism as the primary causal mechanism, as the fear of punishment was articulated explicitly as the main risk by all participants that were interviewed, and two of them specifically linked those perceptions of risk to the state-level partisan makeup. In fact, in interview 2 the participant even explicitly mentioned that they felt that before they joined the movement, because California is a “blue” state, that they felt they had some level of protection, and consciously used that when they were weighing their decisions to join the protest. Moreover, when asked a hypothetical question if they would still participate in an encampment if it occurred in a red state, interviewee 2 responded by saying: “If I were in Tuscaloosa, Alabama I would be way more scared. I would tell my friends and people involved not even to try it. Being in California gives us some form of leeway.” This response clearly demonstrates that the regional political context is a major factor in whether an individual will decide to join an encampment to a severe extent. This response strongly bolsters my hypothesis and demonstrates the significant impact the punishment mechanism has in explaining the hypothesis.

Furthermore, as all three interviewees believed that the university faced outward political pressure to use force to end the encampment, it furthers the idea that at the very least, these perceptions of political pressures impact these risk calculations that potential encampment participants must weigh. Given that all interviewees identified themselves as center-left to left-wing, and two explicitly identified some level of ideological congruence with the Democratic party, I argue that this demonstrates a clear connection between the political context and the risk calculation potential encampment participants have to make. The biggest deterrent from their activism being linked to political pressures seems to validate my hypothesis that the partisan makeup of a given area impacts the decision making process of potential participants of the pro-Palestine movement.

However, there is also evidence in the interviews that can also suggest that the preference mechanism might also be a potential factor, as one participant mentioned that they felt that there would be less support for their movement in a “red” area that would impact the size of a potential encampment. All three also perceived the average UCSD student to be center-left. Moreover, two of the three interviewees claimed that the Pro-Palestine movement at UCSD is explicitly left-wing or leftist. Additionally, all three said that they felt the average student at UCSD was generally supportive of the pro-Palestine movement and their encampment. This does suggest that there was a feeling of general support from the student community.

Despite this evidence in favor of the preference mechanism, I argue that the findings of the interviews do demonstrate that the more prescient mechanism is the punishment mechanism. None of the participants mentioned a feeling of support as a necessary condition for them to join the movement, but all three did mention that the risk to their participation was a fear of some form of repression by either some governmental agency.

6 Conclusion

6.1 Discussion

I argue that the overall results provide substantial evidence in favor of my hypothesis, which is that the local partisan political context impacts the existence and size of the pro-Palestine encampments. More specifically, the data shows that the universities that existed in democratic precincts in democratic states were more likely to have encampments than other universities.

In the universal large N cut of data, the independent variables of the percentage of votes Biden received in the county, if the state was governed by a Democrat, and the dummy variable of “Blue” County and “Blue” state variables all had significant positive relationships with the existence of encampments. That said, while the control variable of university population was also significant, I do not think this alone disproves my hypothesis. This is for several reasons. First, addressing concerns of university population impacting the local political context, if that were the case, then the relationships for the two other variables measuring partisanship would also be expected to be significant across all models, but they are not. This indicates that while the university population may also be causing the existence of these encampments, it is likely an independent causal factor, and not necessarily disproving the potential causality of the local partisanship on the existence of the encampments. Additionally, the poverty variable was also barely significant in the universal dataset. However, this was not a trend continued into the encampments only dataset, which I argue means that poverty is likely not a major causal variable for the outcome of the encampments. I argue that the independent variables of Biden’s vote and the Democratic governance of a state are much more likely to be major causal factors because they remain consistent amongst both cuts of data, both the universal and isolated encampment only dataset. The fact that the dummy variable for a Blue county in a Blue state was also significant underscores the fact that the political context, regardless of how it’s operationalized as a variable, paints a consistent narrative in favor of the hypothesis across all cuts of data.

The qualitative data provides contextual evidence of a specific case study that further validates my hypothesis. All interviewees acknowledged that punishment was the first and main risk they perceived when deciding whether to participate in the encampment. Additionally, two identified that this risk would become insurmountable and outweigh their calculation of whether to join if the local partisan context were to become much more Republican. While the qualitative data does give some evidence to both potential causal mechanisms, it is clear that the overlying narrative from the interviewees is one where the predominant causal mechanism is the punishment mechanism.

Another strength of the results is that reverse causality is extremely unlikely, given that the measurements of partisanship were collected before these protests materialized, so the existence of the encampments could not affect the operationalized context of political context. Additionally, while these protests were controversial, there has been no empirical peer-reviewed evidence to suggest that these protests created a massive party shift/ideological shift in the American populace over the course of just a few months. This further builds credibility for the results in favor of the hypothesis.

6.2 Limitations

With any research design centering around a regression analysis, one of the most apparent limitations is the problem of correlation not causation. While this paper includes several control variables, and even qualitative data to try and rectify this problem, this concern is still a potential limitation on the research.

Another potential limitation is the operationalization of the data itself. How people perceive their political context may differ from the actual reality of the political context itself. By measuring voting data as a proxy for the political context, it may miss qualitative judgements by university students on how supportive their political context is towards the pro-Palestine encampments that the voting data does not capture. Moreover, the classification of a political context as a binary “red” or “blue” in certain variables could be seen as failing to capture the variance of political contexts, including the idea of “purple” or swing states, that do not have a dominant partisan ideology and instead tend to swing between the two political parties.

Finally, it is important to mention some of the inherent limitations with qualitative data from the interviews. There is always the potential of research bias, especially in the interpretation of the themes discussed in the interviews. Moreover, the interviews, while in depth and highly informative, were limited in quantity. These interviews were also limited to just one university that exists in one political context, which means the results of the qualitative data on their own are difficult to generalize. Additionally, since the research relied on personal and professional connections, there is further risk that the interviews were not wholly representative. Again, while the interviews were not the crux of the research and many of these concerns are mitigated by the mixed methods design that relies on quantitative data, this is still an important limitation.

6.3 Future Research

What is interesting about these results is the fact that the evidence seems to provide support for political process theory, which recently has fallen out of favor (Meyer 2004). One of the possible reasons that the statistically significant results in favor of my hypothesis despite historically mixed results for political process theory could be because of an increase in political polarization. Partisan political polarization has been increasing in the United States, with the impacts of this increasing polarization impacting even the brands from which consumers purchase on the basis that they view that brand as supportive to their partisan political ideology (Pierson and Schickler 2020; Schoenmueller et. al. 2023). Thus, it stands to reason that as political polarization continues to dominate the individual actions of individuals, this could further galvanize people in certain political strongholds to join protests they find supportive of their political party. It could also be that policymakers, in an extremely polarized environment, feel more concerned with repressing social movements that they view as contrary to their own party, creating a chilling effect on the rates of participation of protests in these local contexts. That said, the results certainly seem to indicate that there may be a need to revisit political process theory in an era of heightened partisan polarization.

Additionally, there are still a plethora of other ways in which to evaluate the data collected from perspectives in political science and even in related fields of political sociology and even social psychology. This could include looking at more recent electoral results, such as the results from the 2024 election. There could also be a more in depth breakdown at demographic information, such as data on race, ethnicity, and even religion could be used to identify if there are other potential causal variables.

Moreover, with the recent actions from the Trump administration in relation to these protests, it further raises questions regarding the differential treatment exerted on protests and protestors by differing political parties (Allen 2025). It will be important in the future to evaluate whether these increasingly sharp attacks on political enemies' protests manifest in an impact on the existence of the protests and their own size. Another portion of additional research would also be to further scrutinize and evaluate the subsequent action taken by governmental forces after a demonstration occurs. While this paper briefly mentions the difference in protests ending in peace or by force, future research could center this question as the main hypothesis. This is an especially prominent possible focus for future research given that the results found in this paper fail to find any strong evidence of a relationship existing between any of the collected variables and the usage of force/peace in ending the encampments.

Finally, there is a large amount of future research that could be done through further qualitative analysis of the members of these encampments. Interviewing participants of encampments at other universities, particularly those in differing political contexts in “red” states, would be highly insightful to further evaluate my hypothesis.

While this is an extremely contentious political problem, political science should not shy away from covering issues because they are controversial or personal. If anything, it is imperative to try and objectively assess phenomena within the field of political science to make sense of new and often unique situations that arise in contemporary politics. It is with this goal in mind that this paper seeks to contribute knowledge to the field of political science.

Appendices

Appendix A: Interview Guide

The interviewee

1. Did you participate in the Pro-Palestine encampment?
    a. In what capacity? What was your role?
2. What was your general experience participating in the encampment?
3. What motivated you to participate in it?
4. When did you decide to join the encampment? What explained this timing?
5. Did you ever consider leaving the encampment?
6. What were the main risks you considered when deciding whether to join the encampment?
    a. How did you assess them?
7. What do you think the goal of the encampment was?
    a. Did you agree with it fully?
8. When you got involved, what did you expect the response of the admin to be?
    a. Why?
9. On a 10 point ideology scale, with 0 being far left and 10 being far right, where would you place yourself?
10. Did the fact that UCSD is in a blue state shape your perceptions of risk at all?
11. Did the fact that UCSD is in a large, mostly progressive city shape your decision to participate?
12. Have you ever been involved in political activities before this?
    a. What kind?
13. Have you voted in national or local elections?
    a. Which ones?
14. Did this experience change you in terms of your politics?
15. Hypothetical: if you were a student at a similar university but one in a “red” state, do you think you would have joined? why/why not? Do you think the protest would have occurred at all? why/why not?
    a. Would go way up not even try it. Some sort of leeway
    b. What if you were in a “red” city or local area?

Other participants

1. What do you think motivated other participants to participate?
2. How would you describe fellow encampment members politically?
3. On a 10 point ideology scale, with 0 being far left and 10 being far right, where would you place other encampment members?
4. Do you think the leadership was distinct in terms of their politics from rank and file members of the encampment?
    a. How so?
5. Why do you think leadership decided to have a protest at UCSD?
    a. What do you think they expected the result to be?
6. Were participants primarily from campus?

    a. Were there any participants not on campus?

Campus

1. Do you think other students on campus that did not join the encampments supported your protest?
    a. Did that support impact your ability to have an encampment and sustain it?
2. On a 10 point ideology scale, with 0 being far left and 10 being far right, where would you place the average student at UCSD?
3. Did you feel that your protest was supported by different student groups on campus?
    a. Was their support important to your protest?
    b. Did you face any opposition from any organizations or students on campus?
        i. On a 10 point ideology scale, with 0 being far left and 10 being far right, where would you place the average student/organization that opposed your protest? Why?
    c. Do you think a lot of groups and students were neutral or indifferent to the protest? Why?
4. Did you become aware of more student groups when participating?
5. How would you describe the participating student groups politically? Were they from the same side of the political spectrum, or were there a mix across the political spectrum?

Campus admin

1. How did your campus administration respond to the encampment?
    a. If the campus was in a red state [red city] do you think the campus administration would have reacted the same way? Why?
2. Why do you think campus administration acted as they did?
3. Do you think the campus administration was politically motivated?
    a. How so?
4. On a 10 point ideology scale, with 0 being far left and 10 being far right, where would you place the members of campus administration at UCSD?
5. Do you think campus administration faced pressures to react the way they did?
    a. From whom?
6. Do you think that the administration had the best interests of the students in mind during their response to the encampments?
    a. (If not), whose interests did they have in mind in your opinion?

Thank you! This study was about the politics associated with different campus political environments in relation to how universities responded to Pro-Palestine encampments. Knowing this now, is there anything you wish to add? How did you feel?

Thank you for your responses.

Appendix B: Quantitative Dataset

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	35.89	0	0	0	0	0	0	0	5433	18.2	31.9	3.6	46,433	1
0		0	26.46	0	0	0	0	0	0	0	6335	13.3	29	3.3	61,798	1
0		0	85.26	0	1	1	1	0	0	0	10505	11.9	60.1	3.3	135,366	1
0		0	48.14	0	1	1	1	0	0	0	3664	21.7	29.3	3.7	53,942	1
0		0	54.11	0	1	1	1	0	0	0	9312	5.8	48.7	3.1	135,528	1
0		0	74.22	0	1	1	1	0	0	0	1944	13.2	41.9	4.4	76,614	1
0		0	39.13	0	0	1	0	0	0	0	2285	10.6	22.3	4.2	67,486	1
0		0	60.85	0	0	0	0	0	0	0	2259	12.4	38.4	2.8	72,129	1
0		0	83.09	0	0	0	0	0	0	0	1468	13.3	46.7	3.3	76,736	1
0		0	53.31	0	0	0	0	0	0	0	1074	14.1	33.2	1.8	66,952	1
0		0	39.26	0	0	0	0	0	0	0	1129	9.9	41.3	3.2	82,769	1
0		0	64.55	0	1	1	1	0	0	0	1450	12.9	45.2	3.3	76,997	1
0		0	64.55	0	1	1	1	0	0	0	3103	12.9	45.2	3.3	76,997	1
0		0	69.62	0	0	0	0	0	0	0	7260	26.4	23.2	4.3	42,629	0
0		0	83.29	0	1	1	1	0	0	0	2990	27.7	22	6.8	45,864	1
0		0	58.05	0	1	1	1	0	0	0	1730	12.5	41.1	3.9	84,615	1
0		0	43.57	0	0	1	0	0	0	0	2005	14	22.2	4.3	59,652	1
0		0	45.08	0	0	1	0	0	0	0	2016	11.9	27.2	3.5	72,157	1
0		0	29.1	0	1	1	1	0	0	0	2776	15	24.6	4.3	55,466	1
0		0	30.69	0	0	1	0	0	0	0	2143	12.6	21.2	3.7	54,774	1
0		0	60.21	0	1	1	1	0	0	0	4023	10.1	42.1	3.9	98,365	1
0		0	34.95	0	0	1	0	0	0	0	1781	16.3	19	4.4	58,074	1
0		0	45.08	0	0	1	0	0	0	0	2984	11.9	27.2	3.5	72,157	1
0		0	69.07	0	0	1	0	0	0	0	2319	17.1	33.9	3.8	58,375	1
0		0	64.89	0	0	0	0	0	0	0	1183	13.8	34.8	3.8	70,871	1
0		0	63.35	0	0	0	0	0	0	0	8517	15.6	34.1	3.3	62,776	1
0		0	63.35	0	0	0	0	0	0	0	8517	15.6	34.1	3.3	62,776	1
0		0	62.41	0	0	1	0	0	0	0	5969	6.9	52.3	2.8	106,743	1
0		0	50.13	0	0	1	0	0	0	0	17069	11.1	35.9	3.4	83,668	1
0		0	72.57	0	0	0	0	0	0	0	1570	13	58	3.4	89,798	1
0		0	57.73	0	1	1	1	0	0	0	3419	17.6	28.9	4.3	64,030	1
0		0	86.42	0	1	1	1	0	0	0	2172	16.5	39.6	4.6	95,514	1
0		0	43.77	0	0	0	0	0	0	0	52455	14.8	33.7	2.7	87,259	1
0		0	79.55	0	1	1	1	0	0	0	2973	10.5	55.6	3.3	87,619	1
0		0	92.15	0	1	1	1	0	0	0	17561	15.2	63.6	4.9	99,897	1
0		0	72.12	0	1	1	1	0	0	0	2767	12.4	51.1	2.9	81,878	1
0		0	28.27	0	0	0	0	0	0	0	4760	13.5	26.4	2.8	62,708	1
0		0	60.16	0	0	0	0	0	0	0	1782	13	20.1	3.6	58,926	1
0		0	60.16	0	0	0	0	0	0	0	1782	13	20.1	3.6	58,926	1
0		0	45.34	0	0	1	0	0	0	0	3967	13.6	30.2	4.2	61,790	1
0		0	27.07	0	0	0	0	0	0	0	11732	14.6	25.1	3.5	60,348	0
0		0	57.58	0	1	1	1	0	0	0	1806	10.9	39	3.5	86,078	1
0		0	71.03	0	1	1	1	0	0	0	1118	13.7	35.5	5	82,455	1
0		0	57.52	0	1	1	1	0	0	0	1067	9	35.3	2.3	76,227	1
0		0	53.14	0	0	1	0	0	0	0	23259	18.6	47.7	3	57,888	1
0		0	51.91	0	0	1	0	0	0	0	1913	10.5	39.6	3.2	76,923	1
0		0	62.41	0	0	1	0	0	0	0	4257	6.9	52.3	2.8	106,743	1
0		0	50.13	0	0	1	0	0	0	0	1188	11.1	35.9	3.4	83,668	1
0		0	50.13	0	0	1	0	0	0	0	1044	11.1	35.9	3.4	83,668	0
1	1	4	50.13	0	0	1	0	0	0	0	87678	11.1	35.9	3.4	83,668	0
0		0	50.13	0	0	1	0	0	0	0	10608	11.1	35.9	3.4	83,668	0
0		0	50.13	0	0	1	0	0	0	0	9752	11.1	35.9	3.4	83,668	0
0		0	50.13	0	0	1	0	0	0	0	3663	11.1	35.9	3.4	83,668	0
0		0	30.95	0	0	0	0	0	0	0	15053	16.1	27.8	2.7	60,580	0
0		0	23.62	0	0	0	0	0	0	0	11954	13.5	24.6	3.9	57,881	0
0		0	71.03	0	1	1	1	0	0	0	2981	13.7	35.5	5	82,455	1
0		0	32.6	0	0	1	0	0	0	0	1991	10.3	32.4	3.5	69,216	1
0		0	32.6	0	0	1	0	0	0	0	2175	10.3	32.4	3.5	69,216	1
0		0	60.21	0	1	1	1	0	0	0	33440	10.1	42.1	3.9	98,365	1
0		0	24.77	0	0	0	0	0	0	0	5568	13.5	22.1	3.4	62,037	1
0		0	57.58	0	1	1	1	0	0	0	2978	10.9	39	3.5	86,078	1
0		0	70.46	0	1	1	1	0	0	0	4025	10.1	53.3	2.6	89,418	1
0		0	67.89	0	0	0	0	0	0	0	14608	22.2	24.1	4.6	50,079	1
0		0	54.81	0	1	1	1	0	0	0	3047	14.8	24.1	5.1	62,652	1
0		0	43.85	0	0	0	0	0	0	0	2476	9.7	34.6	1.8	75,623	1
0		0	56.14	0	1	1	1	0	0	0	7131	8.4	37.5	5.1	93,475	1
0		0	24.39	0	0	0	0	0	0	0	1625	10.9	23.7	3.7	66,141	1
0		0	42.3	0	0	0	0	0	0	0	11626	12.6	31.7	3.7	67,478	0
0		0	37.27	0	0	0	0	0	0	0	1334	10.5	39.5	2.9	81,821	1
0		0	59.82	0	0	0	0	0	0	0	1761	12	33.5	3.4	62,509	1
0		0	59.82	0	0	0	0	0	0	0	1761	12	33.5	3.4	62,509	1
0		0	71.03	0	1	1	1	0	0	0	10969	13.7	35.5	5	82,455	1
0		0	67.03	0	1	1	1	0	0	0	4222	7.7	57.6	3.1	115,770	1
0		0	68.04	0	0	1	0	0	0	0	2760	13.3	52	2.6	67,482	1
0		0	66.36	0	0	0	0	0	0	0	4293	16	35.9	3.8	60,808	1
0		0	42.35	0	0	0	0	0	0	0	25208	19.4	25.7	3.8	54,059	0
0		0	42.35	0	0	0	0	0	0	0	25208	19.4	25.7	3.8	54,059	0
0		0	64.42	0	0	0	0	0	0	0	1032	18.2	34.2	4.3	61,452	1
0		0	53.89	0	1	1	1	0	0	0	3385	8	39.7	3.3	90,740	1
1		5	86.42	0	1	1	1	0	0	0	3696	16.5	39.6	4.6	95,514	1
0	1	0	53.31	0	0	0	0	0	0	0	8728	14.1	33.2	1.8	66,952	1
0		0	50.95	0	0	1	0	0	0	0	1445	18.8	20.3	4.9	51,535	1
0		0	74.95	0	1	1	1	0	0	0	1285	8.8	55.9	3.4	116,044	1
0		0	47.04	0	1	1	1	0	0	0	2752	13	23.4	3	62,848	1
0		0	57.73	0	1	1	1	0	0	0	3937	17.6	28.9	4.3	64,030	1
0		0	55.94	0	0	0	0	0	0	0	10496	16	33.7	4.3	68,748	1
0		0	37.49	0	0	0	0	0	0	0	22706	16.7	27.8	3.7	63,160	1
0		0	73.4	0	0	0	0	0	0	0	5756	21	31.1	3.1	47,479	1
0		0	58.87	0	0	1	0	0	0	0	4087	16.2	36.6	3.9	64,719	1
0		0	58.87	0	0	1	0	0	0	0	4087	16.2	36.6	3.9	64,719	1
0		0	42.84	0	0	0	0	0	0	0	14569	4.9	41.9	2.2	98,619	1
0		0	35.46	0	0	1	0	0	0	0	1771	12.5	26	3.4	65,430	1
0		0	54.66	0	0	1	0	0	0	0	1307	11.2	25.7	3.4	67,430	1
0		0	47.24	0	1	1	1	0	0	0	5137	17.1	32.3	3.5	59,882	0
0		0	68.4	0	0	0	0	0	0	0	2055	15.9	41.1	3	61,010	1
0		0	31.71	0	0	1	0	0	0	0	2628	13.6	22.9	3.4	59,085	1
0		0	57.66	0	1	1	1	0	0	0	4446	6.6	51.4	3.4	102,383	1
0		0	62.09	0	1	0	1	0	0	0	1141	11.9	41.2	2.5	69,249	1
0		0	71.47	0	1	1	1	0	0	0	6212	7.7	59	2.9	118,494	1

