THE EFFECTS OF COVID-19 SHELTER IN PLACE POLICIES ON US DEMONSTRATIONS

by

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The following individuals read and discussed the thesis submitted by student David A. Newton, and they evaluated the student's presentation and response to questions during the final oral examination. They found that the student passed the final oral examination.

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DEDICATION

I am dedicating this thesis to my niece Marie Newton who not only inspired me through her only perseverance but allowed me to share in our mutual journey of recovery through life's physical challenges. She allowed me to be a large part of her life sharing her dreams and future goals that included possible educational pursuits. Even when things were hard, she never gave up hope for a better life in the future. Marie was a little light in a large world and she helped to bolster my life daily.

Unfortunately, Marie's life was cut short at the age of 17 through medical difficulties that arose during her eighth surgery in one year. Gone forever away from our loving eyes and who left a void never to be filled in our lives. Though your life was short, I will make sure your memory lives on as long as I shall live. I love you Marie and miss you more than words can say.

May she find peace and happiness in Paradise. And may we all find comfort knowing that she is no longer in pain. Thank you so much for letting me be your uncle and for being my daughter. I will never forget you.

Ecclesiastes 12:7
"And the dust returns to the earth as it was,
and the spirit returns to God who gave it."
Amen.

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ABSTRACT

This study provides evidence of a link between Shelter in Place (SIP) policy response during the pandemic and demonstration events. Through the combination of daily county-level government policy response to SIP implementation to limit the spread of the COVID-19 outbreak in the United States (US) and cell phone mobility data, this research studied how demonstrations and violence are affected following shutdown policies. A dynamic framework is visible due to the staggered effect of policies implementation across the US. At the national level, the results showed reduced participation in demonstration events at the national level, suggesting that increasing social costs may limit public demonstrations. However, regional results indicate dependence on population density (urban vs. rural) or location (west vs. east coast), along with the benefits of pursuing social well-being, outweigh the additional costs SIP police bring. The research will conclude with a discussion on potential reasons behind this heterogeneity and why it is essential to understand the repercussions of blanketed US policies on individual behavior and social well-being. The research of this paper contributes to the study of pandemic modeling on demonstrations in the US. First, it provides a theoretical framework using multiple economic modeling approaches to study the relationship between SIP policies and demonstrations. Second, this county/day level data is one of the first studies to look at the individual behavior effects in the US. Third, a fuller view of the region is observed by using a combination of statistical analyses, qualitative assessments, and geographical clustering.

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LIST OF ABBREVIATIONS

ACLED Armed Conflict Location & Event Data

BLM Black Lives Matter

DRC Democratic Republic of the Congo

i.i.d Independent and Identically Distributed

LDVs Lagged Dependent Variables

OLS Ordinary Least Squares

SCI Social Capital Index

SIC Schwarz Information Criterion

SIP Shelter in Place

US United States

ZIP Zero Inflated Poisson

LIST OF SYMBOLS

T	Number of time periods
α	Entity fixed effect
β	Model coefficient
$\in$	Regression residual
λ	Poisson distribution
λ	Time fixed effect
i	Entity (state or county)
n	Number of entities
t	Time period (day)

SECTION 1: INTRODUCTION

"The ultimate measure of a man is not where he stands
in moments of convenience and comfort,
but where he stands at times of challenge and controversy."

Martin Luther King, Jr.

Demonstrations form a crucial part of the American political landscape and are inexorably tied to the country's birth, as seen by historical events like the Boston tea party (1773). Demonstration movements tend to come when there are divisions in a society where political systems cannot handle inequalities in well-being and sustainability issues. In recent years, the US has seen the rise of such divisions, with equality and political polarization, bringing with it a substantial surge in demonstrations. With the occurrence of increasing demonstrations, with an exogenous[1] shock of the Novel Coronavirus SARS-CoV-2 (COVID-19) pandemic, a unique opportunity presents itself to explore changes in individual behavior. These changes could show how participation in demonstrations could influence future generations' well-being.

[1]An exogenous shock defines a period of prolonged and widespread crisis in which actors struggle to reconstitute all aspects of social life (Soluk *et al.*, 2021).

Also, with the indifference of many states to implement the policies, it allows for the use of quasi-experimental environment methods[2].

This research shows that during the initial implementations of the SIP policies, there was a decrease in demonstration events that led to a reduction in violence. This reduction suggests that when the economy is under pressure and low-income families struggle, the same tools that society uses to help increase equality, justice, and well-being may also be underutilized. The study looks at a moment during the early days of the pandemic when the government issued SIP policies. Its focus is to see how human behavior may run contrary to expectations, where during times of great strain and stress, social trends should push for more equality and demonstrators. But due to high opportunity cost, the outcomes seen are decreasing behavior.

During the early part of 2020, unemployment increased, and incomes were dropping. Unrest in both Black Lives Matter (BLM) and pandemic policies groups were rising, yet there was a decrease in demonstration events as well as violence across the US. In this study, fixed effect lagged modeling[3] facilitated controls for entity and time biases across panel data. The data set contained 50 states over approximately three months from February to May 2020. Society has gained a greater awareness of demonstrations through technology and lower barriers to access information. It is also due to the increased opportunity seen through decreased mobility of society. The extra time, through reduced movement, gives individuals additional time to focus on current events with the SIP policies keeping individuals' home.

[2]Quasi-experimental methods look to manipulate the independent variable of participants but outside of a controlled environment. But like an experimental method, there is still treatment and a controlled grouping through observing the agent's participation in the independent variable. Unlike a controlled experiment where participants are randomly assigned, there is still the issue of confounding variables which will need to be addressed (Chiang *et al.*, 2015)

[3]Section 4.3 explains the methodology in more detail

The research of this paper contributes to the study of pandemic modeling on demonstrations in the US. First, it provides a theoretical framework using multiple economic modeling approaches to study the relationship between SIP policies and demonstrations. Second, this county/day level data is one of the first studies to look at the individual behavior effects in the US. Third, by using a combination of several methods, especially statistical analyses, qualitative assessments, and geographical clustering of country cases, a more robust view of the region is observed.