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	43.06	0	0	0	0	0	0	0	9038	12.8	32.3	2.9	71,237	1
0		0	27.75	0	0	0	0	0	0	0	3623	12	28	3.1	53,862	1
0		0	27.75	0	0	0	0	0	0	0	1407	12	28	3.1	53,862	1
0		0	47.74	0	0	1	0	0	0	0	19811	21	30.8	4.5	54,642	0
0		0	43.78	0	0	1	0	0	0	0	1135	8.2	39.6	2.7	81,295	1
0		0	39.26	0	0	0	0	0	0	0	4493	9.9	41.3	3.2	82,769	0
0		0	43.32	0	1	1	1	0	0	0	12717	15.2	35.3	5.1	71,737	0
0		0	36.59	0	0	1	0	0	0	0	1759	14.7	27.4	4.5	57,975	1
0		0	26.07	0	0	0	0	0	0	0	2664	15.6	35.2	2	52,621	0
0		0	51.11	0	0	0	0	0	0	0	1084	14.5	33.1	3.1	70,203	1
0		0	72.57	0	0	0	0	0	0	0	1330	13	58	3.4	89,798	1
0		0	57.66	0	1	1	1	0	0	0	29481	6.6	51.4	3.4	102,383	1
0		0	60.22	0	1	1	1	0	0	0	1023	8.6	45.1	4.1	102,073	1
0		0	55.94	0	0	0	0	0	0	0	1558	16	33.7	4.3	68,748	1
0		0	62.51	0	1	1	1	0	0	0	2598	9.1	37.7	2.7	96,304	1
0		0	75.78	0	1	0	1	0	0	0	4801	7.8	55.8	1.6	86,579	1
1	0	3	53.48	0	1	1	1	0	0	0	11951	9.2	43.4	3.6	106,047	1
0		0	71.03	0	1	1	1	0	0	0	1490	13.7	35.5	5	82,455	1
0		0	55.51	0	0	0	0	0	0	0	3935	11	49	2.4	79,969	1
0		0	50.95	0	1	1	1	0	0	0	2468	7.5	33	4.3	91,149	1
0		0	63.06	0	1	1	1	0	0	0	1962	11.3	41.7	3.8	84,551	0
0		0	59.43	0	0	1	0	0	0	0	2959	11.6	44.8	3.3	71,973	1
0		0	81.21	0	0	1	0	0	0	0	1839	20.3	34.6	4.2	56,385	1
0		0	74.22	0	1	1	1	0	0	0	3303	13.2	41.9	4.4	76,614	0
0		0	66.74	0	0	1	0	0	0	0	1284	22.7	16.7	4.7	43,871	1
0		0	64.42	0	0	0	0	0	0	0	2347	18.2	34.2	4.3	61,452	1
0		0	55.51	0	0	0	0	0	0	0	4484	11	49	2.4	79,969	1
0		0	74.95	0	1	1	1	0	0	0	2545	8.8	55.9	3.4	116,044	1
0		0	66.24	0	0	0	0	0	0	0	2489	21.7	19.4	4.4	42,209	1
0		0	71.03	0	1	1	1	0	0	0	2355	13.7	35.5	5	82,455	1
0		0	71.03	0	1	1	1	0	0	0	1771	13.7	35.5	5	82,455	1
0		0	23.96	0	0	1	0	0	0	0	5131	14.2	23.3	4.2	57,844	0
0		0	72.57	0	0	0	0	0	0	0	4465	13	58	3.4	89,798	1
0		0	57.58	0	1	1	1	0	0	0	4304	10.9	39	3.5	86,078	1
0		0	47.58	0	0	0	0	0	0	0	1175	9.6	32.9	2.9	73,492	1
0		0	54.37	0	0	0	0	0	0	0	1338	11.5	42.2	2.6	74,424	1
0		0	43.11	0	1	1	1	0	0	0	4891	19	24.6	4.4	59,451	1
0		0	84.94	0	0	0	0	0	0	0	7863	17.3	21.3	4.1	57,625	0
0		0	23.71	0	0	0	0	0	0	0	31991	16.8	27.3	2.9	55,333	0
0		0	66.36	0	0	0	0	0	0	0	17600	16	35.9	3.8	60,808	0
0		0	32.92	0	0	0	0	0	0	0	11621	12.9	26.6	3.4	61,375	0
0		0	29.38	0	0	0	0	0	0	0	3905	19.9	15	3.3	48,245	1
0		0	55.61	0	0	0	0	0	0	0	1766	9.9	34.8	3.5	74,134	1
0		0	46.95	0	0	0	0	0	0	0	1322	22.3	19.7	3.3	50,427	1
0		0	48.57	0	1	1	1	0	0	0	2976	11.5	30.9	2.6	63,191	1
0		0	53.85	0	1	0	1	0	0	0	1215	7.7	38.1	1.9	84,898	1
0		0	43.5	0	1	1	1	0	0	0	4120	11	28	3.7	69,851	1
0		0	55.51	0	0	0	0	0	0	0	12242	11	49	2.4	79,969	0
0		0	83.29	0	1	1	1	0	0	0	3222	27.7	22	6.8	45,864	1
0		0	57.73	0	1	1	1	0	0	0	1666	17.6	28.9	4.3	64,030	1
0		0	37.58	0	1	1	1	0	0	0	2110	11	28.6	6.2	84,738	1
0		0	54.37	0	0	0	0	0	0	0	1313	11.5	42.2	2.6	74,424	1
0		0	41.98	0	1	1	1	0	0	0	14598	13.1	35.8	4.9	91,582	0
0		0	57.58	0	1	1	1	0	0	0	4053	10.9	39	3.5	86,078	1
0		0	20.27	0	0	0	0	0	0	0	1882	13.6	25.4	4.9	53,009	1
0		0	57.88	0	1	1	1	0	0	0	8900	7.4	50.7	2.9	102,413	1
1	0	4	42.75	0	1	1	1	0	0	0	2964	7.3	41.1	3.3	82,248	1
0		0	34.8	0	1	1	1	0	0	0	10137	11.9	30.6	3.5	69,578	0
0		0	57.88	0	1	1	1	0	0	0	8161	7.4	50.7	2.9	102,413	0
0		0	49.57	0	1	1	1	0	0	0	6718	13.5	25	4.4	58,314	0
0		0	56.22	0	1	1	1	0	0	0	40148	10.2	51.7	2.8	88,338	0
0		0	42.75	0	1	1	1	0	0	0	30267	7.3	41.1	3.3	82,248	1
0		0	39.39	0	1	1	1	0	0	0	2330	10.5	23.9	5	70,108	1
0		0	68.4	0	0	0	0	0	0	0	1480	15.9	41.1	3	61,010	1
0		0	54.82	0	0	0	0	0	0	0	9384	14.4	51	2.5	63,981	1
0		0	74.22	0	1	1	1	0	0	0	8166	13.2	41.9	4.4	76,614	1
0		0	68.4	0	0	0	0	0	0	0	2509	15.9	41.1	3	61,010	1
1	1	5	86.42	0	1	1	1	0	0	0	50996	16.5	39.6	4.6	95,514	1
0		0	64.68	0	0	0	0	0	0	0	1284	15.1	42	3.1	69,762	1
0		0	61.4	0	0	0	0	0	0	0	9481	20.7	29.7	4.2	53,740	0
0		0	22.1	0	0	0	0	0	0	0	2080	19.7	20.7	4.4	43,917	0
0		0	67.57	0	1	1	1	0	0	0	1462	9.3	52.5	3.4	108,037	1
0		0	50.74	0	1	1	1	0	0	0	2644	13.1	39	2.1	79,357	1
0		0	71.41	0	0	0	0	0	0	0	2644	10.2	55.5	3.3	95,151	1
0		0	72.44	0	0	1	0	0	0	0	1466	14.6	58.1	3.3	80,941	1
0		0	74.22	0	1	1	1	0	0	0	7174	13.2	41.9	4.4	76,614	1
0		0	53.48	0	1	1	1	0	0	0	4639	9.2	43.4	3.6	106,047	1
0		0	26.5	0	0	0	0	0	0	0	3620	6.9	31.6	2	77,778	1
0		0	79.21	0	1	1	1	0	0	0	5455	12.8	48.6	3.6	79,432	1
0		0	71.5	0	1	1	1	0	0	0	6166	11.9	45.5	2.7	75,041	1
0		0	44.13	0	0	1	0	0	0	0	6549	4.8	50.4	2.6	97,778	1
0		0	56.92	0	1	1	1	0	0	0	2493	12.4	34.6	3.6	80,159	1
0		0	35.6	0	0	0	0	0	0	0	1602	14	25.7	2.9	58,535	1
0		0	86.42	0	1	1	1	0	0	0	1323	16.5	39.6	4.6	95,514	1
0		0	87.28	0	1	1	1	0	0	0	2908	20.2	35.4	2.9	54,735	0
0		0	48.86	0	1	1	1	0	0	0	1411	14.1	26	3.7	70,861	1
0		0	55.61	0	0	0	0	0	0	0	1286	9.9	34.8	3.5	74,134	1
1	0	4	73.51	0	1	1	1	0	0	0	34682	15.7	59.2	3.1	72,025	1
0		0	16.93	0	0	0	0	0	0	0	1139	14.1	19	2.6	59,708	1
0		0	38.71	0	0	0	0	0	0	0	1105	14.1	32.4	2.6	55,751	1
0		0	54.37	0	0	0	0	0	0	0	11004	11.5	42.2	2.6	74,424	1
0		0	46.37	0	1	1	1	0	0	0	1699	4.6	50.5	2.4	117,602	1
0		0	53.89	0	1	1	1	0	0	0	3830	8	39.7	3.3	90,740	1
0		0	21.3	0	0	0	0	0	0	0	1221	15.3	16.5	2.9	57,053	1
0		0	29.94	0	0	0	0	0	0	0	3095	6.6	37.2	2.7	88,462	1
0		0	86.42	0	1	1	1	0	0	0	22122	16.5	39.6	4.6	95,514	0
0		0	76.78	0	1	1	1	0	0	0	20147	19.1	41.3	5.5	73,244	0
0		0	86.42	0	1	1	1	0	0	0	17805	16.5	39.6	4.6	95,514	0
0		0	86.42	0	1	1	1	0	0	0	11015	16.5	39.6	4.6	95,514	0

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	86.42	0	1	1	1	0	0	0	27203	16.5	39.6	4.6	95,514	0
0		0	86.42	0	1	1	1	0	0	0	17769	16.5	39.6	4.6	95,514	0
0		0	83.29	0	1	1	1	0	0	0	16943	27.7	22	6.8	45,864	0
0		0	76.78	0	1	1	1	0	0	0	6059	19.1	41.3	5.5	73,244	0
0		0	76.78	0	1	1	1	0	0	0	17642	19.1	41.3	5.5	73,244	0
0		0	72.03	0	1	1	1	0	0	0	22053	13.8	35.3	4.6	80,180	0
0		0	72.03	0	1	1	1	0	0	0	8801	13.8	35.3	4.6	80,180	0
0		0	67.03	0	1	1	1	0	0	0	2989	7.7	57.6	3.1	115,770	1
0		0	49.66	0	1	1	1	0	0	0	3231	14.1	36.9	3.8	69,888	1
0		0	56.46	0	1	1	1	0	0	0	3075	14.1	36.9	3.8	69,888	1
0		0	35.21	0	0	0	0	0	0	0	3551	9.4	34.7	1.9	74,668	1
0		0	31.32	0	0	0	0	0	0	0	1137	9.4	25	1.7	63,753	1
0		0	64.89	0	0	0	0	0	0	0	2739	13.8	34.8	3.8	70,871	1
0		0	29.05	0	0	0	0	0	0	0	5197	15.5	19.3	3.9	61,680	0
1	1	4	61.29	0	1	0	1	0	0	0	10253	9.4	44.8	1.9	81,205	1
0		0	51.91	0	0	1	0	0	0	0	7148	10.5	39.6	3.2	76,923	1
0		0	66.68	0	0	1	0	0	0	0	2910	10.2	48.6	3.4	80,645	1
0		0	51.19	0	1	1	1	0	0	0	5657	11.7	26.7	4.5	71,866	0
0		0	51.53	0	0	1	0	0	0	0	2775	6.7	43.9	3	105,202	1
0		0	64.78	0	0	0	0	0	0	0	3631	38.7	26.6	3.6	39,984	0
0		0	35.02	0	0	0	0	0	0	0	3082	9.7	29.3	3.1	76,596	1
0		0	79.55	0	1	1	1	0	0	0	1230	10.5	55.6	3.3	87,619	1
1	1	4	74.22	0	1	1	1	0	0	0	25295	13.2	41.9	4.4	76,614	1
0		0	23.74	0	0	0	0	0	0	0	2399	10.8	19.9	3.2	68,301	1
0		0	23.74	0	0	0	0	0	0	0	2399	10.8	19.9	3.2	68,301	1
0		0	56.52	0	0	0	0	0	0	0	1901	11.5	39.5	2.9	77,369	1
0		0	53.05	0	0	1	0	0	0	0	3985	12.1	33.4	3.6	72,590	1
0		0	86.42	0	1	1	1	0	0	0	1318	16.5	39.6	4.6	95,514	1
0		0	54.2	0	1	1	1	0	0	0	2239	13.2	22.9	4.7	78,779	1
0		0	83.09	0	0	0	0	0	0	0	1138	13.3	46.7	3.3	76,736	1
0		0	74.22	0	1	1	1	0	0	0	22110	13.2	41.9	4.4	76,614	1
0		0	43.78	0	0	1	0	0	0	0	2772	8.2	39.6	2.7	81,295	1
0		0	16.6	0	0	0	0	0	0	0	1699	9.6	27.2	1.5	86,963	0
0		0	74.95	0	1	1	1	0	0	0	1370	8.8	55.9	3.4	116,044	1
0		0	66.05	0	0	1	0	0	0	0	1679	29.6	32.6	7.9	40,632	1
0		0	22.52	0	0	0	0	0	0	0	13327	10.6	33.3	2.8	75,572	1
0		0	34.36	0	0	0	0	0	0	0	2810	10.5	20.1	2.4	72,948	1
0		0	50.3	0	1	1	1	0	0	0	2126	15.2	42.1	3.1	99,839	1
0		0	74.22	0	1	1	1	0	0	0	3900	13.2	41.9	4.4	76,614	1
0		0	82.33	0	1	1	1	0	0	0	2369	8.7	60.5	3.3	135,960	1
0		0	15.85	0	0	0	0	0	0	0	1979	6.9	30.4	1.9	75,994	1
0		0	56.52	0	0	0	0	0	0	0	5952	11.5	39.5	2.9	77,369	1
0		0	51.14	0	1	1	1	0	0	0	2707	4.8	57.2	3.7	131,562	1
1	0	4	81.21	0	0	1	0	0	0	0	28508	20.3	34.6	4.2	56,385	1
0		0	38.71	0	0	0	0	0	0	0	2032	14.1	32.4	2.6	55,751	1
1	1	4	80.42	0	0	1	0	0	0	0	35280	10.6	53.5	3.1	79,524	1
0		0	59.43	0	0	1	0	0	0	0	10939	11.6	44.8	3.3	71,973	1
0		0	34.41	0	0	0	0	0	0	0	1113	17.3	20.2	3.4	51,622	1
0		0	34.41	0	0	0	0	0	0	0	1113	17.3	20.2	3.4	51,622	1
0		0	53.96	0	0	1	0	0	0	0	34648	19.4	33.9	3.9	57,319	0
0		0	26.87	0	0	0	0	0	0	0	4109	13.9	29.7	3.1	56,077	0
0		0	52.43	0	0	1	0	0	0	0	6488	9.6	27.9	4.5	79,824	0
0		0	30.96	0	0	0	0	0	0	0	16253	16.3	33.5	3.3	64,270	0
0		0	26.61	0	0	0	0	0	0	0	2031	17.2	22.5	4.7	64,636	1
0		0	46.79	0	1	1	1	0	0	0	5587	12.4	34.6	3.9	80,159	0
0		0	35.59	0	1	1	1	0	0	0	9861	17.3	27.1	4.4	57,712	1
0		0	35.45	0	0	1	0	0	0	0	16828	13.8	34.2	3.9	60,994	0
0		0	72.44	0	0	1	0	0	0	0	18301	14.6	58.1	3.3	80,941	0
0		0	27.27	0	1	1	1	0	0	0	5825	19.3	21.3	3.6	47,854	0
0		0	28.47	0	1	1	1	0	0	0	3285	13.6	24.9	3.9	57,091	0
0		0	62.75	0	0	1	0	0	0	0	4167	10.8	41.6	3.2	83,856	1
0		0	45.96	0	1	1	1	0	0	0	13716	12.5	32.1	4.2	69,079	0
0		0	49.44	0	0	0	0	0	0	0	2228	11.3	35.8	2.8	66,427	1
0		0	75.46	0	0	1	0	0	0	0	2455	10	54.4	2.3	85,189	1
0		0	49.66	0	0	1	0	0	0	0	4904	14.5	29.6	3.8	56,489	0
0		0	51.11	0	0	0	0	0	0	0	2511	14.5	33.1	3.1	70,203	1
0		0	49.41	0	0	1	0	0	0	0	2390	15.5	26.9	4.1	59,066	0
0		0	41.17	0	0	1	0	0	0	0	2419	8.6	31	2.7	82,434	1
0		0	57.66	0	1	1	1	0	0	0	4120	6.6	51.4	3.4	102,383	1
0		0	42.21	0	1	1	1	0	0	0	1032	16.9	26.9	4	56,664	1
0		0	45.1	0	0	1	0	0	0	0	8707	12.5	27.7	3.4	61,034	1
0		0	34.53	0	0	1	0	0	0	0	3522	12.8	35.9	3.6	64,187	1
0		0	42.38	0	0	0	0	0	0	0	14797	11.9	27.2	3.3	64,601	1
1	1	4	80.64	0	1	1	1	0	0	0	6324	15.1	49.9	6.2	84,738	1
0		0	80.64	0	1	1	1	0	0	0	2351	15.1	49.9	3.2	84,548	1
0		0	14.8	0	0	0	0	0	0	0	1087	16.9	16.9	3.2	49,940	1
1	1	4	83.09	0	0	0	0	0	0	0	26950	13.3	46.7	3.3	76,736	1
0		0	43.1	0	0	1	0	0	0	0	6575	13.7	27.7	2.6	55,863	0
0		0	63.44	0	1	1	1	0	0	0	5294	9.6	42.3	3.5	92,118	1
0		0	32.98	0	0	0	0	0	0	0	1106	15.3	19.3	3.7	50,325	1
0		0	38.71	0	0	0	0	0	0	0	2387	14.1	32.4	2.6	55,751	1
0		0	55.97	0	0	0	0	0	0	0	2692	10.8	39.6	6.2	84,738	1
0		0	64.55	0	1	1	1	0	0	0	23067	12.9	45.2	3.3	76,997	1
0		0	62.9	0	1	1	1	0	0	0	6685	11.3	41.7	3.9	81,042	1
0		0	51.14	0	1	1	1	0	0	0	4013	4.8	57.2	3.7	131,562	1
0		0	57.44	0	1	1	1	0	0	0	8376	6.6	52.6	3.9	113,885	1
0		0	34.5	0	0	0	0	0	0	0	4426	14.7	25.8	4	58,855	0
0		0	49.27	0	1	1	1	0	0	0	11492	7	39.9	3.4	119,253	1
0		0	86.42	0	1	1	1	0	0	0	9843	16.5	39.6	4.6	95,514	0
0		0	57.4	0	0	1	0	0	0	0	7590	15.3	27.2	4.7	58,013	0
0		0	57.44	0	1	1	1	0	0	0	3050	6.6	52.6	3.9	113,885	1
0		0	34.98	0	0	1	0	0	0	0	12733	18.4	22.7	5.3	56,096	0
0		0	71.03	0	1	1	1	0	0	0	2327	13.7	35.5	5	82,455	1
0		0	64.52	0	1	1	1	0	0	0	1315	14.9	35.9	4.1	89,334	1
0		0	80.64	0	1	1	1	0	0	0	1710	15.1	49.9	3.2	84,548	1
0		0	57.58	0	1	1	1	0	0	0	7506	10.9	39	3.5	86,078	0
0		0	36.06	0	0	0	0	0	0	0	3204	6.1	48.6	2.7	103,757	1
0		0	63.32	0	0	0	0	0	0	0	11014	17.6	48.6	3.1	61,560	1
0		0	55.97	0	0	0	0	0	0	0	34297	10.8	39.6	3	76,713	0

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	39.95	0	0	0	0	0	0	0	17084	12.1	30.8	3.2	71,607	0
0		0	41.08	0	0	0	0	0	0	0	7838	10.3	33.5	3	74,899	1
0		0	53.31	0	0	0	0	0	0	0	65410	14.1	33.2	1.8	66,952	0
0		0	53.31	0	0	0	0	0	0	0	1230	14.1	33.2	1.8	66,952	1
0		0	42.16	0	0	0	0	0	0	0	1679	13	22.6	3.7	61,941	0
0		0	42.16	0	0	0	0	0	0	0	4169	13	22.6	3.7	61,941	1
1	0	3	63.32	0	0	0	0	0	0	0	50842	17.6	48.6	3.1	61,560	0
0		0	61.17	0	0	0	0	0	0	0	1386	9.7	46.9	3.7	52,278	1
0		0	61.17	0	0	0	0	0	0	0	1386	9.7	46.9	3	79,609	1
1	1	4	83.29	0	1	1	1	0	0	0	19631	27.7	22	6.8	45,864	1
0		0	26.97	0	0	1	0	0	0	0	16425	15.6	39.5	1.9	61,675	0
0		0	57.61	0	1	1	1	0	0	0	4085	11.5	47.3	3	79,358	0
0		0	47.17	0	0	0	0	0	0	0	3692	17.3	24.3	3.8	58,471	0
0		0	71.47	0	1	1	1	0	0	0	5540	7.7	59	2.9	118,494	0
0		0	48.29	0	0	0	0	0	0	0	4764	18.8	23.6	3	52,650	0
0		0	29.98	0	0	0	0	0	0	0	3822	16.1	20.6	5.1	54,272	1
0		0	41.17	0	0	1	0	0	0	0	3173	8.6	31	2.7	82,434	1
0		0	31.79	0	0	0	0	0	0	0	1294	7.2	33.3	2.7	83,036	1
0		0	31.79	0	0	0	0	0	0	0	1294	7.2	33.3	2.7	83,036	1
0		0	57.52	0	1	0	1	0	0	0	2498	9	35.3	2.3	76,227	1
0		0	64.68	0	0	0	0	0	0	0	7272	15.1	42	3.1	69,762	1
0		0	18.62	0	0	0	0	0	0	0	2578	16.7	19.2	3.1	57,732	1
0		0	52.9	0	1	1	1	0	0	0	5038	17.7	23.9	7.5	68,693	1
0		0	42.64	0	0	1	0	0	0	0	2046	13.6	31.6	2.9	64,720	1
0		0	42.93	0	0	1	0	0	0	0	2723	10.6	41.7	3.1	76,633	1
0		0	29.89	0	1	1	1	0	0	0	5719	18.8	21.1	2.8	50,582	0
0		0	60.85	0	0	0	0	0	0	0	26899	12.4	38.4	2.8	72,129	1
0		0	71.03	0	1	1	1	0	0	0	2578	13.7	35.5	5	82,455	1
0		0	39.91	0	0	0	0	0	0	0	3527	11.3	40	2.6	71,833	1
0		0	92.15	0	1	1	1	0	0	0	2174	15.2	63.6	4.9	99,897	1
0		0	49.66	0	0	1	0	0	0	0	5108	14.5	29.6	3.8	56,489	1
0		0	33.05	0	0	1	0	0	0	0	4166	17.2	21.1	3.5	53,170	1
0		0	40.38	0	0	1	0	0	0	0	1705	10.4	28.3	4.1	67,135	1
0		0	46.12	0	1	1	1	0	0	0	5128	10.6	29.2	3.5	77,969	1
1	1	4	92.15	0	1	1	1	0	0	0	33278	15.2	63.6	4.9	99,897	1
0		0	36.55	0	0	1	0	0	0	0	1875	10	33.2	3.3	86,169	1
1	1	4	92.15	0	1	1	1	0	0	0	25662	15.2	63.6	4.9	99,897	1
0		0	50.05	0	0	0	0	0	0	0	7935	21.4	24.1	4.2	49,883	0
0		0	58.4	0	0	0	0	0	0	0	12641	11.4	38.7	2.9	83,918	0
0		0	72.57	0	0	0	0	0	0	0	48378	13	58	3.4	89,798	0
0		0	50.05	0	0	0	0	0	0	0	8678	21.4	24.1	4.2	49,883	0
0		0	37.36	0	0	0	0	0	0	0	30116	23.7	30.8	3.4	49,471	0
0		0	51.97	0	0	0	0	0	0	0	3548	26.3	21.3	4.5	44,677	0
0		0	72.57	0	0	0	0	0	0	0	41786	13	58	3.4	89,798	0
0		0	34.85	0	1	1	1	0	0	0	2688	10	33.7	4.2	81,152	1
0		0	32.13	0	0	1	0	0	0	0	3357	9.3	24.8	2.6	76,554	1
0		0	22.5	0	0	0	0	0	0	0	1861	26.4	19.9	5.3	44,938	0
0		0	85.26	0	1	1	1	0	0	0	2940	11.9	60.1	3.3	135,366	1
0		0	67.81	0	1	1	1	0	0	0	1360	10.9	39.2	3.9	85,427	1
0		0	45.96	0	1	1	1	0	0	0	8902	12.5	32.1	4.2	69,079	1
0		0	63.44	0	1	1	1	0	0	0	2446	9.6	42.3	3.5	92,118	1
0		0	63.44	0	1	1	1	0	0	0	1651	9.6	42.3	3.5	92,118	1
0		0	34.99	0	0	0	0	0	0	0	1205	11.7	19.7	4	63,777	1
0		0	34.99	0	0	0	0	0	0	0	1205	11.7	19.7	4	63,777	1
1	0	3	62.28	0	1	1	1	0	0	0	2520	9.8	41.4	2.9	54,735	1
0		0	53.11	0	1	1	1	0	0	0	5685	7.2	36.5	4.2	97,076	0
0		0	51.91	0	0	1	0	0	0	0	1267	10.5	39.6	3.2	76,923	1
0		0	23.31	0	0	0	0	0	0	0	2208	9.4	24.6	3.4	71,611	1
0		0	23.31	0	0	0	0	0	0	0	2208	9.4	24.6	3.4	71,611	1
0		0	29.44	0	0	0	0	0	0	0	1841	18.3	24.3	2.4	51,749	1
0		0	50.13	0	0	1	0	0	0	0	110404	11.1	35.9	3.4	83,668	1
0		0	38.35	0	0	1	0	0	0	0	26284	9	37.5	3	85,968	0
0		0	56.52	0	0	0	0	0	0	0	2243	11.5	39.5	2.9	77,369	1
0		0	53.85	0	1	0	1	0	0	0	2135	7.7	38.1	1.9	84,898	0
0		0	52.74	0	0	1	0	0	0	0	6988	5.3	56.9	2.4	99,174	1
0		0	20.74	0	0	0	0	0	0	0	4215	9	17.5	3.8	88,757	0
0		0	60.84	0	0	1	0	0	0	0	1170	14.8	38.1	3.9	63,822	1
0		0	28.02	0	1	1	1	0	0	0	1354	13.6	21.2	4.2	66,071	1
0		0	42.47	0	0	0	0	0	0	0	2313	10.3	28.2	2.9	69,566	1
0		0	36.25	0	0	1	0	0	0	0	2277	12.6	25.1	3.8	57,702	1
0		0	60.84	0	0	1	0	0	0	0	1754	14.8	38.1	3.9	63,822	1
0		0	50.31	0	1	1	1	0	0	0	2892	8.7	35.7	2.2	78,091	1
0		0	62.41	0	0	1	0	0	0	0	3357	6.9	52.3	2.8	106,743	1
0		0	57.55	0	1	1	1	0	0	0	1194	13.9	30.3	5.5	78,779	1
0		0	41.15	0	1	1	1	0	0	0	2738	15.7	27.8	3.7	63,894	1
1	0	3	71.5	0	1	1	1	0	0	0	3724	11.9	45.5	2.7	75,041	1
0		0	32.12	0	0	0	0	0	0	0	1304	12.1	18.1	3.1	64,214	1
0		0	32.12	0	0	0	0	0	0	0	1304	12.1	18.1	3.1	64,214	1
0		0	26.46	0	0	0	0	0	0	0	2515	13.3	29	3.3	61,798	1
0		0	19.36	0	0	0	0	0	0	0	5598	15.7	19.8	3.5	56,866	1
0		0	81.93	0	0	0	0	0	0	0	1803	20.1	40.2	3.7	52,278	0
0		0	81.93	0	0	0	0	0	0	0	1803	20.1	40.2	3.7	52,278	0
0		0	53.4	0	0	1	0	0	0	0	4460	12.9	34.3	3.2	67,813	1
0		0	46.21	0	1	1	1	0	0	0	1581	14.2	33.9	3.8	68,962	1
1	0	4	71.47	0	1	1	1	0	0	0	49569	7.7	59	2.9	118,494	1
0		0	71.03	0	1	1	1	0	0	0	1210	13.7	35.5	5	82,455	1
0		0	28.75	0	0	0	0	0	0	0	1191	11.9	28.8	2.1	64,212	1
1	0	4	62.75	0	0	1	0	0	0	0	1959	10.8	41.6	3.2	83,856	1
0		0	62.51	0	1	1	1	0	0	0	4842	9.1	37.7	2.7	96,304	1
0		0	31.98	0	0	0	0	0	0	0	1507	12.8	20.7	3.6	63,221	1
0		0	40.95	0	0	0	0	0	0	0	3607	18.9	25.5	4.7	50,519	0
0		0	33.71	0	0	0	0	0	0	0	1492	12.9	33.2	2.9	63,429	1
0		0	44.89	0	1	1	1	0	0	0	1403	16.1	18.9	5.8	63,058	1
0		0	75.46	0	0	1	0	0	0	0	3097	10	54.4	2.3	85,189	1
0		0	60.84	0	0	1	0	0	0	0	6596	14.8	38.1	3.9	63,822	1
0		0	56.46	0	1	1	1	0	0	0	1007	14.1	36.9	3.8	69,888	1
0		0	25.25	0	0	1	0	0	0	0	2327	14.8	20.6	4.2	60,070	1
0		0	42.95	0	0	0	0	0	0	0	1343	12.9	31.5	3.5	72,965	1
0		0	48.48	0	1	1	1	0	0	0	2410	8.2	37.2	3.3	76,601	1