Section two briefly goes over the background of the demonstration environment during the pandemic. In section three, we conduct a comprehensive literature review focusing on the linkage between policy, demonstration, and violence. The reviews look at how exogenous shocks can affect demonstration event numbers, how COVID-19 influences behavior response, and case studies of how SIP affect both global demonstration and the Sub-Saharan region. Section four covers the data collection, modeling techniques, statistical breakdown, and the assumption and inherent biases in the model. Section five presents the model results and regional analysis with sensitivity tests. The discussion, in section six, looks at how the decrease in demonstration events could affect policies and political change through the scope of social well-being. We believe that this paper will convey the importance of understanding the impact of broad SIP policies on peripheral social behaviors. A peripheral behavior includes demonstration participation[4] which can affect third-tier social well-being pursuits[5].

[4]In this context, SIP policies do not have the intent to directly impact demonstrations. But it is reasonable to expect it to have a situational influence through limiting societies movement.

[5]Limited changes in policies through reduced freedom of movement in the pursuits of demonstrations for future generations.

SECTION 2:
BACKGROUND

2.1 Demonstrations During the Pandemic

2020 was fraught with political unrest and the global pursuit of demonstrations for racial justice. With the introduction of the pandemic, this increased stress and division in the way of decreased incomes and increased unemployment has only intensified the environment. The death of George Floyd also ignited a new fight against injustice that brought forceful arrests, rubber bullets, and teargas against the civilian population. Were these incidences of violence exaggerated by social media and the lagging workforce sitting at home surfing the net? Or was there already an increasing environment of demonstrations leading to an inevitable violent clash between the US population, organizations, and the government.

In her essay on local and national civil rights movements, Yvonne Frear from the San Jacinto College explains that the civil rights movement has been on the march since the 1950s (Haynes & Wintz, 2016). The very violence that she has seen throughout history has not only highlighted the inequalities in society but also helped form avenues of change in the US. The essay points out that other countries see the US as a violent environment for demonstrations, but sometimes violence is needed for change. The significant difference between past and current demonstrations is how social media informs the nation and the world. In the past, a consumer would have to seek out the information, and it was second or third-hand accounts at best. Now, consumers get first-hand accounts through cell phone video, but individuals will be inundated with the same report told ten different ways by multiple outlets. It can feel like one incident can have a more significant impact due to over publication. The issue is how to ascertain if first-hand videos make accounts more accurate or too many biased viewpoints in the mix.

While the US has been an environment that supports freedom through demonstration, 2020 has seen an increasing trend of demonstrations. In Roudabeh Kishi's research, she found demonstrations have spread to additional states, and statistics indicate that demonstrations that clashed with government authorities increased by more than five times (Kishi, 2020b). In 2020 government authorities implementing "use of force" had increased six times which illustrated a rise in violence in 2020 compared to 2019. One of the main findings was how participation in different specific demonstration groups had begun to shift away from the BLM movement and towards COVID-related issues in the latter part of 2020.

These types of demonstrations could range from medical care to moratorium[1] issues not just case number and death rates. In comparison, BLM demonstrations are specific to violence against the populous and were from particular events that stemmed from violence against minorities. Even considering the differentiation between organizations, the data observed a shift that initially saw BLM consisting of 78% of demonstrations in June of 2020. By August, only 25% of demonstrations were BLM. This shift was significant as BLM had become prevalent in the wake of the killing of George Floyd (May 25, 2020). The pandemic exacerbated the envi-

[1] A moratorium is a delay or suspension of an activity or a law. CDC Issues Eviction Moratorium Order in Areas of Substantial and High COVID-19 Transmission (CDC, 2021).

ronment as the country saw higher unemployment rates, increasing participation in demonstrations. Midway through 2020, one of the most significant driving factors for COVID-related demonstrations became the rise in students' and teachers' opposition to an unsafe school environment (Kishi, 2020a).

Current studies have tried to compare the numbers of deaths to the number of demonstrations to explain the correlation between demonstrations with the number of new deaths (Kishi, 2020a). But due to collection and reporting bias, this may be difficult to do. In these studies, there was a large portion of demonstrations related to election events and rallies by November after the general election. Over 70% of demonstrations were attributed to such events as "Stop the Steal" or "Count Every Vote." By now, COVID had become so politicized it may be hard to see which events were purely about political voting rights and not spillover from COVID agendas.

While it did seem that demonstrations followed a similar pattern to those of deaths from the pandemic, there are expected lagged effects in demonstration responses to fatalities. The lags are partly due to the dynamic environment and individual behavior for processing and setting up demonstrations. Also, reports of deaths are not instantaneous, are backdated and reported to the public retroactively. So even if society took to the streets as soon as demonstrators heard the news of the death count, it would not be current data points (Kishi, 2020a). This lagged effect led to SIP data research with a dynamic approach.

2.2 Impact of Government Pandemic Policies

Clashes between groups or vandalism may not purely drive violence during demonstrations. Sometimes, there is a strategic desire for change. For some, violence through demonstration may be the only option available to grab the attention of policymakers and the social community. Omar Wasow, a professor of politics at Princeton University, examined the strategic reasoning behind the violence during the demonstration. Wasow explains that it isn't an easy question to answer as non-violence is the best course of action if good media and public backing are available. This will help keep the general public on the demonstrator's side and compassionate to their cause. But when there's no good media and public backing, violence may be the only means to gain attention and support for the policy changes needed to create a more balanced social environment (Wasow, 2020). Even then, it is hard to anticipate what will happen, as seen in the 1960s when some white moderates were willing to advance racial equality but keeping order was also a priority.

This meant that racial equality was part of their plan but only if there was no violence on the part of the demonstrations as this would push them to the opposing side. When looking at how SIP policies may play in the dynamics of the demonstration landscape, consideration needs to be given about individuals' decision-making process. That even if an individual, or a group, wants to demonstrate, demonstrators may consider holding off as going against the SIP police may be viewed as having a negative external effect through disobeying non-related policy. However, with demonstrations for civil justice going back decades, viral videos show first-hand accounts of current demonstration issues and governments' unwillingness to release body-cam footage. Could this non-transparency override an individual's behavior to stay home during the pandemic?

Because COVID-19 came on so rapidly with a rise in cases, government intervention was needed to curtail the pressures on the health industries. At this time, there was a shift in individual behavior as SIP policies were implemented, and behavioral change shows the psychological effect of the pandemic on the socioeconomic environment. Due to the inconsistency of the local government's implementation of these policies, it can be hard to see the actual effectiveness of these policies. It shows that some results can be attributed to a health contention society where individuals were distancing themselves without mandates. At the same time, businesses and industries needed government guidance through the SIP policies. There is also the "spillover effect" from neighboring states that implemented SIP policies that would influence social behavior.