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	54.11	0	1	1	1	0	0	0	12873	5.8	48.7	3.1	135,528	1
0		0	37.52	0	0	1	0	0	0	0	3184	9.2	22.2	3	62,910	1
0		0	81.21	0	0	1	0	0	0	0	3660	20.3	34.6	4.2	56,385	1
0		0	53.34	0	1	1	1	0	0	0	2435	6.4	44.9	2	116,796	1
0		0	38.35	0	0	1	0	0	0	0	3947	9	37.5	3	85,968	1
0		0	53.48	0	1	1	1	0	0	0	1580	9.2	43.4	3.6	106,047	1
0		0	29.1	0	1	1	1	0	0	0	1151	15	24.6	4.3	55,466	1
0		0	55.94	0	0	0	0	0	0	0	4508	16	33.7	4.3	68,748	1
0		0	13.19	0	0	0	0	0	0	0	1315	14.8	19.9	4.3	53,455	1
0		0	92.15	0	1	1	1	0	0	0	13635	15.2	63.6	4.9	99,897	1
0		0	71.47	0	1	1	1	0	0	0	2091	7.7	59	2.9	118,494	1
1	1	4	64.48	0	1	1	1	0	0	0	7705	16.7	32.1	4.6	57,660	0
0		0	23.81	0	0	0	0	0	0	0	1695	8.9	23.1	3	59,491	1
0		0	23.81	0	0	0	0	0	0	0	1695	8.9	23.1	3	59,491	1
0		0	44.23	0	1	1	1	0	0	0	4229	12.6	30.5	3.1	60,761	1
0		0	71.41	0	0	0	0	0	0	0	1232	10.2	55.5	3.3	95,151	1
0		0	86.42	0	1	1	1	0	0	0	14219	16.5	39.6	4.6	95,514	1
0		0	36.91	0	0	0	0	0	0	0	13645	11.9	30.2	3.1	62,120	0
0		0	33.11	0	1	1	1	0	0	0	1438	13.9	23.3	4.2	64,842	1
0		0	74.22	0	1	1	1	0	0	0	7629	13.2	41.9	4.4	76,614	1
1	0	2	50.27	0	1	1	1	0	0	0	24258	11	46.9	3.9	71,825	0
0		0	50.27	0	1	1	1	0	0	0	2118	11	46.9	3.9	71,825	1
0		0	57.76	0	0	1	0	0	0	0	2992	6.2	56.6	2.6	117,326	1
0		0	53.04	0	0	0	0	0	0	0	12602	9.5	38.6	2.7	91,713	1
0		0	43.16	0	0	0	0	0	0	0	3246	13	31.1	3.1	65,967	1
0		0	43.16	0	0	0	0	0	0	0	3846	13	31.1	3.1	65,967	1
0		0	41.47	0	0	0	0	0	0	0	12614	20.2	25.9	3.8	52,286	0
0		0	30.6	0	0	1	0	0	0	0	11480	16.5	26.9	4.1	53,040	0
1		2	63.12	0	0	0	0	0	0	0	52280	17.7	49.1	3.3	64,299	0
1	1	4	63.12	0	0	0	0	0	0	0	52280	17.7	49.1	3.3	64,299	0
0		0	34.41	0	0	0	0	0	0	0	3882	17.3	20.2	3.4	51,622	0
0		0	32.74	0	0	0	0	0	0	0	3627	12.7	20	5	59,960	0
0		0	56.67	0	0	0	0	0	0	0	4370	14.3	24.9	5	66,169	0
1		2	63.35	0	0	0	0	0	0	0	38885	15.6	34.1	3.3	62,776	0
1	0	3	63.35	0	0	0	0	0	0	0	38885	15.6	34.1	3.3	62,776	0
0		0	51.98	0	0	0	0	0	0	0	5635	14.2	32.6	3.9	61,028	0
0		0	41.79	0	0	0	0	0	0	0	5293	10.2	31.3	2.8	74,264	0
0		0	29.43	0	0	0	0	0	0	0	5235	20	20.4	3.5	51,053	1
0		0	29.43	0	0	0	0	0	0	0	5235	20	20.4	3.5	51,053	1
0		0	67.57	0	1	1	1	0	0	0	4310	9.3	52.5	3.4	108,037	1
0		0	57.16	0	0	0	0	0	0	0	38575	14.9	53.3	2.1	68,720	0
0		0	73.51	0	1	1	1	0	0	0	6727	15.7	59.2	3.1	72,025	1
0		0	51.11	0	0	0	0	0	0	0	4740	14.5	33.1	3.1	70,203	1
0		0	35.23	0	0	0	0	0	0	0	2761	7.8	36.6	2.4	86,374	1
0		0	66.36	0	0	0	0	0	0	0	3973	16	35.9	3.8	60,808	1
0		0	71.63	0	1	1	1	0	0	0	1530	8.3	44.9	4.1	119,667	1
1	0	4	87.28	0	1	1	1	0	0	0	48359	20.2	35.4	2.9	54,735	1
0		0	66.68	0	0	1	0	0	0	0	1621	10.2	48.6	3.4	80,645	1
0		0	60.52	0	1	1	1	0	0	0	6862	12.7	32.2	3.3	74,190	1
0		0	66.68	0	0	1	0	0	0	0	1668	10.2	48.6	3.4	80,645	1
0		0	41.45	0	0	0	0	0	0	0	1301	13.8	40.2	2.8	70,013	1
0		0	56.14	0	1	1	1	0	0	0	1536	8.4	37.5	5.1	93,475	1
0		0	23.84	0	0	1	0	0	0	0	1768	13	18.2	4.3	58,170	1
0		0	58.22	0	0	1	0	0	0	0	1869	13	40.8	3.7	69,689	1
0		0	59.82	0	0	0	0	0	0	0	1742	12	33.5	3.4	62,509	1
0		0	59.82	0	0	0	0	0	0	0	1742	12	33.5	3.4	62,509	1
0		0	50.71	0	0	1	0	0	0	0	25635	18	48	2.6	55,876	0
0		0	33.36	0	0	1	0	0	0	0	1000	11.5	29.1	2.4	57,563	1
0		0	67.01	0	1	1	1	0	0	0	15950	8.9	38.6	4.7	96,483	0
0		0	57.52	0	1	0	1	0	0	0	3934	9	35.3	2.3	76,227	0
0		0	64.48	0	0	0	0	0	0	0	23904	12.7	35.8	2.9	70,834	1
0		0	56.3	0	0	0	0	0	0	0	45452	8.8	50.4	2.8	96,798	0
0		0	42.95	0	0	0	0	0	0	0	30612	12.9	31.5	3.5	72,965	0
0		0	26.74	0	0	0	0	0	0	0	1863	15.7	16	4.2	54,167	0
0		0	48.53	0	0	1	0	0	0	0	2805	11.8	31.8	3.6	58,456	0
0		0	35.07	0	0	1	0	0	0	0	1104	16.2	25.2	4.3	65,949	1
0		0	27.3	0	0	0	0	0	0	0	2276	11.4	24.3	3.3	68,334	1
0		0	53.84	0	0	1	0	0	0	0	2415	17.9	22.8	5	57,443	1
0		0	39.35	0	1	1	1	0	0	0	1851	12.3	25	3.2	62,637	1
0		0	31.57	0	0	1	0	0	0	0	1710	13.5	21.5	6.2	84,738	1
0		0	23.23	0	0	0	0	0	0	0	2043	13.5	26.6	3.5	54,361	1
0		0	42.26	0	0	1	0	0	0	0	2912	16.4	25	4.3	59,358	1
0		0	46.12	0	1	1	1	0	0	0	1597	16.3	20.3	5.5	57,666	1
0		0	45.08	0	0	1	0	0	0	0	8799	11.9	27.2	3.5	72,157	0
0		0	59.43	0	0	1	0	0	0	0	1660	11.6	44.8	3.3	71,973	1
0		0	81.21	0	0	1	0	0	0	0	5440	20.3	34.6	4.2	56,385	1
0		0	52.98	0	1	1	1	0	0	0	2397	11.3	25.1	4.8	86,350	1
0		0	49.64	0	0	1	0	0	0	0	3407	9.8	33.8	3.5	75,468	1
0		0	38.52	0	0	0	0	0	0	0	1049	18.1	22.5	2.8	55,852	1
0		0	42.45	0	0	0	0	0	0	0	1214	10.1	30.5	3.4	76,163	1
0		0	49.66	0	0	1	0	0	0	0	5145	14.5	29.6	3.8	56,489	1
0		0	60.78	0	1	1	1	0	0	0	1979	8.2	47	5	101,621	1
0		0	37.62	0	0	1	0	0	0	0	2291	13.6	21.9	5.9	58,924	0
0		0	41.06	0	0	1	0	0	0	0	3154	8.9	27.3	2.5	65,008	1
0		0	48.62	0	0	0	0	0	0	0	18057	20.1	19.4	6.3	55,065	0
0		0	41.17	0	0	1	0	0	0	0	2580	8.6	31	2.7	82,434	1
0		0	37.95	0	0	0	0	0	0	0	4193	16.9	25.6	3.5	49,867	0
0		0	42.82	0	0	0	0	0	0	0	1290	18.6	26	3.3	57,070	1
0		0	25.29	0	0	0	0	0	0	0	2374	11.2	30.5	3.1	76,331	0
0		0	71.47	0	1	1	1	0	0	0	2420	7.7	59	2.9	118,494	1
0		0	56.24	0	0	1	0	0	0	0	3432	8.3	50.2	2.9	90,801	1
1		3	44.13	0	0	1	0	0	0	0	1960	6.3	32	2.6	78,808	1
0	0	0	58.88	0	1	1	1	0	0	0	4066	13.6	38.1	3.5	70,939	1
0		0	33.3	0	0	1	0	0	0	0	2441	8.7	24	2.8	69,490	1
0		0	21.48	0	0	0	0	0	0	0	6180	15	24.6	3.5	62,666	1
0		0	23.17	0	0	1	0	0	0	0	1058	15.9	21.9	3	53,894	1
0		0	49.64	0	0	1	0	0	0	0	8928	9.8	33.8	3.5	75,468	1
0		0	30.79	0	0	1	0	0	0	0	3159	11.9	24.9	3.3	63,934	1
0		0	71.47	0	1	1	1	0	0	0	5128	7.7	59	2.9	118,494	1

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	30.84	0	0	0	0	0	0	0	3630	16	22.4	4.2	60,932	1
0		0	79.21	0	1	1	1	0	0	0	4020	12.8	48.6	3.6	79,432	1
0		0	53.11	0	1	1	1	0	0	0	7352	7.2	36.5	4.2	97,076	1
0		0	31.86	0	0	0	0	0	0	0	4315	11	26.8	2.8	65,558	0
0		0	56.3	0	0	0	0	0	0	0	3301	8.8	50.4	2.8	96,798	1
0		0	86.42	0	1	1	1	0	0	0	2033	16.5	39.6	4.6	95,514	1
0		0	27.63	0	0	0	0	0	0	0	2229	16.8	18.4	4.2	50,403	1
0		0	28.81	0	1	1	1	0	0	0	1297	14.4	19.9	4.7	53,775	1
0		0	17.01	0	0	0	0	0	0	0	6171	18.6	17.3	3.9	41,087	1
0		0	57.76	0	0	1	0	0	0	0	2514	6.2	56.6	2.6	117,326	0
0		0	32.02	0	0	0	0	0	0	0	2476	9.4	37.5	2.5	70,837	0
0		0	40.23	0	0	0	0	0	0	0	8698	5.5	42.4	2.5	98,925	1
0		0	15.88	0	0	1	0	0	0	0	3216	22.1	18.8	5	44,153	1
0		0	46.12	0	1	1	1	0	0	0	1913	10.6	29.2	3.5	77,969	1
0		0	31.49	0	0	1	0	0	0	0	1074	14.6	21.5	3.4	61,105	1
0		0	31.15	0	0	1	0	0	0	0	3661	15.5	21.3	4	58,892	0
0		0	61.17	0	0	0	0	0	0	0	2125	9.7	46.9	3.7	52,278	1
0		0	61.17	0	0	0	0	0	0	0	2125	9.7	46.9	3	79,609	1
0		0	54.2	0	1	1	1	0	0	0	5959	13.2	22.9	4.7	78,779	1
0		0	54.11	0	1	1	1	0	0	0	16703	5.8	48.7	3.1	135,528	1
0		0	47.58	0	0	0	0	0	0	0	1741	9.6	32.9	2.9	73,492	1
0		0	57.39	0	0	0	0	0	0	0	1508	18.2	28.5	4.2	57,971	1
0		0	71.03	0	1	1	1	0	0	0	11878	13.7	35.5	5	82,455	1
0		0	74.22	0	1	1	1	0	0	0	20366	13.2	41.9	4.4	76,614	1
0		0	87.28	0	1	1	1	0	0	0	6416	20.2	35.4	2.9	54,735	1
0		0	33.12	0	0	0	0	0	0	0	2056	17.1	33.3	3.3	59,138	1
0		0	46.56	0	0	0	0	0	0	0	2337	7.9	31.5	3.2	72,032	1
0		0	28.57	0	0	1	0	0	0	0	1400	12.8	24.8	3.5	61,729	1
0		0	55.97	0	0	0	0	0	0	0	3941	10.8	39.6	3	76,713	1
0		0	71.5	0	1	1	1	0	0	0	2751	11.9	45.5	2.7	75,041	1
0		0	48.21	0	0	0	0	0	0	0	2382	14.1	41.6	2.7	59,603	1
0		0	54.83	0	1	1	1	0	0	0	1245	10.1	39.2	3.2	63,879	0
0		0	39.93	0	0	0	0	0	0	0	1772	12.3	25	3.7	64,557	1
0		0	23.93	0	0	0	0	0	0	0	1762	11.8	21.6	3.1	64,025	1
0		0	23.93	0	0	0	0	0	0	0	1762	11.8	21.6	3.1	64,025	1
0		0	83.29	0	1	1	1	0	0	0	4863	27.7	22	6.8	45,864	1
0		0	86.42	0	1	1	1	0	0	0	1391	16.5	39.6	4.6	95,514	1
0		0	67.57	0	1	1	1	0	0	0	2987	9.3	52.5	3.4	108,037	1
0		0	23.45	0	0	1	0	0	0	0	2142	13	21.5	3.8	61,190	0
0		0	41.48	0	0	1	0	0	0	0	1119	9.3	28.1	2.8	78,728	1
0		0	35.96	0	0	1	0	0	0	0	1919	9.2	22.6	2.7	71,206	1
0		0	63.35	0	0	0	0	0	0	0	4419	15.6	34.1	3.3	62,776	1
0		0	63.35	0	0	0	0	0	0	0	4419	15.6	34.1	3.3	62,776	1
0		0	28.81	0	0	0	0	0	0	0	1663	12.8	20.7	4.2	59,196	1
0		0	53.89	0	1	1	1	0	0	0	7797	8	39.7	3.3	90,740	1
0		0	69.07	0	0	1	0	0	0	0	14361	17.1	33.9	3.8	58,375	1
0		0	37.48	0	0	1	0	0	0	0	1361	13.8	31.5	3.2	54,137	1
0		0	40.13	0	0	0	0	0	0	0	13921	19.8	32.4	3.7	51,017	0
0		0	32.48	0	1	1	1	0	0	0	1159	8.1	24.2	2.9	64,093	1
0		0	87.28	0	1	1	1	0	0	0	2988	20.2	35.4	2.9	54,735	1
0		0	70.7	0	1	1	1	0	0	0	1164	5.6	64.5	1.7	133,068	1
0		0	86.42	0	1	1	1	0	0	0	2311	16.5	39.6	4.6	95,514	1
0		0	26.92	0	0	0	0	0	0	0	1402	9.7	26.8	3	69,713	1
0		0	61.17	0	0	0	0	0	0	0	12436	9.7	46.9	3.7	52,278	1
0		0	61.17	0	0	0	0	0	0	0	12436	9.7	46.9	3	79,609	1
0		0	53.58	0	0	1	0	0	0	0	3274	16.1	30.1	3.7	61,168	1
0		0	80.64	0	1	1	1	0	0	0	2441	15.1	49.9	3.2	84,548	0
0		0	72.44	0	1	1	1	0	0	0	1575	12.5	38.3	3.6	71,102	0
1	1	4	71.47	0	1	1	1	0	0	0	25286	7.7	59	2.9	118,494	1
0		0	61.2	0	1	1	1	0	0	0	1988	8.9	47.4	4.2	89,774	0
0		0	54.16	0	1	1	1	0	0	0	2458	8	48.5	2.1	88,032	1
0		0	36.1	0	0	0	0	0	0	0	1384	8.4	31.2	1.7	79,065	0
0		0	36.34	0	1	1	1	0	0	0	3815	6.4	39.7	1.7	105,096	1
0		0	53.17	0	1	1	1	0	0	0	2588	13.4	30.7	4.6	67,185	1
0		0	26.46	0	0	0	0	0	0	0	1364	13.3	29	3.3	61,798	1
0		0	28.63	0	0	1	0	0	0	0	1034	8.3	33.1	2	73,766	1
0		0	80.64	0	1	1	1	0	0	0	8938	15.1	49.9	3.2	84,548	1
0		0	56.46	0	1	1	1	0	0	0	2530	14.1	36.9	3.8	69,888	1
0		0	69.07	0	0	1	0	0	0	0	7616	17.1	33.9	3.8	58,375	1
0		0	55.51	0	0	0	0	0	0	0	6371	11	49	2.4	79,969	0
0		0	77.89	0	1	1	1	0	0	0	1027	7.3	53.1	3	143,795	1
0		0	61.34	0	0	0	0	0	0	0	10965	22.1	26	4	48,539	1
0		0	67.57	0	1	1	1	0	0	0	11039	9.3	52.5	3.4	108,037	1
0		0	56.52	0	0	0	0	0	0	0	1053	11.5	39.5	2.9	77,369	1
0		0	57.39	0	0	0	0	0	0	0	1865	18.2	28.5	4.2	57,971	1
0		0	49.66	0	0	1	0	0	0	0	3281	14.5	29.6	3.8	56,489	1
0		0	62.25	0	0	1	0	0	0	0	2340	7.2	56.3	3	97,099	1
0		0	63.44	0	1	1	1	0	0	0	6291	9.6	42.3	3.5	92,118	1
0		0	43.78	0	0	1	0	0	0	0	4234	8.2	39.6	2.7	81,295	1
0		0	57.4	0	0	1	0	0	0	0	2276	15.3	27.2	4.7	58,013	1
0		0	86.42	0	1	1	1	0	0	0	1091	16.5	39.6	4.6	95,514	1
0		0	71.5	0	1	1	1	0	0	0	8566	11.9	45.5	2.7	75,041	0
1		4	79.55	0	1	1	1	0	0	0	21004	10.5	55.6	3.3	87,619	0
0	1	0	80.64	0	1	1	1	0	0	0	1542	15.1	49.9	3.2	84,548	1
1		3	37.28	0	0	0	0	0	0	0	22122	11.9	32.5	3.2	74,841	0
1	0	3	65.18	0	0	1	0	0	0	0	62325	16.2	41.3	3.9	60,571	0
0	0	0	41.82	0	0	1	0	0	0	0	8392	17.1	36.6	4.6	55,623	0
0		0	41.6	0	0	0	0	0	0	0	2569	12.9	35.6	2.8	70,923	1
0		0	52.74	0	0	1	0	0	0	0	2156	5.3	56.9	2.4	99,174	1
0		0	61.34	0	0	0	0	0	0	0	9261	22.1	26	4	48,539	0
0		0	41.24	0	0	0	0	0	0	0	24652	9.1	34.4	2.6	77,320	0
0		0	67.96	0	1	0	1	0	0	0	3859	8.7	43.5	1.7	79,526	1
0		0	32.73	0	0	0	0	0	0	0	2158	9.8	21.5	2.2	68,267	1
0		0	42.93	0	0	1	0	0	0	0	1606	10.6	41.7	3.1	76,633	1
0		0	46.93	0	0	0	0	0	0	0	3770	7.8	36	2.7	78,930	1
0		0	28.59	0	0	0	0	0	0	0	6622	17.6	24.8	3.9	56,634	0
0		0	57.66	0	1	1	1	0	0	0	3647	6.6	51.4	3.4	102,383	1
0		0	50.13	0	0	1	0	0	0	0	4895	11.1	35.9	3.4	83,668	1
0		0	41.17	0	0	1	0	0	0	0	8421	8.6	31	2.7	82,434	0