Recent research suggests that additional SIP policies helped increase safety by decreasing cases and deaths during the pandemic (Berry *et al.*, 2021). When observing mobility at the state level, the data shows many states are already seeing a downward trend before the SIP policies were implemented. This mobility decrease may have indicated that the behavioral change is partly due to voluntary social distancing. Government entities influence the social environment of demonstrations and the opportunity cost that drives the demonstrator's ability to participate. Even if areas had already seen a decrease in mobility due to preemptive local advisories, SIP was able to create an even more significant drop in movement among individuals (Berry *et al.*, 2021). The question now is, will this translate to decreased demonstration and political violence, or will there still be enough organizational influences as seen in other regions to cause it to increase?

SECTION 3:
LITERATURE REVIEW

3.1 Determinants of Demonstrations

Policies imposed during a pandemic can have varying outcomes depending on the local characteristics of the economy. A region could see more violence as the economy decreases income opportunities, lowering an individual's opportunity cost for demonstrations and violence (Dal Bó & Dal Bó, 2011). Although if a state has plenty of resources and those resources are not controversial, there may be a decrease in conflict intensity (Besley & Persson, 2009). These policies that restrict mobility to lessen the pandemic impact have increased the participation costs, negatively affecting conflicts around the world (Berman *et al.*, 2021). For example, Lebanon and Iraq had the second and third, respectively, largest demonstration event decreases in the region. These decreases led to a significant reduction in anti-government demonstrations, which would end with the people ousting their prime ministers due to infringement on their freedoms (Pavlik, 2020).

With the risk of high unemployment and loss of wages, individuals are less likely to engage in risk-taking action. Demonstrations are activities that inherently have unknown actors who gather spontaneously at relatively short-lived events during a high health risk environment (Berman *et al.*, 2021). The policies used will directly affect how participants and groups decide to engage in demonstrations. While many will choose to forgo the cost of participating in the risk-taking activity, there will still be those who organize and may induce violent conflict. Implementing policies and mobility restrictions may not be the only deterrent to organized violence. Due to the unstable economic environment, policymakers will also have to identify who the actors are (armed vs. civilian) and the types of tactics the actors are using (rioting vs. peaceful demonstrations) (Chenoweth & Cunningham, 2013).

Observing downward pressure on the economy from the pandemic indicates there would be more demonstrations. Individuals have lower opportunity costs due to more free time through higher unemployment and increased public stresses, motivating more demonstrations (Berman *et al.*, 2021). Looking at what drives demonstrations through public resentment levels[1], greater participation levels are expected during the pandemic environment (Chenoweth & Cunningham, 2013). This study explores how policies raise the private cost of participation, therefore increasing the opportunity cost of demonstrations that lower subsequent incidence of violent activities for the US environment.

3.2 Demonstrations and Sustainability

A paper presented at the Eighteenth J. Seward Johnson Lecture by Robert M. Solow (Solow, 1991) looks at moving away from daily individual life and how economic policies and annual voting might impact sustainability concerns. He acknowledges that no one definition fully encapsulates the idea of sustainability as it is a challenging pursuit, and current goals can be vague. There is an all-encompassing idea that society must ensure that future generations are at least as well off as those living in today's economy (Solow, 1991). The pursuits demonstrators are to identify when

[1]Coordination, mobilization, and participation cost can influence levels of resentment withing a social group

policies and government interventions fall short of equitable endeavors[2] mirror social needs and drive for long-term well-being. These perceived inequalities lead social groups to undertake inefficiencies or unjust policies for current and future generations.

In Pamela Matson's book "Pursuing Sustainability, chapter 2: A framework for Sustainability Analysis" (Matson *et al.*, 2016), she identifies the five clusters that societies pursue to maximize their well-being. These clusters include:

- Natural Capital: Land, water, biotic, mineral resources, climate, and atmosphere, and biodiversity
- Human Capital: Human population (size, distribution, health, education, and other social characteristics
- Manufactured Capital: Buildings (homes, factories, and their products), infrastructure (transportation, energy production, and information provisions)
- Social Capital: Laws, norms, rules, customs, trust, instructions (political, judicial, economic)
- Knowledge Capital: Conceptual, factual, and practical know-how

The above list shows areas where society identifies inefficient utilization of resources. The balance of capital is inadequate or inequitable when communities have little access to resources to maintain their well-being. Inequality pushes the need for change through the pursuit of demonstrations. External factors like SIP policies influence demonstration participation. Matson measures well-being through a life matrix of happiness, health, and personal success (Matson *et al.*, 2016). Since this is, in part, the pursuit of SIP policies to aid in the health and well-being of a community,

[2]These endeavors can range from political, social, the purpose of knowledge, or environmental. It is outside the scope of this research, as this study focuses on the ability to demonstrate more than the reasons for demonstrations

it can still be a complex topic of whether a decrease in the demonstration will assist or be detrimental to long term social well-being.

Expanding into US-specific effects on how US policies affect demonstrations and violence, the commonalities between global and national are observed. There may be similar outcomes of participation but different effects throughout the US region. While the US is under a more unified government, it covers such a vast area with differing economic dynamics. In recent years the diverse nature of our government has caused polarization in policy implementation and influenced social behavior (Doherty *et al.*, 2021). The most significant influence of violence in the US will be through high-density regions, as seen in section 5.2.2.

3.3 COVID-19 & Behavioral Responses

The government's actions in response to the COVID-19 pandemic can induce economic shocks to the general population. US regions have seen what a major crisis, such as the 2008 global financial collapse, can have on the economy (Ilzetzki, 2020). The peripheral and complex effect of the policy is essential to identify the impacts of newly created policies on a region's social behavior. As COVID cases increase in the US, states and counties issue SIP mandates. The issue is that not all US states responded the same to the policy mandates (Baccini & Brodeur, 2020). Some of the characteristics significant to implementing these state-wide mandates were political position, term limits, and ideology. Democratic governors were more likely to implement mandates by 50%, while those with no term limits also implemented them faster. These are also both influenced by the ideology of the area and can differ throughout regions. It is important to note that other characteristics of government officials such as gender and race play a negligible effect on the implementation and speed of the lockdown procedures (Ferreira & Gyourko, 2014).