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	18.49	0	0	0	0	0	0	0	1646	16.9	20.7	3.7	48,912	1
0		0	40.07	0	1	1	1	0	0	0	2414	15.7	24.1	6	60,648	1
0		0	79.83	0	1	1	1	0	0	0	1415	9.5	51.5	4.1	121,190	1
0		0	69.07	0	0	1	0	0	0	0	1166	17.1	33.9	3.8	58,375	1
0		0	69.07	0	0	1	0	0	0	0	3196	17.1	33.9	3.8	58,375	1
0		0	70.46	0	1	1	1	0	0	0	1050	10.1	53.3	2.6	89,418	1
0		0	50.74	0	1	1	1	0	0	0	6222	13.1	39	2.1	79,357	0
1	0	2	50.84	0	1	1	1	0	0	0	16365	14.3	34.5	2.3	68,279	1
0		0	25.82	0	0	0	0	0	0	0	3403	7.4	29.7	2.1	72,091	0
0		0	42.26	0	0	1	0	0	0	0	2955	16.4	25	4.3	59,358	1
0		0	73.4	0	0	0	0	0	0	0	5403	21	31.1	3.1	47,479	1
0		0	52.13	0	0	0	0	0	0	0	28202	25.5	45.8	3.3	47,284	0
0		0	48.04	0	0	0	0	0	0	0	3117	19.9	26.6	3.3	49,344	0
0		0	70.21	0	0	0	0	0	0	0	2580	28.8	20	4.9	35,520	0
0		0	61.17	0	0	0	0	0	0	0	5365	9.7	46.9	3	79,609	1
0		0	25.79	0	0	0	0	0	0	0	5711	15.5	25.1	3	53,548	0
0		0	38.71	0	0	0	0	0	0	0	26289	14.1	32.4	2.6	55,751	0
0		0	28.76	0	0	0	0	0	0	0	8898	15.8	31.5	3.1	54,740	1
0		0	30.46	0	0	0	0	0	0	0	1946	17.6	26	3	54,623	1
0		0	36.62	0	0	0	0	0	0	0	5448	15.1	23.3	2.9	56,751	1
0		0	71.5	0	1	1	1	0	0	0	1720	11.9	45.5	2.7	75,041	1
0		0	54.11	0	1	1	1	0	0	0	6297	5.8	48.7	3.1	135,528	1
0		0	39	0	1	1	1	0	0	0	1114	12.1	22	4.2	57,357	1
0		0	47.91	0	1	1	1	0	0	0	7096	6.7	50.6	3.8	117,699	1
0		0	83.29	0	1	1	1	0	0	0	7410	27.7	22	6.8	45,864	1
0		0	52.18	0	0	0	0	0	0	0	19554	8.8	53.1	2.1	83,520	0
0		0	36.6	0	0	0	0	0	0	0	4499	9.9	33.9	2.6	78,216	0
0		0	41.51	0	0	0	0	0	0	0	1229	19	25.6	2.5	50,518	0
0		0	55.7	0	0	0	0	0	0	0	2122	15.8	27.7	3.4	58,898	0
0		0	57.55	0	1	1	1	0	0	0	24106	13.9	30.3	5.5	78,779	0
0		0	59.74	0	0	1	0	0	0	0	1265	12.9	44.6	2.7	67,906	1
0		0	74.22	0	1	1	1	0	0	0	3417	13.2	41.9	4.4	76,614	1
0		0	49.64	0	0	1	0	0	0	0	3311	9.8	33.8	3.5	75,468	1
0		0	38.55	0	0	1	0	0	0	0	10349	24	27	5.2	50,498	0
0		0	72.57	0	0	0	0	0	0	0	2573	13	58	3.4	89,798	1
0		0	72.57	0	0	0	0	0	0	0	1798	13	58	3.4	89,798	1
0		0	87.28	0	1	1	1	0	0	0	9402	20.2	35.4	2.9	54,735	0
0		0	41.23	0	0	0	0	0	0	0	2863	12.9	23.4	2.9	66,830	1
0		0	30.71	0	0	1	0	0	0	0	3111	13.2	23	4.1	54,612	1
0		0	64.68	0	0	0	0	0	0	0	1048	15.1	42	3.1	69,762	1
0		0	72.12	0	1	1	1	0	0	0	2883	12.4	51.1	2.9	81,878	1
0		0	69.07	0	0	1	0	0	0	0	1525	17.1	33.9	3.8	58,375	1
0		0	55.61	0	0	0	0	0	0	0	2074	9.9	34.8	3.5	74,134	1
0		0	57.15	0	0	0	0	0	0	0	2535	13.6	41.4	3.2	67,033	1
0		0	49.24	0	1	1	1	0	0	0	2634	12.7	32.2	3.4	88,532	1
0		0	71.03	0	1	1	1	0	0	0	3458	13.7	35.5	5	82,455	1
0		0	53.34	0	1	1	1	0	0	0	3169	6.4	44.9	2	116,796	1
0		0	27.3	0	0	0	0	0	0	0	2810	11.4	24.3	3.3	68,334	1
0		0	53.05	0	0	1	0	0	0	0	2870	12.1	33.4	3.6	72,590	1
0		0	33.21	0	0	1	0	0	0	0	10745	17.6	32.3	4.4	51,949	0
0		0	71.03	0	1	1	1	0	0	0	1026	13.7	35.5	5	82,455	1
0		0	29.58	0	0	0	0	0	0	0	2622	17.3	20.3	3.8	58,791	1
0		0	77.19	0	1	1	1	0	0	0	1215	11	63.9	2.8	96,584	1
0		0	35.83	0	0	0	0	0	0	0	1788	11.6	34.1	1.9	67,573	1
0		0	74.22	0	1	1	1	0	0	0	8486	13.2	41.9	4.4	76,614	1
0		0	60.21	0	1	1	1	0	0	0	21431	10.1	42.1	3.9	98,365	1
0		0	68.07	0	1	1	1	0	0	0	1686	34.3	12.5	5.2	43,720	1
0		0	69.52	0	1	1	1	0	0	0	3784	14	27.9	7	91,450	0
0		0	59.25	0	1	1	1	0	0	0	3529	13.1	41.2	3.7	68,169	1
0		0	54.37	0	0	0	0	0	0	0	1364	11.5	42.2	2.6	74,424	1
0		0	52.34	0	0	0	0	0	0	0	2374	10.8	41.1	2.1	68,358	0
0		0	62.75	0	0	1	0	0	0	0	2891	10.8	41.6	3.2	83,856	1
0		0	53.66	0	0	0	0	0	0	0	7908	12.9	27.3	5.4	70,838	0
0		0	44.29	0	0	0	0	0	0	0	1022	9.5	39.7	3	78,309	1
0		0	53.85	0	1	1	1	0	0	0	5327	7.7	38.1	1.9	84,898	1
0		0	52.76	0	1	1	1	0	0	0	2600	9	34.3	2.7	84,230	1
0		0	80.64	0	1	1	1	0	0	0	1087	15.1	49.9	3.2	84,548	1
0		0	72.45	0	1	1	1	0	0	0	8871	15.2	47.9	4.4	82,361	0
0		0	77.07	0	1	1	1	0	0	0	13482	14.2	37.9	5.5	74,747	1
0		0	68.41	0	1	1	1	0	0	0	3337	24.7	26.2	4.6	47,675	0
0		0	51.98	0	1	1	1	0	0	0	2517	25.2	21	4.2	42,280	0
1		3	58.03	0	1	1	1	0	0	0	17389	19.8	31.4	3.5	65,034	0
0	1	0	71.03	0	1	1	1	0	0	0	2149	13.7	35.5	5	82,455	1
0		0	54.11	0	1	1	1	0	0	0	8409	5.8	48.7	3.1	135,528	1
0		0	86.42	0	1	1	1	0	0	0	1329	16.5	39.6	4.6	95,514	1
0		0	67.57	0	1	1	1	0	0	0	2593	9.3	52.5	3.4	108,037	1
1		4	86.42	0	1	1	1	0	0	0	76559	16.5	39.6	4.6	95,514	1
0	1	0	37.35	0	0	0	0	0	0	0	1492	17.5	23.5	2.9	55,050	1
0		0	42.64	0	0	1	0	0	0	0	2416	13.6	31.6	2.9	64,720	1
0		0	44.21	0	1	1	1	0	0	0	4324	13.8	27.2	4.1	63,565	1
0		0	57.58	0	1	1	1	0	0	0	1822	10.9	39	3.5	86,078	1
0		0	60.84	0	0	1	0	0	0	0	14746	14.8	38.1	3.9	63,822	0
0		0	80.42	0	0	1	0	0	0	0	9482	10.6	53.5	3.1	79,524	0
1		4	62.25	0	0	1	0	0	0	0	45678	7.2	56.3	3	97,099	0
0	1	0	49.64	0	0	1	0	0	0	0	2102	14.4	21.7	4.6	55,406	1
0		0	57.66	0	1	1	1	0	0	0	3481	6.6	51.4	3.4	102,383	1
0		0	70.46	0	1	1	1	0	0	0	1297	10.1	53.3	2.6	89,418	1
0		0	46.84	0	0	0	0	0	0	0	15380	9.7	43.3	1.7	70,002	0
0		0	39.91	0	0	0	0	0	0	0	2767	11.3	40	2.6	71,833	1
0		0	74.22	0	1	1	1	0	0	0	3583	13.2	41.9	4.4	76,614	1
0		0	60.21	0	1	1	1	0	0	0	13097	10.1	42.1	3.9	98,365	1
0		0	42.95	0	0	0	0	0	0	0	1418	12.9	31.5	3.5	72,965	0
0		0	74.22	0	1	1	1	0	0	0	8323	13.2	41.9	4.4	76,614	0
0		0	34.02	0	0	0	0	0	0	0	8322	18.7	29.4	3.5	49,403	0
1		4	80.64	0	1	1	1	0	0	0	27955	15.1	49.9	3.2	84,548	1
0	1	0	80.64	0	1	1	1	0	0	0	12592	15.1	49.9	3.2	84,548	1
1		4	60.9	0	0	1	0	0	0	0	33051	17.8	39.6	4.2	64,016	0
0	1	0	51.35	0	1	1	1	0	0	0	19732	12.5	32.7	4.7	71,882	0
0		0	39.64	0	0	1	0	0	0	0	18182	10.3	39.5	3.6	74,149	0

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
1	0	2	54.5	0	0	1	0	0	0	0	8388	14.3	35.8	4.6	61,598	0
0		0	66.09	0	1	1	1	0	0	0	1481	18.5	18.8	3.4	56,353	0
0		0	68.66	0	1	0	1	0	0	0	2468	9.6	43.8	2.5	65,190	1
0		0	28.79	0	0	0	0	0	0	0	8049	15.1	25.6	2.8	57,507	0
0		0	28.61	0	0	0	0	0	0	0	2490	10.1	22.8	3.4	70,594	1
0		0	28.61	0	0	0	0	0	0	0	2490	10.1	22.8	3.4	70,594	1
0		0	74.95	0	1	1	1	0	0	0	1585	8.8	55.9	3.4	116,044	1
0		0	74.95	0	1	1	1	0	0	0	1339	8.8	55.9	3.4	116,044	1
0		0	15.85	0	0	0	0	0	0	0	1866	6.9	30.4	1.9	75,994	1
0		0	70.46	0	1	1	1	0	0	0	1393	10.1	53.3	2.6	89,418	1
0		0	16.07	0	0	0	0	0	0	0	2151	18	32.5	1.9	54,020	0
1	0	4	74.22	0	1	1	1	0	0	0	33041	13.2	41.9	4.4	76,614	1
0		0	71.35	0	1	0	1	0	0	0	4817	8.6	47	2	77,432	1
0		0	87.28	0	1	1	1	0	0	0	2606	20.2	35.4	2.9	54,735	1
0		0	64.48	0	0	0	0	0	0	0	25444	12.7	35.8	2.9	70,834	1
0		0	24.89	0	0	0	0	0	0	0	1630	11	19	2.4	66,247	1
0		0	24.89	0	0	0	0	0	0	0	1630	11	19	2.4	66,247	1
0		0	56.24	0	0	1	0	0	0	0	20986	8.3	50.2	2.9	90,801	0
1	0	4	47.96	0	0	0	0	0	0	0	3669	11	27.9	3.8	67,124	1
1	0	3	71.03	0	1	1	1	0	0	0	2556	13.7	35.5	5	82,455	1
0		0	88.41	0	0	0	0	0	0	0	1455	37.1	9.8	5.8	40,683	1
0		0	83.09	0	0	0	0	0	0	0	1683	13.3	46.7	3.3	76,736	1
0		0	25.8	0	0	0	0	0	0	0	2560	11.6	21.3	3.3	75,916	1
0		0	64.68	0	0	0	0	0	0	0	1671	15.1	42	3.1	69,762	1
0		0	23.11	0	0	0	0	0	0	0	3392	14.8	18.9	3.8	58,844	1
0		0	29.42	0	0	0	0	0	0	0	1127	14.1	19.9	3.7	60,384	1
1	1	3	64.68	0	0	0	0	0	0	0	96399	15.1	42	3.1	69,762	1
0		0	29.41	0	0	0	0	0	0	0	1147	14.4	17.9	4.1	54,906	0
0		0	29.67	0	0	0	0	0	0	0	1322	16	13.7	3.4	59,012	0
0		0	35.02	0	0	0	0	0	0	0	3115	9.7	29.3	3.1	76,596	0
0		0	56.55	0	0	0	0	0	0	0	29401	25.3	35.4	4.4	48,265	1
0		0	45.69	0	0	0	0	0	0	0	1892	5	58	2.8	121,528	1
0		0	25.81	0	0	0	0	0	0	0	2097	17.1	21	3.6	52,695	1
0		0	16.19	0	0	0	0	0	0	0	1512	11.1	24.4	2.1	60,719	0
0		0	36.78	0	0	0	0	0	0	0	30037	22	40.1	3	51,236	0
0		0	24.64	0	0	0	0	0	0	0	1146	15.1	30.5	3.4	61,704	1
0		0	48.66	0	0	1	0	0	0	0	1229	10.1	30.4	3.6	71,499	1
0		0	40.51	0	1	1	1	0	0	0	4542	11.5	20.4	5.8	70,494	1
0		0	79.21	0	1	1	1	0	0	0	12791	12.8	48.6	3.6	79,432	0
0		0	28.29	0	1	1	1	0	0	0	5904	19.3	21.5	5.2	54,961	1
1	0	4	67.86	0	1	1	1	0	0	0	38551	16.2	54.4	3	70,117	0
0		0	71.03	0	1	1	1	0	0	0	1738	13.7	35.5	5	82,455	1
0		0	29.57	0	0	1	0	0	0	0	1015	6	25.3	2.5	67,263	1
0		0	64.68	0	0	0	0	0	0	0	3244	15.1	42	3.1	69,762	1
0		0	40.95	0	0	0	0	0	0	0	2083	18.9	25.5	4.7	50,519	1
0		0	58.2	0	0	0	0	0	0	0	3344	14.7	31.5	3.7	65,839	1
0		0	86.42	0	1	1	1	0	0	0	16030	16.5	39.6	6.2	84,738	1
0		0	60.21	0	1	1	1	0	0	0	1106	10.1	42.1	3.9	98,365	1
0		0	53.76	0	1	1	1	0	0	0	3692	9.9	30.1	4.7	92,793	1
0		0	71.03	0	1	1	1	0	0	0	1561	13.7	35.5	5	82,455	1
0		0	69.05	0	1	1	1	0	0	0	1179	8.9	38.5	3.5	98,580	1
0		0	65.54	0	1	1	1	0	0	0	4731	8.1	46.7	3.2	98,706	1
0		0	64.52	0	1	1	1	0	0	0	1161	14.9	35.9	4.1	89,334	1
0		0	55.97	0	0	0	0	0	0	0	4315	10.8	39.6	3	76,713	1
0		0	72.64	0	1	1	1	0	0	0	1343	7.6	55.9	3.5	150,502	1
0		0	47.46	0	0	0	0	0	0	0	11508	6.1	45.6	2.6	93,925	1
0		0	64.89	0	0	0	0	0	0	0	2012	13.8	34.8	3.8	70,871	1
0		0	81.21	0	0	1	0	0	0	0	1298	20.3	34.6	4.2	56,385	1
0		0	28.57	0	0	1	0	0	0	0	5754	12.8	24.8	3.5	61,729	1
0		0	51.42	0	0	1	0	0	0	0		17.1	46.5	2.7	67,654	1
0		0	62.41	0	0	1	0	0	0	0	42223	6.9	52.3	2.8	106,743	0
0		0	27.67	0	0	1	0	0	0	0	2823	14.4	24.1	3.3	57,884	0
0		0	45.08	0	0	1	0	0	0	0	4104	11.9	27.2	3.5	72,157	0
0		0	62.75	0	0	1	0	0	0	0	2824	10.8	41.6	3.2	83,856	0
0		0	49.66	0	0	1	0	0	0	0	1196	14.5	29.6	3.8	56,489	0
0		0	53.4	0	0	1	0	0	0	0	3295	12.9	34.3	3.2	67,813	0
0		0	27.67	0	0	1	0	0	0	0	9623	8.2	24	2.9	73,709	0
0		0	71.03	0	1	1	1	0	0	0	1252	13.7	35.5	5	82,455	1
0		0	26.84	0	0	0	0	0	0	0	11626	11.8	29.2	2.2	61,933	0
0		0	23.95	0	0	1	0	0	0	0	2134		19.7	3	58,642	1
0		0	81.21	0	0	1	0	0	0	0	1411	11	34.6	4.2	56,385	1
0		0	17.42	0	0	0	0	0	0	0	3610	20.3	24.2	3.1	62,428	1
0		0	36.96	0	0	1	0	0	0	0	2883	13.5	32	2.8	51,835	0
1		3	71.03	0	1	1	1	0	0	0	7361	17.3	35.5	5	82,455	1
0	0	0	72.03	0	1	1	1	0	0	0	1231	13.7	35.3	4.6	80,180	1
0		0	61.29	0	1	0	1	0	0	0	1069	13.8	44.8	1.9	81,205	0
0		0	60.21	0	1	1	1	0	0	0	5215	9.4	42.1	6.2	84,738	1
0		0	59.43	0	0	1	0	0	0	0	5491	10.1	44.8	3.3	71,973	1
0		0	38.52	0	0	0	0	0	0	0	4423	11.6	22.5	2.8	55,852	1
1		3	71.03	0	1	1	1	0	0	0	2397	18.1	35.5	5	82,455	1
0	0	0	79.21	0	1	1	1	0	0	0	2296	13.7	48.6	3.6	79,432	0
0		0	33.39	0	0	0	0	0	0	0	26783	12.8	26.6	4.6	75,223	1
0		0	76.78	0	1	1	1	0	0	0	10518	13.9	41.3	5.5	73,244	1
0		0	33.32	0	0	0	0	0	0	0	5990	19.1	17.9	3.2	53,847	1
0		0	34.53	0	0	1	0	0	0	0	1644	16.7	35.9	3.6	64,187	1
1		3	69.14	0	1	1	1	0	0	0	1285	12.8	44.9	3.9	94,832	1
0	1	0	60.52	0	1	1	1	0	0	0	14959	10.6	32.2	3.3	74,190	1
0		0	43.16	0	0	0	0	0	0	0	5923	12.7	31.1	3.1	65,967	0
0		0	43.16	0	0	0	0	0	0	0	9389	13	31.1	3.1	65,967	0
0		0	56.67	0	0	0	0	0	0	0	9389	13	24.9	5	66,169	0
0		0	56.67	0	0	0	0	0	0	0	10505	14.3	24.9	5	66,169	0
1		2	48.75	0	0	0	0	0	0	0	10505	14.3	40.1	2.9	56,088	0
0		0	66.68	0	0	1	0	0	0	0	58024	17.1	48.6	3.4	80,645	1
0		0	25.75	0	1	1	1	0	0	0	2881	10.2	27	3.6	61,747	1
0		0	58.05	0	1	1	1	0	0	0	1498	12.2	41.1	3.9	84,615	1
0		0	57.44	0	1	1	1	0	0	0	11564	12.5	52.6	6.2	84,738	0
0		0	36.57	0	0	0	0	0	0	0	6947	6.6	22.4	3.6	54,517	1
0		0	79.21	0	1	1	1	0	0	0	10519	15	48.6	3.6	79,432	1
0		0	71.47	0	1	1	1	0	0	0	1956	12.8	59	2.9	118,494	1
											4044	7.7				