These findings are significant when understanding how individuals will react during the pandemic. The environment affects how society will attempt to influence policies through their local government. The federal government needs to know how the characteristics of a state will influence stay-at-home order policy implications (Baccini & Brodeur, 2020). Policies are significant when looking at individual behavior as effects vary between states and regions due to varying differences in the timing of implemented orders. Regardless of all other indicators, a state is still sensitive to COVID-19 deaths. Section 5.2.1 illustrates that all but four states implemented stay-at-home orders in the early part of 2020. Evidence shows that during an exogenous event like the pandemic, it is business as usual for politicians during extreme times (Baccini & Brodeur, 2020). Through cost-benefit analysis, individuals will have choices that significantly influence policies that governments do or do not implement.

Even before mandates are enforced, there is a substantial decrease in mobility which would suggest social distancing was not purely SIP induced (Gupta *et al.*, 2020). Event studies show 55% of the populous increased hours spent at home due to emergency declarations, while the other 45% was from non-policy-driven trends. Both factors help in decreasing the epidemic size so the medical industry can redistribute caseload over time (Peak *et al.*, 2020). In a democracy, it is a question of personal freedoms and how policies will affect the socioeconomic environment for each community. Identifying the most robust social distancing policies to minimize pandemic health numbers and economic impact while maintaining personal freedoms is essential (Schwartz & Cheek, 2017). While procedures did cause mobility patterns in human behavior to slow through preemptive means[3], it is essential to remember that after

[3]Business and restaurant closures, restrictions, and emergency declarations.

the first announcements of confirmed cases in the US, a reduction in mobility had already begun (Gupta *et al.*, 2020).

3.4 COVID-19, SIP, and Conflict

Recent research has shown that implementing government policies to help reduce the spread of COVID-19 during the pandemic had increased the costs on the participation rate of demonstrations across countries (Berman *et al.*, 2021). When policies are imposed nationwide, not only does this cause the number of demonstrations to drop by 0.8%, but it also indicates an overall increase in transit costs through policy implementation. The increased opportunity cost leads to participants in decreasing mobility and demonstration pursuits. The additional effects these policies have had on different regions include declines in GDP which indicates a global recession and higher unemployment which pushes declining household per capita income levels. These changes can push world societies into extreme poverty if the economy does not recover soon (Berman *et al.*, 2021).

The findings in the global environment showed a decrease in violence for organized armed groups as well. There is heterogeneity[4] between poorer and authoritarian countries than in developed nations. While there is a decline in demonstrations, there is an attenuation of public desire for change due to the subsequential economic downturn (Berman *et al.*, 2021). Expectations with prolonged restrictive policies show that armed conflict in some areas will increase violence. The poorer nations will see the additional influence of violence due to organizational involvement, especially when the countries are not democratic institutions or already have elevated levels of social poverty. These high-risk areas may see a longer effect from the pandemic environment

[4]Heterogeneity is the quality or state of being diverse in character or content. Identified here are the differences between not only SIP implementation but regional characteristics through economics.

due to a conflict-poverty cycle that international corporations will need to provide aid to increase welfare (Berman *et al.*, 2021). Trends like these are transferable when observing demonstrations and policy implications on a regional or state level.

The Sub-Saharan region of Africa saw increased violence from the COVID-19 pandemic shock and the pressures of lockdown policies in 2020. Research conducted in the region suggests that the surge in violence is only partly to do with the "COVID-19 unrest" (Basedau & Deitch, 2021). It primarily stemmed from the government's reaction to the pandemic and the stringency of its policies. The rigor of the policies exacerbates an already fragile environment of areas with deficient health levels and low development. And it allowed armed groups to take advantage of low socioeconomic regions by oppressing travel and movement even further. Looking at pandemic data from before and after SIP policies implementation, it showed a rise in fatalities which indicated a 20% increase in violence (Basedau & Deitch, 2021).

Even though the pandemic has not directly increased violence in the regions, it has mitigated the effects through increased opportunities for armed groups, notably the jihadist groups (Basedau & Deitch, 2021). Even with the understanding that the guidelines have worsened the conflict in higher fragility[5] areas, officials warn that removing them was risky. Policymakers have warned not to sound the all-clear for possible pandemic relapses. Conditions of the pandemic could worsen in the Sub-Saharan region despite the rise in violence. It is vital to notice that in the areas of the Democratic Republic of the Congo (DRC) and Nigeria, the significant increase in violence that occurred was perpetrated by armed Jihadist groups[6] (Basedau &

[5]Fragility is the quality of being easily damaged or vulnerable. For the Sub-Saharan region, aspects include prior environments of corruption, low development, and previous conflict.

[6]Boko Haram in Nigeria, and the Allied Democratic Forces (ADF) in the DRC, a group originating in Uganda that pledged allegiance to the so-called Islamic State (IS) in 2019. Jihadist and other violence produced approximately 1,000 more victims in Mali and Mozambique, the latter the

Deitch, 2021). While there is a need for pandemic politics and policies matter, the fallout of these policies through conflict can have a lasting effect on future social pursuits. These effects worsen when the global environment is also feeling the impact of the pandemic, and developing nations are struggling to acquire vaccines in efficient quantities.

Through global and regional research, there is a consistent impact on individual behavior when SIP policies get used. Upon implementing international policies, there is an 0.8% decrease in worldwide participation in the number of demonstration events. When SIP policies get implemented regionally, as seen in the Sub-Saharan regions of Africa, there can be changes in the proportion of violence due to transit costs and organizational involvement. These spill-over effects show how direct pandemic policies may not just influence primary COVID-19 indicators but also have a significant impact on individual behavior. In this study, the results show a consistent decreasing effect on demonstration events in the US. These results are comparable to the global findings. Upon implementation of SIP policies in the US demonstration decrease in the US by 0.2% to 0.5%. However, unlike the Sub-Saharan region, this study finds decreases in demonstration violence when SIP policies get implemented. These findings support the previous studies of SIP exogenous influence. This study extends the regional understanding of the heterogeneity observed across the global environment.

latest theatre of insurgencies with affiliates of Al-Qaida and IS south of the Sahara.

SECTION 4:
DATA & ECONOMETRIC STRATEGIES

4.1 Data Sources

4.1.1 ACLED Disaggregated Data Collection

The Armed Conflict Location & Event Data (ACLED) Project collects politically motivated data to include demonstration events, violence, fatalities, strategic indicators, locations, and the actors involved. The ACLED database includes locations all over the globe and can be used to conduct descriptive analyses and aid in conflict scenarios and exploration. The data was accessed through the ACLED site on 28 June 2021, which offers individuals the ability to download for examination or testing as an open-source dataset. Individuals must request a key to register for access to the portal, which monitors access to the data. The data requested include 31 variables that encompass both quantitative and qualitative values. A subset of this data is combined with additional data sources to create a new data set for this research paper (Raleigh *et al.*, 2010).

4.1.2 Replication Data from Harvard Dataverse

This study takes advantage of replication data from the research conducted by Berry et al. (2021). Access to the data is from the Harvard Dataverse site on 15 Jun 2021. Harvard Dataverse Repository is a publicly accessible data repository where researchers from both outsides and inside the University may utilize it for exploration and research. The file used from this site and study is CountyData.dta and is publicly available. The data set includes ten variables and 42 lagged variables. A subset of this data is combined with additional data sources to create a new data set for this research paper (Fowler, 2021)[1]

4.1.3 Working Dataset

The consolidated indicators the working dataset consists of including the date, county name, two alpha state IDs, and fips[2] ID. Demonstration types get broken down into two primary categories from the ACLED dataset. In addition to these primary categories, there are five subcategories for further sensitivity evaluation. Each occurrence is collapsed down to the county level to observe the accumulative effect of its cities. From the Harvard dataset, the SIP, new cases, new deaths, and mobility indicators get combined. Geographic shapefiles get added to evaluate heterogeneity between states and counties. The data set is uniquely identified for each observation at the county-date level. There are 3,035 counties with 297,430 observations from 24 Feb to 31 May 2020. The time increment of the data set is daily.

4.2 Summary Statistics

To employ a comprehensive analysis of shelter in place policies' effect on the environment of demonstrations, clean and consolidated data that was publicly available (See Section 4.1) was constructed. This section describes the data used and reports on the summary statistics.

[1]Fowler is the data manager for the research team. This citation is the preferred formate for the data portion of the research.

[2]FIPS codes deal with US states and counties. US states are identified by a 2-digit number, while US counties are identified by a 3-digit number. For example, a FIPS code of 06071 represents California -06 and San Bernardino County -071.

4.2.1 Variable Description

Table 4.1: Summary Statistics of County Level Day Indicators

	Mean	SD	Min	Max	N
Demonstration indicators					
Non-Violent Protesters	0.00918	0.10828	0.0	8.0	297430
Peaceful Protesters	0.00870	0.10449	0.0	7.0	297430
Protest w/Interveition	0.00042	0.02090	0.0	2.0	297430
Exec/Force on Protesters	0.00005	0.00733	0.0	1.0	297430
Riotous Protests	0.00082	0.03105	0.0	4.0	297430
Group Violence	0.00079	0.03045	0.0	4.0	297430
Mob Violence	0.00003	0.00550	0.0	1.0	297430
COVID-19 indicators					
Shelter in Place Policy	0.40410	0.49072	0.0	1.0	297430
Civilan Cell Phone Mobility	-0.17787	0.19706	-1.0	1.8	297430
Daily COVID-19 Cases	32.60760	239.01525	-2,725.0	79,493.1	297430
Daily COVID-19 Deaths	1.31285	10.52347	-383.6	1,064.2	297430

Note: Demonstration indicators are number of events for each type.
Note: SIP policy is a dummy indicator with implementation = 1.
Note: Mobility is the proportional change in location through cellphone data.
Note: Cases and deaths reported as daily counts.

There were seven indicators from the ACLED dataset and four indicators from the Harvard dataset to analyze SIP effects on demonstrations. In Table 4.1 the consolidated data is balanced as all indicators have consistent samples of 297,430 (N). The dataset consists of 3,035 locations, including counties, census areas, or political borough[3] (n) within the 98 days (T) of the data set. The table is broken up into

[3] A borough is an administrative division in various English-speaking countries. In principle, the term borough designates a self-governing walled town, although, in practice, official use of the term

demonstration indicators and COVID indicators. This table includes the mean, standard deviation, min, and max of the data set. The values are minimal due to the high number of counties and the daily observations within the dataset.

The Demonstration indicators include two main grouped observations that are accumulative at the county/day level. These include 'Non-Violent Demonstrationers' and 'Riotous Demonstrationers.' 'Non-Violent Demonstrationers' have three subgroups that show the government's interaction with peaceful demonstrations. 'Peaceful Demonstrations' show those that participate and go home, while 'Demonstration w/Intervetion' are those groups that need encouragement to disperse but are still peaceful. 'Exec/Force on Demonstrationers' indicates when government agents intervene or overstep their authority on peaceful demonstrations, but the demonstrators do not retaliate.

For 'Riotous Demonstrations,' two subgroups show the differences in the size of a violent demonstration. 'Group Violence' is when groups or subgroups of a demonstration become violent, but the larger group can still be peaceful. Whereas the 'Mob[4] Violence' is when the environment turns inward and the whole group participates in violent pursuits, leaving peaceful means behind. It is important to note that while 'Riotous Demonstrations' includes vandalism, road blocking, and other destructive behavior, it does not include the use of lethal weapons.

The COVID-19 Indicators consist of four variables. The 'Shelter in Place Policy' indicator is a binary measure of whether a county implemented a SIP policy or not. Data points get recorded daily, but issuing and removing the policy are the primary observations. The Civilian Cell Phone Mobility indicator shows how active individuals

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varies widely.

[4]Mob: "A large crowd of people, especially one that is disorderly intent on causing trouble, violence, and destruction."

are during the study. The mobility indicator will show a proportional change in mobility activity where the value may be positive or negative. For example, the indicator can have a negative value if individuals reduce their activity compared to the previous period. This data was collected using cell phone data and is collected daily. 'Daily COVID-19 Cases, Deaths' have been normalized[5] to standardize to formate of the data points, per million residents.