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	79.55	0	1	1	1	0	0	0	7538	10.5	55.6	3.3	87,619	1
0		0	29.53	0	0	0	0	0	0	0	1704	6.6	39.5	2.6	99,932	1
0		0	86.42	0	1	1	1	0	0	0	4199	16.5	39.6	4.6	95,514	1
0		0	51.59	0	1	1	1	0	0	0	9174	12.4	37.3	3.3	80,040	1
0		0	60.52	0	1	1	1	0	0	0	8190	12.7	32.2	3.3	74,190	0
0		0	60.52	0	1	1	1	0	0	0	3428	12.7	32.2	3.3	74,190	1
0		0	64.42	0	0	0	0	0	0	0	2411	18.2	34.2	4.3	61,452	1
1	0	3	55.94	0	0	0	0	0	0	0	11186	16	33.7	4.3	68,748	1
0		0	69.14	0	1	1	1	0	0	0	5766	10.6	44.9	3.9	94,832	1
0		0	44.29	0	0	0	0	0	0	0	2055	9.5	39.7	3	78,309	1
0		0	52.81	0	1	0	1	0	0	0	2552	6.5	40.6	2.3	96,415	1
0		0	59.43	0	0	1	0	0	0	0	4867	11.6	44.8	3.3	71,973	1
0		0	59.25	0	1	1	1	0	0	0	1995	13.1	41.2	3.7	68,169	1
0		0	59.25	0	1	1	1	0	0	0	20200	13.1	41.2	3.7	68,169	1
0		0	56.24	0	0	1	0	0	0	0	1471	8.3	50.2	2.9	90,801	1
0		0	86.42	0	1	1	1	0	0	0	1721	16.5	39.6	4.6	95,514	1
0		0	49.98	0	0	1	0	0	0	0	1563	14.7	24.6	6.2	62,557	1
0		0	59.82	0	0	0	0	0	0	0	4159	12	33.5	3.4	62,509	1
0		0	59.82	0	0	0	0	0	0	0	4159	12	33.5	3.4	62,509	1
0		0	36.6	0	0	0	0	0	0	0	1273	9.9	33.9	2.6	78,216	1
0		0	57.88	0	1	1	1	0	0	0	2046	7.4	50.7	2.9	102,413	1
0		0	26.3	0	0	0	0	0	0	0	1388	9	36.9	2.6	95,085	1
0		0	45.19	0	1	1	1	0	0	0	1778	3.7	60.9	2.9	140,768	1
0		0	63.52	0	1	1	1	0	0	0	5862	7.9	51.8	2.5	101,158	1
0		0	21.52	0	0	0	0	0	0	0	3809	9.6	25.6	6.2	84,738	0
0		0	60.85	0	0	0	0	0	0	0	3747	12.4	38.4	2.8	72,129	1
0		0	74.22	0	1	1	1	0	0	0	5724	13.2	41.9	6.2	84,738	1
0		0	60.78	0	1	1	1	0	0	0	2952	8.2	47	5	101,621	1
0		0	41.47	0	0	0	0	0	0	0	2552	20.2	25.9	3.8	52,286	1
0		0	53.66	0	1	1	1	0	0	0	2044	12.9	27.3	5.4	70,838	1
0		0	62.41	0	0	1	0	0	0	0	1013	6.9	52.3	2.8	106,743	1
0		0	49.99	0	1	1	1	0	0	0	23638	8.4	35.8	4.3	97,851	0
0		0	74.22	0	1	1	1	0	0	0	5365	13.2	41.9	4.4	76,614	1
0		0	51.59	0	1	1	1	0	0	0	2752	12.4	37.3	3.3	80,040	1
0		0	65.91	0	1	1	1	0	0	0	8332	12.3	35.3	4.8	81,372	0
1	0	4	60.22	0	1	1	1	0	0	0	69755	8.6	45.1	4.1	102,073	1
0		0	77.07	0	1	1	1	0	0	0	15191	14.2	37.9	5.5	74,747	0
0		0	62.9	0	1	1	1	0	0	0	10896	11.3	41.7	3.9	81,042	1
0		0	52.81	0	1	0	1	0	0	0	2690	6.5	40.6	2.3	96,415	1
0		0	62.25	0	0	1	0	0	0	0	1405	7.2	56.3	3	97,099	1
0		0	37.58	0	1	1	1	0	0	0	13081	11	28.6	2.8	72,378	0
0		0	71.41	0	0	0	0	0	0	0	4300	10.2	55.5	3.3	95,151	1
0		0	51.14	0	1	0	1	0	0	0	1580	4.8	57.2	3.7	131,562	1
0		0	30.71	0	0	1	0	0	0	0	3330	13.2	23	4.1	54,612	1
0		0	59.25	0	1	1	1	0	0	0	4418	13.1	41.2	3.7	68,169	1
0		0	37.58	0	1	1	1	0	0	0	2134	11	28.6	2.8	72,378	1
0		0	66.45	0	1	1	1	0	0	0	2434	6.9	52.2	2.4	88,571	1
0		0	81.21	0	0	1	0	0	0	0	7940	20.3	34.6	4.2	56,385	1
0		0	39.35	0	0	0	0	0	0	0	11331	10.5	28	3.3	65,933	1
0		0	81.93	0	0	0	0	0	0	0	17516	20.1	40.2	3.7	52,278	1
0		0	81.93	0	0	0	0	0	0	0	17516	20.1	40.2	3.7	52,278	1
0		0	57.46	0	1	1	1	0	0	0	2014	9.9	37.2	4.1	88,560	1
0		0	41.47	0	0	0	0	0	0	0	1407	20.2	25.9	3.8	52,286	1
0		0	51.98	0	0	0	0	0	0	0	2054	14.2	32.6	3.9	61,028	1
0		0	71.63	0	1	1	1	0	0	0	4655	8.3	44.9	4.1	119,667	1
0		0	49.07	0	1	1	1	0	0	0	6015	12.1	32.1	2.3	65,699	1
0		0	75.78	0	1	0	1	0	0	0	2143	7.8	55.8	1.6	86,579	1
0		0	45.49	0	0	1	0	0	0	0	2594	9.7	32.4	2.7	72,398	1
0		0	72.45	0	1	1	1	0	0	0	3707	15.2	47.9	4.4	82,361	1
0		0	35.16	0	0	1	0	0	0	0	2088	10.8	31.8	3.5	71,152	1
0		0	74.22	0	1	1	1	0	0	0	4411	13.2	41.9	4.4	76,614	1
0		0	63.44	0	1	1	1	0	0	0	8518	9.6	42.3	3.5	92,118	0
0		0	30.25	0	0	0	0	0	0	0	1168	14.4	25.9	3.3	57,764	1
0		0	47.72	0	1	1	1	0	0	0	9718	15.4	29.1	2.5	68,851	0
0		0	62.41	0	0	1	0	0	0	0	1624	6.9	52.3	2.8	106,743	1
0		0	63.89	0	1	1	1	0	0	0	3331	11.3	53	2.6	92,795	1
0		0	33.39	0	0	0	0	0	0	0	24407	22.4	21.4	4.6	53,301	0
0		0	79.83	0	1	1	1	0	0	0	2569	9.5	51.5	4.1	121,190	1
0		0	60.21	0	1	1	1	0	0	0	40053	10.1	42.1	3.9	98,365	1
1		3	85.26	0	1	1	1	0	0	0	30596	11.9	60.1	3.3	135,366	0
1	0	3	72.64	0	1	1	1	0	0	0	39794	7.6	55.9	3.5	150,502	0
0	0	0	72.64	0	1	1	1	0	0	0	10459	7.6	55.9	3.5	150,502	1
0		0	67.57	0	1	1	1	0	0	0	2037	9.3	52.5	3.4	108,037	1
0		0	58.62	0	0	0	0	0	0	0	16051	15.2	36.8	2.9	64,029	1
0		0	58.62	0	0	0	0	0	0	0	4001	15.2	36.8	2.9	64,029	0
0		0	71.03	0	1	1	1	0	0	0	1036	13.7	35.5	5	82,455	1
1		3	74.22	0	1	1	1	0	0	0	4179	13.2	41.9	4.4	76,614	1
0	1	0	86.42	0	1	1	1	0	0	0	5247	16.5	39.6	4.6	95,514	1
0		0	23.51	0	0	0	0	0	0	0	1502	12	31.2	3.5	59,619	1
0		0	71.03	0	1	1	1	0	0	0	1344	13.7	35.5	5	82,455	1
0		0	74.95	0	1	1	1	0	0	0	4452	8.8	55.9	3.4	116,044	1
0		0	74.95	0	1	1	1	0	0	0	8581	8.8	55.9	3.4	116,044	1
0		0	77.07	0	1	1	1	0	0	0	11614	14.2	37.9	5.5	74,747	1
0		0	35.16	0	0	1	0	0	0	0	2366	10.8	31.8	3.5	71,152	1
0		0	62.25	0	0	1	0	0	0	0	1609	7.2	56.3	3	97,099	1
0		0	28.33	0	0	0	0	0	0	0	4081	18.6	18	4.8	48,465	0
0		0	43.77	0	0	0	0	0	0	0	3665	14.8	33.7	2.7	87,259	0
0		0	43.78	0	0	1	0	0	0	0	6921	8.2	39.6	2.7	81,295	0
0		0	28.81	0	0	0	0	0	0	0	1670	17	24.9	3.2	56,651	1
0		0	64.55	0	1	1	1	0	0	0	4252	12.9	45.2	3.3	76,997	1
0		0	39.13	0	0	1	0	0	0	0	2437	10.6	22.3	4.2	67,486	1
0		0	80.64	0	1	1	1	0	0	0	7499	15.1	49.9	3.2	84,548	1
0		0	40.51	0	0	0	0	0	0	0	1605	5.8	32.7	2.6	90,943	1
0		0	32.28	0	1	1	1	0	0	0	1083	13.2	23.3	5.1	66,312	1
0		0	51.62	0	1	1	1	0	0	0	3596	7.2	43.8	2.9	93,341	1
0		0	33	0	0	1	0	0	0	0	9801	9.3	38.6	3.1	81,507	0
0		0	72.12	0	1	1	1	0	0	0	3780	12.4	51.1	2.9	81,878	1
0		0	72.64	0	1	1	1	0	0	0	1582	7.6	55.9	3.5	150,502	1
1		2	74.52	0	1	1	1	0	0	0	9259	9.1	37.8	3.6	96,312	0
	0															

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	66.24	0	0	0	0	0	0	0	2908	21.7	19.4	4.4	42,209	0
0		0	41.45	0	0	0	0	0	0	0	6267	13.8	40.2	2.8	70,013	1
0		0	35.83	0	0	0	0	0	0	0	2920	11.6	34.1	1.9	67,573	1
0		0	29.65	0	0	0	0	0	0	0	2259	22.5	13.5	3.6	48,792	0
0		0	55.94	0	0	0	0	0	0	0	1250	16	33.7	4.3	68,748	1
0		0	52.71	0	0	0	0	0	0	0	1013	13.2	37.2	2.9	74,091	1
0		0	26.62	0	0	0	0	0	0	0	11205	12.6	33.9	2.7	64,118	0
0		0	62.25	0	0	1	0	0	0	0	3790	7.2	56.3	3	97,099	1
0		0	20.8	0	0	0	0	0	0	0	6164	18.1	24.4	2.9	53,782	0
0		0	42.16	0	0	0	0	0	0	0	10410	13	22.6	3.7	61,941	1
0		0	44.14	0	0	0	0	0	0	0	3212	12.9	37	3.2	75,127	1
0		0	32.66	0	0	0	0	0	0	0	4894	23.3	20.4	4.3	47,278	0
0		0	71.03	0	1	1	1	0	0	0	1481	13.7	35.5	5	82,455	1
0		0	58.05	0	1	1	1	0	0	0	11055	12.5	41.1	3.9	84,615	0
1	0	2	49.22	0	1	1	1	0	0	0	16170	20.7	35.1	4.4	44,756	0
0		0	42.04	0	1	1	1	0	0	0	15303	11.1	30.8	4.1	67,441	0
0		0	64.89	0	0	0	0	0	0	0	15204	13.8	34.8	3.8	70,871	1
0		0	53.85	0	1	0	1	0	0	0	144645	7.7	38.1	1.9	84,898	1
0		0	46.77	0	1	1	1	0	0	0	5813	12.6	30.6	4.3	68,239	0
0		0	60.85	0	0	0	0	0	0	0	1875	12.4	38.4	2.8	72,129	1
0		0	39.95	0	0	0	0	0	0	0	1297	12.1	30.8	3.2	71,607	1
0		0	19.49	0	0	0	0	0	0	0	13780	11.6	30.3	2.6	66,499	0
0		0	23.71	0	0	0	0	0	0	0	1614	16.8	27.3	2.9	55,333	1
0		0	19.11	0	0	0	0	0	0	0	3548	14.6	21	3.1	53,693	1
0		0	35.94	0	1	1	1	0	0	0	7698	11.2	28.6	2.5	70,958	0
0		0	32.17	0	0	0	0	0	0	0	2273	7.4	28.6	3.7	89,314	1
0		0	49.31	0	0	0	0	0	0	0	2986	11	34.5	3.7	76,285	1
0		0	60.21	0	1	1	1	0	0	0	18957	10.1	42.1	3.9	98,365	1
0		0	30.03	0	0	1	0	0	0	0	1744	15.2	24.3	3	56,416	1
0		0	71.03	0	1	1	1	0	0	0	1130	13.7	35.5	5	82,455	1
0		0	22.16	0	0	0	0	0	0	0	5523	18.2	33.3	2.8	54,056	0
0		0	49.56	0	0	0	0	0	0	0	1942	6.4	47.4	3.4	101,891	1
0		0	58.87	0	0	1	0	0	0	0	1902	16.2	36.6	3.9	64,719	1
0		0	58.87	0	0	1	0	0	0	0	1902	16.2	36.6	3.9	64,719	1
0		0	72.57	0	0	0	0	0	0	0	2834	13	58	3.4	89,798	1
0		0	39.49	0	0	1	0	0	0	0	3628	13.7	23	4	61,299	1
0		0	57.73	0	1	1	1	0	0	0	3820	17.6	28.9	4.3	64,030	1
0		0	34.17	0	1	1	1	0	0	0	3160	18.6	20.7	4.3	52,383	1
0		0	71.5	0	1	1	1	0	0	0	5163	11.9	45.5	2.7	75,041	1
0		0	76.78	0	1	1	1	0	0	0	3332	19.1	41.3	5.5	73,244	1
0		0	43.11	0	1	1	1	0	0	0	3086	19	24.6	4.4	59,451	1
0		0	48.94	0	1	1	1	0	0	0	3772	10.3	29.7	2.6	77,962	1
0		0	49.44	0	0	0	0	0	0	0	29046	11.3	35.8	2.8	66,427	1
0		0	48.64	0	0	1	0	0	0	0	1186	28.6	14.8	6.3	45,996	1
0		0	72.03	0	1	1	1	0	0	0	22603	13.8	35.3	4.6	80,180	1
0		0	82.33	0	1	1	1	0	0	0	5837	7	39.9	3.4	119,253	1
0		0	76.78	0	1	1	1	0	0	0	6051	19.1	41.3	5.5	73,244	1
0		0	41.57	0	1	1	1	0	0	0	1990	8.4	35.1	2	112,154	0
0		0	58.2	0	0	0	0	0	0	0	4170	14.7	31.5	3.7	65,839	1
0		0	50.3	0	1	1	1	0	0	0	2116	15.2	42.1	3.1	99,839	1
0		0	53.31	0	0	0	0	0	0	0	6558	14.1	33.2	1.8	66,952	1
1	1	3	72.64	0	1	1	1	0	0	0	32626	7.6	55.9	3.5	150,502	
1	1	3	59.51	0	1	1	1	0	0	0	8794	12.7	37.1	3.4	79,340	0
0		0	33.6	0	0	0	0	0	0	0	14301	19.6	26.5	4.3	51,708	0
0		0	42.38	0	0	0	0	0	0	0	5475	11.9	27.2	3.3	64,601	1
0		0	72.45	0	1	1	1	0	0	0	8411	15.2	47.9	4.4	82,361	1
0		0	62.28	0	1	1	1	0	0	0	4290	9.8	41.4	2.9	54,735	1
0		0	52.71	0	1	1	1	0	0	0	11479	11.9	31.2	5.9	76,108	0
0		0	54.92	0	1	1	1	0	0	0	3217	12.7	30.6	4.1	80,702	1
1	1	3	49.27	0	1	1	1	0	0	0	32161	7	39.9	3.4	119,253	0
0		0	92.15	0	1	1	1	0	0	0	3148	15.2	63.6	4.9	99,897	1
0		0	52.71	0	0	0	0	0	0	0	2122	13.2	37.2	2.9	74,091	1
0		0	83.09	0	0	0	0	0	0	0	7441	13.3	46.7	3.3	76,736	1
0		0	89.26	0	1	1	1	0	0	0	2760	11	36.1	2.2	93,833	1
0		0	51.53	0	0	1	0	0	0	0	2190	6.7	43.9	3	105,202	1
0		0	39.91	0	0	0	0	0	0	0	2806	11.3	40	2.6	71,833	1
0		0	64.42	0	0	0	0	0	0	0	4102	18.2	34.2	4.3	61,452	1
0		0	71.41	0	0	0	0	0	0	0	3401	10.2	55.5	3.3	95,151	1
0		0	80.64	0	1	1	1	0	0	0	8115	15.1	49.9	3.2	84,548	1
0		0	46.83	0	0	0	0	0	0	0	2769	13.7	45.3	3.2	52,388	0
0		0	58.87	0	0	1	0	0	0	0	3897	16.2	36.6	3.9	64,719	1
0		0	58.87	0	0	1	0	0	0	0	3897	16.2	36.6	3.9	64,719	1
0		0	64.55	0	1	1	1	0	0	0	20764	12.9	45.2	3.3	76,997	0
0		0	38.93	0	1	1	1	0	0	0	4883	16.7	25.1	4.3	55,644	0
1	1	3	67.57	0	1	1	1	0	0	0	4657	9.3	52.5	3.4	108,037	0
0		0	59.25	0	1	1	1	0	0	0	8887	13.1	41.2	3.7	68,169	0
0		0	56.46	0	1	1	1	0	0	0	9915	14.1	36.9	3.8	69,888	0
0		0	39.73	0	1	1	1	0	0	0	5782	11.3	30.6	3.5	75,077	0
0		0	54.11	0	1	1	1	0	0	0	5716	5.8	48.7	3.1	135,528	0
0		0	38.8	0	1	1	1	0	0	0	8877	14.9	21.9	4.3	59,335	0
0		0	51.82	0	1	1	1	0	0	0	6024	13.7	26.8	3.5	65,272	0
0		0	43.11	0	1	1	1	0	0	0	3799	19	24.6	4.4	59,451	0
0		0	34.02	0	1	1	1	0	0	0	2563	13.5	25	4.2	67,975	0
0		0	58.88	0	1	1	1	0	0	0	2585	13.6	38.1	3.5	70,939	0
0		0	29.1	0	1	1	1	0	0	0	4303	15	24.6	4.3	55,466	0
0		0	43.11	0	1	1	1	0	0	0	3614	19	24.6	4.4	59,451	0
0		0	39.71	0	1	1	1	0	0	0	3605	16.3	26.7	4	61,424	0
0		0	47.83	0	1	1	1	0	0	0	8078	16	28.3	4.2	58,274	0
0		0	76.78	0	1	1	1	0	0	0	3868	19.1	41.3	5.5	73,244	0
0		0	51.62	0	1	1	1	0	0	0	11890	7.2	43.8	2.9	93,341	0
0		0	83.29	0	1	1	1	0	0	0	2009	27.7	22	6.8	45,864	0
0		0	43.5	0	1	1	1	0	0	0	3021	11	28	3.7	69,851	0
0		0	46.21	0	1	1	1	0	0	0	7770	14.2	33.9	3.8	68,962	0
0		0	41.15	0	1	1	1	0	0	0	3533	15.7	27.8	3.7	63,894	0
0		0	25.6	0	0	1	0	0	0	0	2785	10.9	21.4	4.2	56,385	1
1		3	62.75	0	0	1	0	0	0	0	2466	10.8	41.6	3.2	83,856	1
1	0	3	58.88	0	1	1	1	0	0	0	26900	13.6	38.1	3.5	70,939	1
0	0	0	17.28	0	0	0	0	0	0	0	15301	15.8	32.5	3.5	60,093	1
0		0	29.43	0	0	0	0	0	0	0	2610	20	20.4	3.5	51,053	1