4.2.2 Scatter Plots

Figure 4.1: Daily Demonstrations by State, 24 February - 31 May, 2020

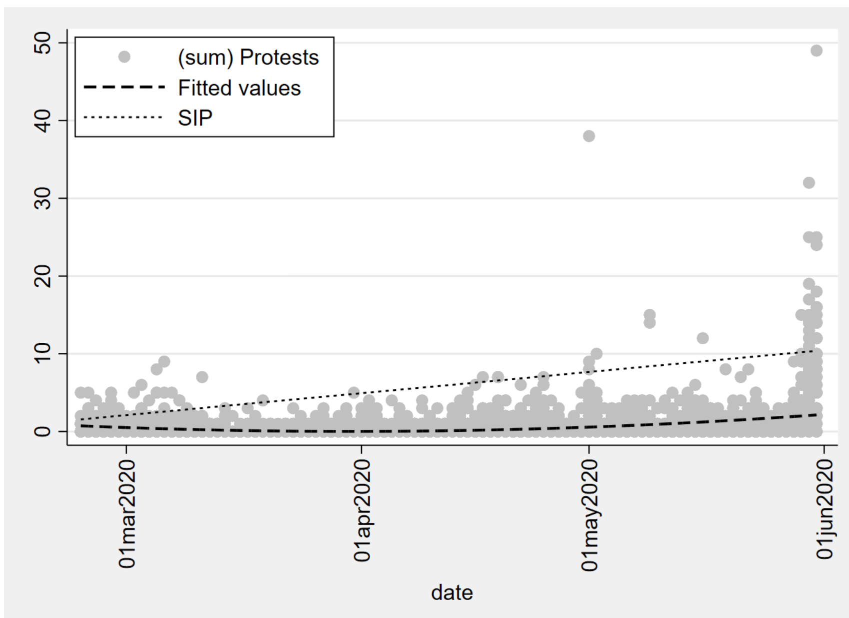


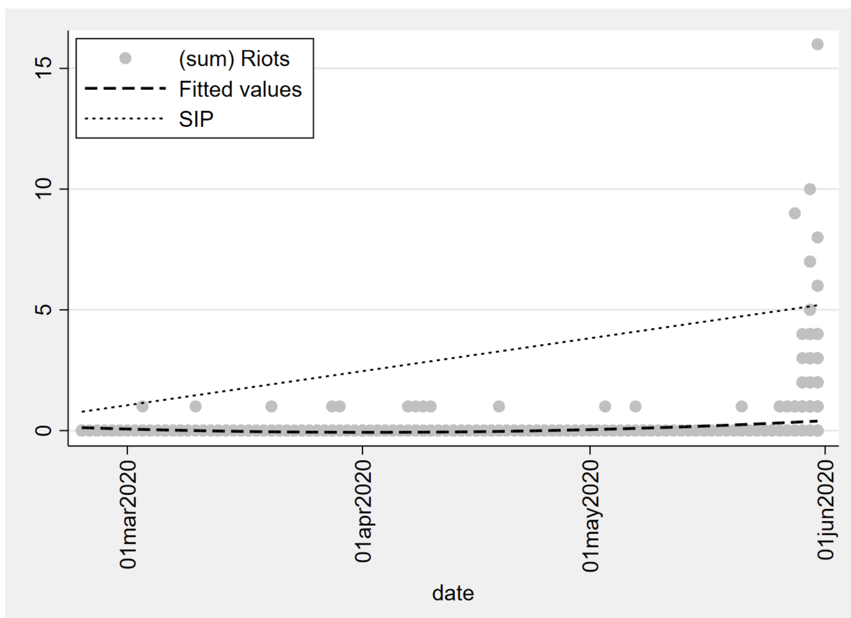
Figure 4.1 demonstrates the daily events by states between 24 Feb and 31 May of 2020. Observing the fitted values curve shows events increase as the data approach the months leading up to the George Floyd demonstrations. The trend of the involvement in SIP policies[6] across the states also increased. From this graph, through the

[5]The steps to normalize are 1. Calculate the range of the data set 2. Subtract the minimum x value from the value of this data point 3. Insert these values into the formula and divide 4. Repeat with additional data points.

[6]sip variable was scaled by ten for visualization due to actual value between 0-1

participation in SIP policies, it's expected that the demonstration environment would still have a positive relationship. However, when looking at state-by-state level graphs (See Figure A.1 thru A.3) the graphs show that not all states implement their SIP policies at the same time. Some states chose not to implement the policy during this period, while others implemented and kept the policy extending outside this dataset's scope. Yet other states ended their SIP policies and have increased participation in demonstrations.

Figure 4.2: Daily Riots by State, 24 February - 31 May, 2020



Similar trends are observed within the riot data, as seen in 4.2. During the majority of the period, there was little violent activity in the US until the days leading up to the George Floyd demonstrations. The low violence data also alludes to the fact that violent political demonstrations may not be as prevalent outside of immediate social upheavals. Even though most states participated in SIP policies, we look at individual agents to see how ending these state-mandated policies may have influenced specific regions. Dropping the policy may have caused premature lowing of social and transitory cost to the demonstrator (See Figure A.4 thru A.6).

4.3 Modeling Strategy

Through panel data that includes both entity and time variables, fixed effect modeling will be utilized to control biases. Fixed effects modeling[7] will remove omitted variable bias unobservant between entities' characteristics and demonstrate no change over time. This approach measures changes within groups across the limited time frame in the data to omit unknown differences between counties and their characteristics. Some constants observed over time across entities (states) would be age, sex, or ethnicity. These are an example of traits that would not change or, at a minimum, change at a constant rate over time but could be different between entities. Through fixed effects modeling individual observational behavior capturing any slow-moving county characteristics[8]. Equation 4.1 is an example of a fixed-effect model.

$$\mathrm{DV}_{it} \equiv \beta_0 + \beta_1 \mathrm{SIP}_{it} + \alpha_i + \lambda_t + \epsilon \tag{4.1}$$

This research uses lagged modeling due to the dynamic effect[9] of SIP policies on human behavior. Using lagged[10] variables in the model will help estimate rela-

[7]Fixed-effects models are a class of statistical models in which the levels (i.e., values) of independent variables are assumed to be fixed (i.e., constant), and only the dependent variable changes in response to the levels of independent variables.

[8]These characteristics can include culture, institutions or political systems that influence demonstrations

[9]Human behavior changes due to many factors to include psychological processes, biological needs, socio-cultural considerations, learning, and even new experiences. These dynamic behavioral influences determine the elements that make changes in human behavior.

[10]Distributed lags in a time series are used to predict current values of dependent variables using

tionships between the expected human behavior from past action due to SIP policy implementation. This approach will help provide a more robust estimator of the effects of the independent variables. This approach will help identify which explanatory variables have the expected exogenous impact or endogenous to each entity. Equation 4.2 is an example of a time series lagged model.

$$\mathrm{DV}_t \equiv \beta_0 \mathrm{DV}_t + \beta_1 \mathrm{DV}_{t-1} + ... + \beta_k \mathrm{DV}_{t-k} + \epsilon \tag{4.2}$$

The data has a unique distribution due to high occurrences of lower daily observations and fewer occurrences of higher daily observations. This type of distribution leads to a Poisson Regression Model approach (equation 4.3) where (λ) represents the type of distribution of the dependent values. The Poisson Model will better fit and interpret the data. Because the dependent variable is a count variable (demonstrations), this log-likelihood model gives a rate-ratio explanatory coefficient. Equation 4.3 is an example of the complete Poisson Model.

$$\log(\lambda_i) \equiv \beta_0 + \beta_1 \mathrm{SIP}_i \tag{4.3}$$

When solving for β_1 in equation 4.3, the rate ratio is identified on the left-hand side with the interpretability of the coefficient on the right. (See proof 4.4). The rate ratio will give the relative risk, representing a percentage change of a unit change in X. The model will indicate how the independent variables increase or decrease the dependant variables through a percentage change. Through the use of statistical software, the

current values of explained variables and "lagged" past period values.

coefficient is already exponentially evaluated. The value in the regression table will represent the rate ratio in decimal form and not the unprocessed beta coefficient.

$$
\begin{aligned}
log(\lambda_i) &\equiv \beta_0 + \beta_1 \mathrm{SIP}_i \\
log(\lambda_{i+1}) &\equiv \beta_0 + \beta_1 \mathrm{SIP}_{i+1} \\
log(\lambda_{i+1}) - log(\lambda_i) &\equiv \beta_1 \\
log(\frac{\lambda_{SIP+i}}{\lambda_{SIP}}) &\equiv \beta_1 \\
\frac{\lambda_{SIP+i}}{\lambda_{SIP}} &\equiv e^{\beta_1} \\
RateRatio &\equiv 1 - e^{\beta_1}
\end{aligned}
\tag{4.4}
$$

Due to the diverse nature of the US, SIP policies will have different effects on states and counties. A geographical heterogeneity[11] and spatial clustering[12] evaluation is used to examine these effects. These visual representations will illustrate the differences in sip and demonstration participation by the various counties. With the combined modeling approaches, individual state coefficients will demonstrate the influences of financial and transportation costs, labor pools, or possible social makeup of the location. Observing the different identifiers through each state's political, economic, and social characteristics will show the differences in the coefficient. Magnitude may be different due to population, location, or an event's epicenter. Utilizing Malmberg, Solvell, Zander's clustering model (Boja, 2011), identifying clustering or

[11]The statistical study of dissimilar quality or state of diverse elements. In the case the difference in demonstration participation of States concerning the involvement of the exogenous SIP policy.

[12]Spatial clustering aims to partition spatial data into a series of meaningful subclasses, called spatial clusters, such that spatial objects in the same cluster are similar to each other, and are dissimilar to those in different clusters.

divergence in states or dense urbane environments get visualized.

4.4 Assumptions and Biases

Several assumptions are used to help identify and understand the modeling process. When making economic decisions, these assumptions get broken down into the model's three main modeling approaches. While there may be outliers in some situations, the data consists of assumptions that are true of the majority of observations. However, even with the processed data and the assumptions given, some biases may be inherent in the data.

4.4.1 Fixed Effect Assumptions

The first assumption is a zero conditional mean term. It assumes that there is no omitted variable bias and that the mean error ϵ_{it} does not depend on past, present, or future values of the X entities[13]. The second assumption shows no autocorrelation between entities with an F-test of 7.7. The data is assumed to be independently and identically distributed with Independent and Identically Distributed (i.i.d) across entities. Assumptions three and four are consistent when the panel data consist of large observations (n). This data set contains 98 time periods (t) with 3,035 entities (n) culminating in 297,430 observations (N) (Stock & Watson, 2015).

1. ϵ_{it} has conditional mean zero: $E(\epsilon_{iT}|X_{i1}, X_{i2}, ..., X_{iT}, a_i) = 0$
2. $(X_{i1}, X_{i2}, ..., X_{iT}, \epsilon_{i1}, \epsilon_{i2}, ..., \epsilon_{iT}), i = 1$ are i.i.d. and draws from their joint distribution.
3. Large outliers are unlikely: (X_{iT}, ϵ_{it}) have nonzero finite fourth moments.
4. There is no perfect multicollinearity.

[13]This assumption is also control for n the lagged effects.

4.4.2 Distributed Lag Assumptions

The first assumption identifies the exogenous nature of the primary independent variable. The homogeneity of all past values of X_T will provide an error term with a conditional mean of zero. Schwarz Information Criterion (SIC) unit root test identifies the efficient number of lags for the model. The second assumption requires that the distribution of the variable be stationary. When testing for stationary within the data, the variable is stationary with a t-test of 11.8. Assumptions three and four are consistent when the panel data consist of large observations (n). This data set contains 98 time periods (t) with 3,035 entities (n) culminating in 297,430 observations (N) (Stock & Watson, 2015).

1. ϵ_{it} has conditional mean zero: $E(\epsilon_{iT}|X_{i1}, X_{i2}, ..., X_{iT}, a_i) = 0$
2. $(X_{i1}, X_{i2}, ..., X_{iT}, \epsilon_{i1}, \epsilon_{i2}, ..., \epsilon_{iT}), i = 1$ are i.i.d. draws from their joint distribution.
3. Large outliers are unlikely: (X_{iT}, ϵ_{it}) have nonzero finite fourth moments.
4. There is no perfect multicollinearity.

4.4.3 Poisson Regression Assumptions

Assumptions one implies that a dependent variable is a whole number that can differ over time. Demonstrations are collected at the event level and are in absolute value, and the data has lower value observation occurring more frequently while larger valued data occurrences happen less regularly. Assumption two states that observations must be independent, where the past observation is a different observational input from the previous one (not accumulative). The collection site that compiled the data collects data at the event/day level, and there should be no accumulative effect. Assumptions three and four look at multiple output levels when taking the mean and variance of the input. In Table 4.2 the means and standard deviations are similar and do not vary broadly. It can also be conceptually identified that the means construct a linear mean rate and not an exponential rate (Legler, 2021).

1. Poisson Response: The response variable is a count per unit of time or space described by a Poisson distribution.
2. Independence: The observations must be independent of one another.
3. Mean = Variance: By definition, the mean of a Poisson random variable must be equal to its variance.
4. Linearity: The log of the mean rate, $log(\lambda)$, must be a linear function of x.