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	29.43	0	0	0	0	0	0	0	2610	20	20.4	3.5	51,053	1
0		0	86.42	0	1	1	1	0	0	0	5922	16.5	39.6	4.6	95,514	1
0		0	55.61	0	1	1	1	0	0	0	1023	12.6	21.6	6.2	84,738	1
0		0	81.21	0	0	1	0	0	0	0	46015	20.3	34.6	4.2	56,385	0
0		0	27.34	0	0	0	0	0	0	0	11533	17.3	29.2	3.5	54,996	0
0		0	19.09	0	0	0	0	0	0	0	1278	14.9	17.5	4.2	60,950	1
0		0	61.05	0	0	0	0	0	0	0	9351	22.5	20.9	4	56,289	1
0		0	41.43	0	0	0	0	0	0	0	81678	23.7	42.5	3.1	60,355	1
0		0	23.07	0	0	0	0	0	0	0	13510	12.7	21.9	4.1	68,019	1
0		0	47.85	0	0	0	0	0	0	0	12293	17.3	23.7	4.2	60,250	1
0		0	48.56	0	0	0	0	0	0	0	7900	22.1	23.7	4.6	51,342	1
0		0	44.65	0	0	0	0	0	0	0	2670	11.5	27.2	4.5	62,412	0
0		0	58.2	0	0	0	0	0	0	0	7479	14.7	31.5	3.7	65,839	0
0		0	28.09	0	0	0	0	0	0	0	2506	14.8	22.1	4.2	52,460	0
0		0	49.31	0	0	0	0	0	0	0	14068	11	34.5	3.7	76,285	1
0		0	37.04	0	0	0	0	0	0	0	1832	8.1	30.9	3.4	86,043	1
0		0	55.94	0	0	0	0	0	0	0	8357	16	33.7	4.3	68,748	0
0		0	56.04	0	0	0	0	0	0	0	9341	23.5	20.6	5.4	49,583	1
0		0	54.41	0	0	0	0	0	0	0	41737	9.8	41.9	3.3	89,074	0
0		0	33.12	0	0	0	0	0	0	0	45569	17.1	33.3	3.3	59,138	1
0		0	33.12	0	0	0	0	0	0	0	10184	17.1	33.3	3.3	59,138	0
0		0	66.66	0	0	0	0	0	0	0	2547	18.5	25.4	4.4	53,441	1
0		0	49.31	0	0	0	0	0	0	0	2769	11	34.5	3.7	76,285	1
0		0	45.15	0	0	0	0	0	0	0	18115	6.1	48.4	3.5	102,711	1
0		0	92.15	0	1	1	1	0	0	0	7186	15.2	63.6	4.9	99,897	1
0		0	74.22	0	1	1	1	0	0	0	1386	13.2	41.9	4.4	76,614	1
0		0	71.03	0	1	1	1	0	0	0	3186	13.7	35.5	5	82,455	1
0		0	28.61	0	0	0	0	0	0	0	1414	10.1	22.8	3.4	70,594	1
0		0	28.61	0	0	0	0	0	0	0	1414	10.1	22.8	3.4	70,594	1
0		0	69.14	0	1	1	1	0	0	0	9439	10.6	44.9	3.9	94,832	0
0		0	64.55	0	1	1	1	0	0	0	4522	12.9	45.2	3.3	76,997	1
0		0	56.64	0	1	1	1	0	0	0	4428	13.3	32.5	3.2	63,141	1
0		0	30.69	0	0	0	0	0	0	0	2651	9.2	24.7	2.8	70,121	1
1	0	4	57.46	0	1	1	1	0	0	0	2941	9.9	37.2	4.1	88,560	0
0		0	86.42	0	1	1	1	0	0	0	1663	16.5	39.6	4.6	95,514	1
0		0	71.03	0	1	1	1	0	0	0	2878	13.7	35.5	5	82,455	1
0		0	80.64	0	1	1	1	0	0	0	1296	15.1	49.9	3.2	84,548	1
1	1	3	86.42	0	1	1	1	0	0	0	12064	16.5	39.6	4.6	95,514	1
0		0	51.42	0	0	1	0	0	0	0	112931	17.1	46.5	2.7	67,654	1
0		0	58.87	0	0	1	0	0	0	0	4949	16.2	36.6	3.9	64,719	1
0		0	58.87	0	0	1	0	0	0	0	4949	16.2	36.6	3.9	64,719	1
0		0	30.32	0	0	0	0	0	0	0	5548	10.6	29.7	2.9	72,658	1
0		0	60.64	0	0	0	0	0	0	0	12017	11.4	45.9	2.9	68,210	0
0		0	28.4	0	0	0	0	0	0	0	1563	12.9	35.5	2.4	57,497	0
0		0	52.71	0	0	0	0	0	0	0	10960	13.2	37.2	2.9	74,091	1
0		0	64.42	0	0	0	0	0	0	0	8256	18.2	34.2	4.3	61,452	0
0		0	44.14	0	0	0	0	0	0	0	13754	12.9	37	3.2	75,127	0
1	1	3	41.45	0	0	0	0	0	0	0	39517	13.8	40.2	2.8	70,013	0
0		0	21.99	0	0	0	0	0	0	0	8082	18.6	21.6	3.6	49,815	0
1	1	2	49.31	0	0	0	0	0	0	0	52044	11	34.5	3.7	76,285	0
0		0	71.41	0	0	0	0	0	0	0	67083	10.2	55.5	3.3	95,151	0
1	1	3	64.89	0	0	0	0	0	0	0	32772	13.8	34.8	3.8	70,871	0
0		0	66.66	0	0	0	0	0	0	0	27843	18.5	25.4	4.4	53,441	0
0		0	58.2	0	0	0	0	0	0	0	38396	14.7	31.5	3.7	65,839	0
0		0	29.52	0	0	0	0	0	0	0	11071	13.2	27.7	3.6	67,978	0
0		0	55.94	0	0	0	0	0	0	0	16413	16	33.7	4.3	68,748	0
0		0	58.2	0	0	0	0	0	0	0	9476	14.7	31.5	3.7	65,839	0
0		0	37.95	0	0	0	0	0	0	0	5759	11.5	34.3	4.3	75,947	0
0		0	25.49	0	0	0	0	0	0	0	6536	11.7	16.6	3.3	64,868	0
0		0	58.04	0	0	0	0	0	0	0	36826	26.9	20.3	6.1	48,825	0
0		0	81.21	0	0	1	0	0	0	0	2074	20.3	34.6	4.2	56,385	1
0		0	25.42	0	0	0	0	0	0	0	2593	12.9	23.1	3.5	61,417	1
0		0	41.51	0	0	0	0	0	0	0	14804	14	28.9	3.1	61,634	1
0		0	36.25	0	0	1	0	0	0	0	1003	12.6	25.1	3.8	57,702	1
0		0	48.57	0	1	1	1	0	0	0	1912	11.5	30.9	2.6	63,191	1
0		0	69.14	0	1	1	1	0	0	0	10804	10.6	44.9	3.9	94,832	0
0		0	81.21	0	0	1	0	0	0	0	13939	20.3	34.6	4.2	56,385	1
0		0	39.26	0	0	1	0	0	0	0	2351	10.6	37.6	3.7	77,284	1
0		0	39.8	0	0	0	0	0	0	0	1502	18.4	23.6	3.5	52,236	1
0		0	31.98	0	0	0	0	0	0	0	3375	12.8	20.7	3.6	63,221	1
0		0	20.08	0	0	0	0	0	0	0	1943	15.6	14.9	3.6	51,980	1
0		0	43.36	0	0	0	0	0	0	0	1120	10	48.9	2.5	80,641	1
0		0	86.42	0	1	1	1	0	0	0	14139	16.5	39.6	4.6	95,514	1
0		0	63.65	0	1	1	1	0	0	0	1719	10.3	28.4	4.7	92,711	1
0		0	53.66	0	0	0	0	0	0	0	1986	12.9	27.3	5.4	70,838	1
0		0	62.28	0	1	1	1	0	0	0	25129	9.8	41.4	2.9	54,735	0
0		0	59.25	0	0	1	0	0	0	0	1275	15.7	47.3	3.4	63,667	1
0		0	27.89	0	0	0	0	0	0	0	4155	10.2	24.7	2.7	73,250	1
0		0	43.16	0	0	0	0	0	0	0	1041	13	31.1	3.1	65,967	1
0		0	43.16	0	0	0	0	0	0	0	1041	13	31.1	3.1	65,967	1
0		0	74.22	0	1	1	1	0	0	0	1390	13.2	41.9	4.4	76,614	1
1		2	63.06	0	1	1	1	0	0	0	2921	11.3	41.7	3.8	84,551	1
0	0	0	60.78	0	1	1	1	0	0	0	1918	8.2	47	5	101,621	1
0		0	58.2	0	0	0	0	0	0	0	3581	14.7	31.5	3.7	65,839	1
0		0	92.15	0	1	1	1	0	0	0	2179	15.2	63.6	4.9	99,897	1
0		0	16.26	0	0	0	0	0	0	0	3226	10.8	24.3	2.3	62,100	1
0		0	35.89	0	0	0	0	0	0	0	5339	18.2	35	3.6	46,433	0
0		0	35.89	0	0	0	0	0	0	0	5339	18.2	35	3.6	46,433	0
1		3	71.47	0	1	1	1	0	0	0	17113	7.7	59	2.9	118,494	1
0	0	0	18.51	0	0	0	0	0	0	0	1940	14.8	17.7	4.2	50,410	1
0		0	56.58	0	1	1	1	0	0	0	2907	14	35.1	3.5	74,206	1
0		0	52.34	0	0	0	0	0	0	0	1015	10.8	41.1	2.1	68,358	1
0		0	15.93	0	0	1	0	0	0	0	1416	26.1	13.5	5.8	36,573	1
0		0	57.15	0	0	0	0	0	0	0	1106	13.6	41.4	3.2	67,033	1
0		0	42.82	0	0	0	0	0	0	0	3713	18.6	26	3.3	57,070	1
0		0	42.75	0	1	1	1	0	0	0	4673	7.3	41.1	3.3	82,248	1
0		0	56.92	0	1	1	1	0	0	0	1562	12.4	34.6	3.6	80,159	0
0		0	54.11	0	1	1	1	0	0	0	1336	5.8	48.7	3.1	135,528	1
0		0	49.24	0	1	1	1	0	0	0	6454	12.7	32.2	3.4	88,532	1

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	55.82	0	1	1	1	0	0	0	5517	6.3	45.2	1.8	112,525	1
0		0	60.21	0	1	1	1	0	0	0	2286	10.1	42.1	3.9	98,365	1
0		0	76.78	0	1	1	1	0	0	0	3361	19.1	41.3	5.5	73,244	1
0		0	79.83	0	1	1	1	0	0	0	3782	9.5	51.5	4.1	121,190	1
0		0	50.76	0	1	1	1	0	0	0	1784	12.7	34.8	3	63,619	1
1	0	4	56.46	0	1	1	1	0	0	0	37642	14.1	36.9	3.8	69,888	1
0		0	53.92	0	0	0	0	0	0	0	18608	12.9	35.3	3.7	66,034	0
1	1	4	58.41	0	0	1	0	0	0	0	58335	14	35.9	3.8	64,007	0
0		0	46.49	0	0	0	0	0	0	0	32804	13.5	34.6	2.3	62,100	0
0		0	59.98	0	0	0	0	0	0	0	10287	15.7	37.4	3.2	57,057	0
0		0	35.12	0	0	0	0	0	0	0	3059	20.6	23.3	4.2	48,635	0
0		0	59.98	0	0	0	0	0	0	0	7949	15.7	37.4	3.2	57,057	0
0		0	30.73	0	0	0	0	0	0	0	6533	12.8	24.4	3.4	52,679	0
0		0	87.28	0	1	1	1	0	0	0	4930	20.2	35.4	2.9	54,735	0
0		0	62.9	0	1	1	1	0	0	0	4811	11.3	41.7	3.9	81,042	1
1	0	4	79.83	0	1	1	1	0	0	0	54449	9.5	51.5	4.1	121,190	0
1	0	3	69.48	0	1	1	1	0	0	0	52829	15.3	44.1	4.7	82,359	0
0		0	85.26	0	1	1	1	0	0	0	1374	11.9	60.1	3.3	135,366	0
1	1	4	53.48	0	1	1	1	0	0	0	45633	9.2	43.4	3.6	106,047	0
1	1	5	71.03	0	1	1	1	0	0	0	69845	13.7	35.5	5	82,455	0
1	1	3	53.84	0	1	1	1	0	0	0	10802	18.6	14.8	9	65,253	0
1	0	4	52.98	0	1	1	1	0	0	0	30913	11.3	25.1	4.8	86,350	0
1	1	4	60.21	0	1	1	1	0	0	0	55842	10.1	42.1	3.9	98,365	0
1	1	3	85.26	0	1	1	1	0	0	0	16914	11.9	60.1	3.3	135,366	0
1	1	3	64.52	0	1	1	1	0	0	0	31335	14.9	35.9	4.1	89,334	0
1	1	4	78.44	0	1	1	1	0	0	0	23091	12.6	43.6	5.7	99,256	0
0		0	33.71	0	0	0	0	0	0	0	11890	12.9	33.2	2.9	63,429	0
1	0	2	60.85	0	0	0	0	0	0	0	77982	12.4	38.4	2.8	72,129	0
0		0	30.1	0	0	0	0	0	0	0	11236	13.6	29.1	3.3	60,086	0
0		0	41.76	0	0	0	0	0	0	0	3427	15.6	29.3	3.6	55,160	1
1	1	4	74.22	0	1	1	1	0	0	0	30198	13.2	41.9	4.4	76,614	1
0		0	57.15	0	0	0	0	0	0	0	48594	13.6	41.4	3.2	67,033	0
0		0	77.19	0	1	1	1	0	0	0	46885	11	63.9	2.8	96,584	0
0		0	42.75	0	1	1	1	0	0	0	13971	7.3	41.1	3.3	82,248	0
1	1	3	54.7	0	1	1	1	0	0	0	37449	9.8	41.5	3.3	84,551	0
0		0	63.06	0	1	1	1	0	0	0	1683	11.3	41.7	3.8	84,551	0
0		0	64.89	0	0	0	0	0	0	0	2962	13.8	34.8	3.8	70,871	1
0		0	50.18	0	0	0	0	0	0	0	14723	15.2	30.5	3.8	62,794	1
0		0	67.81	0	1	1	1	0	0	0	28522	10.9	39.2	3.9	85,427	0
1	0	3	79.55	0	1	1	1	0	0	0	17194	10.5	55.6	3.3	87,619	1
0		0	47.58	0	0	0	0	0	0	0	2711	9.6	32.9	2.9	73,492	1
0		0	44.31	0	0	0	0	0	0	0	2905	13.8	27.1	3.2	57,997	1
0		0	62.71	0	0	0	0	0	0	0	69252	18.5	47.7	3.1	58,783	0
1	1	2	70.12	0	0	0	0	0	0	0	50880	24.1	48.7	3.3	49,832	0
0		0	63.06	0	1	1	1	0	0	0	7965	11.3	41.7	3.8	84,551	1
0		0	66.88	0	1	1	1	0	0	0	3729	16.5	30.9	3	71,143	0
0		0	62.51	0	1	1	1	0	0	0	22457	9.1	37.7	2.7	96,304	0
0		0	62.51	0	1	1	1	0	0	0	3526	9.1	37.7	2.7	96,304	0
0		0	81.93	0	0	0	0	0	0	0	1273	20.1	40.2	3.7	52,278	1
0		0	81.93	0	0	0	0	0	0	0	1273	20.1	40.2	3.7	52,278	1
0		0	55.94	0	0	0	0	0	0	0	52610	16	33.7	4.3	68,748	0
0		0	55.94	0	0	0	0	0	0	0	9873	16	33.7	4.3	68,748	0
0		0	55.94	0	0	0	0	0	0	0	16610	16	33.7	6.2	84,738	0
0		0	30.33	0	0	0	0	0	0	0	5416	14.1	19.7	4.1	67,905	0
0		0	49.67	0	0	0	0	0	0	0	13185	14.3	44.9	2.7	60,108	0
0		0	74.22	0	1	1	1	0	0	0	47263	13.2	41.9	4.4	76,614	0
0		0	46.52	0	1	1	1	0	0	0	5004	11.9	35.1	4.3	73,684	0
1	0	3	59.71	0	1	1	1	0	0	0	65110	16.2	46.6	4.1	61,205	0
0		0	63.35	0	0	0	0	0	0	0	6647	15.6	34.1	3.3	62,776	1
0		0	63.35	0	0	0	0	0	0	0	6647	15.6	34.1	3.3	62,776	1
1	1	2	70.57	0	0	0	0	0	0	0	41273	15.5	54.6	2.4	74,909	0
0		0	26.87	0	0	0	0	0	0	0	1402	11	24.4	1.8	65,633	1
1	1	3	68.04	0	0	1	0	0	0	0	35685	13.3	52	2.6	67,482	0
0		0	59.25	0	0	1	0	0	0	0	42216	15.7	47.3	3.4	63,667	0
0		0	71.03	0	1	1	1	0	0	0	7953	13.7	35.5	5	82,455	1
0		0	58.87	0	0	1	0	0	0	0	29210	16.2	36.6	3.9	64,719	0
0		0	58.87	0	0	1	0	0	0	0	29210	16.2	36.6	3.9	64,719	0
0		0	44.23	0	1	1	1	0	0	0	14221	12.6	30.5	3.1	60,761	0
0		0	48.57	0	1	1	1	0	0	0	4665	11.5	30.9	2.6	63,191	0
0		0	46.4	0	1	1	1	0	0	0	2260	13.6	29.9	3.5	52,159	0
0		0	39.04	0	1	1	1	0	0	0	1790	12.1	22.4	3.9	51,562	0
0		0	39.04	0	1	1	1	0	0	0	1650	12.1	22.4	3.9	51,562	0
0		0	28.27	0	0	0	0	0	0	0	4355	7.7	38.7	1.7	83,111	1
0		0	44.65	0	0	0	0	0	0	0	4537	11.5	27.2	4.5	62,412	1
0		0	41.8	0	1	1	1	0	0	0	3411	22.9	17.1	3.2	53,590	0
0		0	62.28	0	1	1	1	0	0	0	15909	9.8	41.4	2.9	54,735	0
0		0	89.26	0	1	1	1	0	0	0	50709	11	36.1	2.2	93,833	0
0		0	87.28	0	1	1	1	0	0	0	14456	20.2	35.4	2.9	54,735	0
0		0	57.58	0	1	1	1	0	0	0	6492	10.9	39	3.5	86,078	0
1	1	4	72.12	0	1	1	1	0	0	0	37327	12.4	51.1	2.9	81,878	0
0		0	80.64	0	1	1	1	0	0	0	18381	15.1	49.9	3.2	84,548	0
0		0	54.92	0	1	1	1	0	0	0	9075	12.7	30.6	4.1	80,702	0
0		0	71.47	0	1	1	1	0	0	0	20126	7.7	59	2.9	118,494	0
0		0	64.42	0	0	0	0	0	0	0	25467	18.2	34.2	4.3	61,452	0
0		0	53.31	0	0	0	0	0	0	0	29973	14.1	33.2	1.8	66,952	1
1	1	3	72.44	0	0	1	0	0	0	0	72512	14.6	58.1	3.3	80,941	0
0		0	53.84	0	0	1	0	0	0	0	7793	17.9	22.8	5	57,443	0
0		0	34.88	0	1	1	1	0	0	0	2799	10.7	28.1	2.9	69,538	1
0		0	56.64	0	1	1	1	0	0	0	11858	13.3	32.5	3.2	63,141	1
0		0	37.8	0	1	1	1	0	0	0	1729	8.9	30.8	2.4	69,171	1
1	0	4	70.46	0	1	1	1	0	0	0	70641	10.1	53.3	2.6	89,418	1
0		0	42.99	0	0	0	0	0	0	0	34161	14.1	44.3	2.5	61,736	0
0		0	54.82	0	0	0	0	0	0	0	41145	14.4	51	2.5	63,981	0
1		2	59.82	0	0	0	0	0	0	0	19161	12	33.5	3.4	62,509	0
1	0	3	59.82	0	0	0	0	0	0	0	19161	12	33.5	3.4	62,509	0
0		0	61.17	0	0	0	0	0	0	0	15528	9.7	46.9	3.7	52,278	0
0		0	61.17	0	0	0	0	0	0	0	15528	9.7	46.9	3	79,609	0
0		0	43.6	0	0	1	0	0	0	0	2880	17.1	21.3	3.7	55,635	1
0		0	39.93	0	0	0	0	0	0	0	2716	12.3	25	3.7	64,557	1

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	26.78	0	0	0	0	0	0	0	7139	8.1	34.6	1.8	67,809	0
0		0	54.37	0	0	0	0	0	0	0	17931	11.5	42.2	2.6	74,424	0
0		0	54.37	0	0	0	0	0	0	0	8723	11.5	42.2	2.6	74,424	0
0		0	52.34	0	0	0	0	0	0	0	31540	10.8	41.1	2.1	68,358	1
0		0	53.66	0	0	0	0	0	0	0	36573	12.9	27.3	5.4	70,838	0
0		0	50.82	0	0	0	0	0	0	0	25000	9.9	33.2	4.1	80,245	0
0		0	54.9	0	1	0	1	0	0	0	8505	8.1	34.6	2.6	81,315	1
1	1	3	56.53	0	1	1	1	0	0	0	18021	9.3	38.5	2.1	82,845	0
0		0	58.05	0	1	1	1	0	0	0	8096	12.5	41.1	3.9	84,615	1
1	1	3	61.01	0	1	1	1	0	0	0	29086	13.5	37.4	3.5	65,034	0
1	0	3	59.74	0	0	1	0	0	0	0	4117	12.9	44.6	2.7	67,906	0
1	1	4	74.82	0	0	1	0	0	0	0	44496	11.7	61.8	2.9	87,780	0
1	1	3	66.68	0	0	1	0	0	0	0	34319	10.2	48.6	3.4	80,645	0
0		0	60.84	0	0	1	0	0	0	0	22811	14.8	38.1	3.9	63,822	0
0		0	40.31	0	0	1	0	0	0	0	9277	27.7	14.6	5	39,931	0
0		0	56.16	0	0	1	0	0	0	0	1586	14.8	36.9	3.5	62,992	0
0		0	50.17	0	0	1	0	0	0	0	20394	12.1	44.8	3.1	70,995	0
0		0	41.59	0	0	0	0	0	0	0	16446	12.5	37.2	1.7	64,914	0
1	1	3	51.11	0	0	0	0	0	0	0	19108	14.5	33.1	3.1	70,203	0
0		0	20.11	0	0	0	0	0	0	0	21923	15.1	31.5	2.7	71,486	0
0		0	45.15	0	0	0	0	0	0	0	45026	6.1	48.4	3.5	102,711	0
0		0	64.89	0	0	0	0	0	0	0	4714	13.8	34.8	3.8	70,871	0
0		0	49.31	0	0	0	0	0	0	0	3657	11	34.5	3.7	76,285	0
0		0	39.56	0	1	0	1	0	0	0	12990	9.1	32	3.3	90,770	1
0		0	53.53	0	0	0	0	0	0	0	11264	14.2	30.1	3.2	62,020	0
0		0	71.5	0	1	1	1	0	0	0	4204	11.9	45.5	2.7	75,041	1
0		0	51.98	0	0	0	0	0	0	0	19035	14.2	32.6	3.9	61,028	1
0		0	41.6	0	0	0	0	0	0	0	33395	12.9	35.6	2.8	70,923	0
1	0	4	60.46	0	1	1	1	0	0	0	26681	14.7	33.4	4	64,192	0
1	1	4	81.21	0	0	1	0	0	0	0	46008	20.3	34.6	4.2	56,385	1
0		0	19.16	0	0	1	0	0	0	0	2651	23.4	16	5.7	41,837	1
0		0	26.13	0	0	1	0	0	0	0	1511	15.9	20.3	4.4	58,112	0
0		0	35.16	0	0	1	0	0	0	0	1595	10.8	31.8	3.5	71,152	0
0		0	30.71	0	0	1	0	0	0	0	2641	13.2	23	4.1	54,612	0
1	0	4	59.43	0	0	1	0	0	0	0	45541	11.6	44.8	3.3	71,973	0
0		0	79.21	0	1	1	1	0	0	0	5027	12.8	48.6	3.6	79,432	1
0		0	38.75	0	0	0	0	0	0	0	1212	12.1	28.7	2.9	59,184	1
1	0	2	53.76	0	1	1	1	0	0	0	2925	9.9	30.1	4.7	92,793	1
0		0	54.2	0	1	1	1	0	0	0	5788	13.2	22.9	4.7	78,779	1
0		0	82.33	0	1	1	1	0	0	0	1584	8.7	60.5	3.3	135,960	1
0		0	58.57	0	1	1	1	0	0	0	20758	9.1	50.5	2.5	99,015	0
0		0	21.67	0	0	0	0	0	0	0	1881	17.4	17.9	4.3	51,449	1
1	1	3	59.25	0	1	1	1	0	0	0	21328	13.1	41.2	3.7	68,169	1
0		0	43.16	0	0	0	0	0	0	0	2800	13	31.1	3.1	65,967	1
0		0	43.16	0	0	0	0	0	0	0	2800	13	31.1	3.1	65,967	1
0		0	63.06	0	1	1	1	0	0	0	3027	11.3	41.7	3.8	84,551	1
0		0	38.05	0	0	1	0	0	0	0	1504	8.3	36.6	2.7	79,117	1
0		0	60.21	0	1	1	1	0	0	0	11226	10.1	42.1	3.9	98,365	1
1	0	3	85.26	0	1	1	1	0	0	0	12077	11.9	60.1	3.3	135,366	0
0		0	53.58	0	0	1	0	0	0	0	6017	16.1	30.1	3.7	61,168	1
0		0	43.85	0	0	0	0	0	0	0	2053	9.7	34.6	1.8	75,623	1
0		0	37.89	0	0	0	0	0	0	0	4461	14.1	31.1	3	67,728	0
0		0	44.38	0	0	0	0	0	0	0	2346	9.5	44.8	2.8	83,687	0
0		0	68.4	0	0	0	0	0	0	0	43203	15.9	41.1	3	61,010	0
0		0	35.6	0	0	0	0	0	0	0	6908	14	25.7	2.9	58,535	0
0		0	54.11	0	0	0	0	0	0	0	11026	17.5	46	2.1	55,263	1
1	1	3	52.71	0	0	0	0	0	0	0	59916	13.2	37.2	2.9	74,091	0
0		0	41.46	0	0	0	0	0	0	0	1882	10.4	34.3	3	72,176	0
0		0	49.44	0	0	0	0	0	0	0	3944	11.3	35.8	2.8	66,427	0
1	1	4	71.03	0	1	1	1	0	0	0	62935	13.7	35.5	5	82,455	1
0		0	44.31	0	0	0	0	0	0	0	11480	13.8	27.1	3.2	57,997	0
0		0	66.45	0	1	1	1	0	0	0	9663	6.9	52.2	2.4	88,571	0
0		0	43.45	0	0	0	0	0	0	0	17101	19	29.5	3	51,344	0
0		0	53.11	0	1	1	1	0	0	0	4062	7.2	36.5	4.2	97,076	1
0		0	71.5	0	1	1	1	0	0	0	11572	11.9	45.5	2.7	75,041	1
0		0	55.94	0	0	0	0	0	0	0	4319	16	33.7	4.3	68,748	1
0		0	60.21	0	1	1	1	0	0	0	5713	10.1	42.1	3.9	98,365	1
0		0	29.52	0	0	0	0	0	0	0	1515	13.2	27.7	3.6	67,978	0
0		0	64.89	0	0	0	0	0	0	0	10487	13.8	34.8	3.8	70,871	1
0		0	16.62	0	0	1	0	0	0	0	20362	26.9	19.8	4.8	43,604	1
0		0	92.15	0	1	1	1	0	0	0	4864	15.2	63.6	4.9	99,897	1
0		0	58.2	0	0	0	0	0	0	0	9512	14.7	31.5	3.7	65,839	1
0		0	24.04	0	0	0	0	0	0	0	1016	17.1	18.1	4.4	46,660	1
0		0	55.61	0	1	1	1	0	0	0	8214	12.6	21.6	6.2	84,738	1
0		0	71.03	0	1	1	1	0	0	0	43748	13.7	35.5	5	82,455	1
0		0	81.21	0	0	1	0	0	0	0	2987	20.3	34.6	4.2	56,385	1
0		0	19.41	0	1	1	1	0	0	0	1020	17	15.3	3.5	59,194	1
0		0	57.39	0	0	0	0	0	0	0	21610	18.2	28.5	4.2	57,971	0
1		3	53.04	0	0	0	0	0	0	0	47336	9.5	38.6	2.7	91,713	0
0	1	0	75.78	0	1	0	1	0	0	0	17417	7.8	55.8	1.6	86,579	0
0		0	74.95	0	1	1	1	0	0	0	7023	8.8	55.9	3.4	116,044	0
1		2	74.95	0	1	1	1	0	0	0	68838	8.8	55.9	3.4	116,044	0
0	0	0	53.76	0	1	1	1	0	0	0	6056	9.9	30.1	4.7	92,793	0
0		0	29.79	0	0	0	0	0	0	0	15073	14.3	22.4	3.3	69,924	0
0		0	79.21	0	1	1	1	0	0	0	1516	12.8	48.6	3.6	79,432	1
0		0	54.26	0	0	1	0	0	0	0	12300	10.8	35.7	2.7	70,564	0
0		0	45.49	0	0	1	0	0	0	0	9769	9.7	32.4	2.7	72,398	0
0		0	55.75	0	0	1	0	0	0	0	11808	12.1	36.1	2.6	70,075	0
1		4	75.46	0	0	1	0	0	0	0	63654	10	54.4	2.3	85,189	0
1	1	3	69.07	0	0	1	0	0	0	0	28132	17.1	33.9	3.8	58,375	0
0	0	0	46.86	0	0	1	0	0	0	0	16731	10.3	31	2.7	69,887	0
0		0	47.55	0	0	1	0	0	0	0	4999	11.3	30.8	3.4	75,067	0
0		0	42.95	0	0	1	0	0	0	0	8557	13.7	24.6	2.9	63,247	0
0		0	42.01	0	0	1	0	0	0	0	6602	8.3	32	3.5	85,508	0
0		0	50.31	0	0	1	0	0	0	0	9429	9.8	33.7	3	71,360	0
0		0	42.07	0	0	1	0	0	0	0	9046	10.9	29.2	3.4	71,434	0
0		0	53.56	0	0	1	0	0	0	0	2945	9.5	27.8	4.3	66,180	0
0		0	39.56	0	0	1	0	0	0	0	13246	10.5	32.3	2.9	73,723	0
0		0	48.84	0	0	0	0	0	0	0	14737	16.7	55.5	2.6	53,537	0

Encampment	Force used	# Protestors	Biden County Vote	Blue County	Blue State	Blue Governor	BlueCounty BlueState	BlueCounty RedState	RedCounty BlueState	RedCounty RedState	Uni_Population	Poverty Rate	Education	Unemployment	Median Household Income	Private Universi
0		0	37.65	0	0	0	0	0	0	0	4275	13.9	18.2	3.2	56,599	1
0		0	58.88	0	1	1	1	0	0	0	3269	13.6	38.1	3.5	70,939	1
0		0	62.41	0	0	1	0	0	0	0	1928	6.9	52.3	2.8	106,743	1
0		0	66.36	0	0	0	0	0	0	0	1372	16	35.9	3.8	60,808	1
0		0	49.24	0	1	1	1	0	0	0	2486	12.7	32.2	3.4	88,532	1
0		0	28.53	0	0	0	0	0	0	0	31436	10.7	40.4	2.3	76,631	0
0		0	26.3	0	0	0	0	0	0	0	44797	9	36.9	2.6	95,085	0
0		0	41.15	0	1	1	1	0	0	0	5353	15.7	27.8	3.7	63,894	1
0		0	43.38	0	0	0	0	0	0	0	13567	19.5	27.1	3.5	52,623	1
0		0	32.7	0	0	0	0	0	0	0	1930	11.5	30	2.1	67,058	0
0		0	45.81	0	0	0	0	0	0	0	3919	9.3	30.1	3.7	84,352	1
0		0	45.81	0	0	0	0	0	0	0	3919	9.3	30.1	3.7	84,352	1
0		0	53.48	0	1	1	1	0	0	0	2717	9.2	43.4	3.6	106,047	1
1	1	3	53.89	0	1	1	1	0	0	0	3598	8	39.7	3.3	90,740	1
0		0	72.03	0	1	1	1	0	0	0	1801	13.8	35.3	4.6	80,180	1
0		0	60.18	0	1	0	1	0	0	0	1901	9.7	36.5	2	73,057	1
0		0	62.75	0	0	1	0	0	0	0	13968	10.8	41.6	3.2	83,856	1
0		0	55.75	0	0	1	0	0	0	0	3012	12.1	36.1	2.6	70,075	1
0		0	24.5	0	0	0	0	0	0	0	1150	10.9	19.5	2.8	66,283	1
0		0	41.98	0	1	1	1	0	0	0	2814	13.1	35.8	4.9	91,582	1
1	1	3	56.16	0	0	1	0	0	0	0	16188	14.8	36.9	3.5	62,992	1
0		0	70.46	0	1	1	1	0	0	0	54019	10.1	53.3	2.6	89,418	1
0		0	35.76	0	0	0	0	0	0	0	3384	11.4	25.1	3.8	66,776	1
0		0	43.79	0	1	1	1	0	0	0	2087	14.9	30.1	4.2	66,542	1
0		0	56.24	0	0	1	0	0	0	0	1985	8.3	50.2	2.9	90,801	1
0		0	39.93	0	0	0	0	0	0	0	3121	12.3	25	3.7	64,557	1
0		0	42.16	0	0	0	0	0	0	0	1205	13	22.6	3.7	61,941	1
0		0	40.96	0	0	0	0	0	0	0	1966	7.8	35.2	2.5	83,797	1
0		0	49.95	0	0	1	0	0	0	0	6833	12.6	32.3	2.7	61,255	0
0		0	37.97	0	0	1	0	0	0	0	1553	9.5	32.8	3.4	70,751	1
0		0	78.61	0	1	1	1	0	0	0	1231	7.2	60.3	1.9	118,020	1
1	0	4	57.3	0	1	1	1	0	0	0	4068	7.1	45.5	3.2	84,551	1
1	0	3	58.22	0	0	1	0	0	0	0	22608	13	40.8	3.7	69,689	0
1	0	2	60.35	0	1	1	1	0	0	0	17351	12.9	38.1	4.3	78,796	0
1	0	2	43.79	0	1	1	1	0	0	0	1873	14.9	30.1	4.2	66,542	1
1	0	2	48.86	0	1	1	1	0	0	0	2511	14.1	26	3.7	70,861	1
1	0	3	72.44	0	1	1	1	0	0	0	3295	12.5	38.3	3.6	71,102	1
1	1	4	58.05	0	1	1	1	0	0	0	28878	12.5	41.1	3.9	84,615	1

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