Table 4.2: Summary of Shelter in Place Policy

Non-Violent	Mean	Std. Dev.	Freq.
0	0.40287816	0.49047749	294,980
1	0.54107143	0.49842155	2,240
2	0.63580247	0.48269653	162
3	0.77777778	0.42163702	36
4	0.625	0.51754917	8
6	0.66666667	0.57735027	3
8	1	0	1
Total	0.40410181	0.49071819	297,430

Note: Incremental Non-Violent values.

4.4.4 Potential Biases and Limitations

All models will have some biases inherently in the data. These biases may come in the way of selection, availability, or oversimplification of the data. Selection bias can occur when collecting demonstration data at the local level, depending on the organization and agents participating in the events. This data uses all state and most county-level aggregated data to control this. The data is collected at the event/incident level and not marked continuously for one event. At the same time, the model collapses the data to the overall categories of demonstrations for this analysis. Availability Bias is an issue when using data that is current and active. This data set is a specific window of time with updated data sources. It is assumed that relevant data may have been overlooked in the past but is now included in the most current data available. The last item of biasness is that the model may give an over-simplification of a more complex picture when it comes to reality (Underfitting Bias). This biased landscape can be seen and is identified in Section 5.2 (Heterogeneity of Model).

There are limitations to this study. Additional controls are not implemented for this model due to the limited timeframe and detailed daily observations of the data. In future studies, longer time series data sets will allow aggregated monthly, quarterly, or annual control indicators. Extended timeframes will allow for economic mechanisms other than mobility and possible instrumental indicators that were not feasible for this 98-day time frame. Also, due to technical limitations, a Zero Inflated Poisson (ZIP) method could not be used through statistical software (Stata). While this study uses a quasi-ZIP method by clustering participating counties from non-participants counties, this is only a proxy for the ZIP process. And a final limitation, while minimal, is some gaps in data coverage. Even with a vast majority of the US covered by the data, some counties have missing observations. A more comprehensive data set will ensure greater sensitivity of SIP policies on demonstrations.

SECTION 5:
RESULTS

5.1 Impact of SIP on Demonstrations

$$\begin{aligned} log(DV_{it}) \equiv \beta_0 + \beta_1 SIP_{it} + \beta_2 cases_{it} + \beta_3 deaths_{it} + \\ \beta_4 mobility_{it} + \sum_{k-1}^{14} \beta_k DV_{i(t-k)} + \alpha_i + \lambda_t \end{aligned} \tag{5.1}$$

The regression model 5.1 utilizes the combination of fixed effects, time lags, and the Poisson modeling approaches. As a log-likely approach, the $log(DV_{it})$ represents either the number of non-violent events or the number of violent events in a county i for each day t. Since the model uses the Poisson model to estimate the maximum likelihood, the interpretation will identify the rate ratio[1] for demonstrations. Poisson estimation technique is preferred due to the Ordinary Least Squares (OLS) estimators having biased outputs due to heteroskedasticity. The heteroskedasticity is represented by the left-skewed distribution of the data.

Due to the dynamic nature of the model 14-day lag ($DV_{i(t-1)} + ... + DV_{i(t-14)}$) get added by utilizing a unit-root test[2]. The lags allow the estimate of the k sample autocorrelation in a population. Adding the Lagged Dependent Variables (LDVs) provides a more robust estimator of the model's independent variables. The lag

[1]Rate Ratio: represents a percent change in the response for a unit change in X.
[2]This study used SIC and Fisher Demonstrations unit-root test to identify the lag length of the model.

values are from $t = 1$ to $T = 14$.

The SIP_{it} indicator is the primary regression variable that denotes the set of observations when a SIP policy gets implemented. It is a dummy variable with the value one indicating that the SIP policy is in place and zeroes indicating it is not. The SIP indicator is at the county i level for each day t. The interpretation is a rate ratio upon implementing the SIP policy. The rate ratio will show a percentage influence on demonstrations events for each model. Not all counties participate in the SIP police, but the data is accurate and complete.

The $cases_{it}$ and $deaths_{it}$ indicators are normalized daily count value of COVID-19 pandemic data. The data is a continuous value due to the normalization process. The interpretation will be a given percentage daily change in demonstration participation with each increase in daily cases or deaths. Whereas $mobility_{it}$ is a proportional change in cellphone movement. The indicator takes a value from $0 - 1$ representing percentage changes in decimal form. The interpretation is that there is a percent change in demonstration participation with each additional proportional change in cellphone movement. Both indicators are at the county i level for each day t.

The α_i value is the county fixed effects indicator for each county i. It accounts for the non-changing (or slow-moving) characteristics in a county region that may affect demonstrations, SIP policy implementations, or the control varables. The λ_t value is the time fixed effects indicator for each day t. It accounts for the daily shocks that the current COVID-19 environment may correlate with SIP policies and seasonal trends that may influence demonstration event participation.

Table 5.1: Rate Ratio on Peaceful Demonstrations

	(1) Non-Violent	(2) Peaceful	(3) Intervention	(4) Exce/Force
SIP Policy	-0.001952***	-0.001684***	-0.000890***	-0.000625***
	(0.000536)	(0.000524)	(0.000116)	(0.000043)
COVID-19 Cases	0.000000	0.000000	-0.000000**	-0.000000**
	(0.000000)	(0.000000)	(0.000000)	(0.000000)
COVID-19 Deaths	0.000023	0.000023	-0.000004**	-0.000005***
	(0.000014)	(0.000014)	(0.000002)	(0.000001)
Cell Phone Mobility	0.002627***	0.002389**	-0.002082***	-0.002124***
	(0.001019)	(0.001000)	(0.000202)	(0.000080)
Observations	254940	254940	254940	254940

Standard errors in parentheses

Clustered-robust standard errors at the county (fips) level.

Lag coefficients suppressed from table output

Data source: ACLED and Harvard Dataverse.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.1 includes Non-violent demonstration indicators. Upon implementation of SIP policies, there is a decrease of 0.19% in the likelihood of peaceful events occurring. In the subgroups, viewed in columns two through four, SIP policies continue to have a negative and significant effect at the 1% level. The negative indicators show that SIP policies significantly change social behavior due to the higher cost associated with peaceful demonstration efforts.

Daily COVID cases and deaths are not significant in the primary non-violent regression of peaceful sub-regression.However, external forces influence non-violent demonstrations there is a statistically significant effect. These coefficient are small due to the larger daily counts but when cases or deaths increase, demonstrations will decrease. These lower occurrences indicate that limiting stressful events may have become a priority with an environment surrounded by high COVID cases and death in society.

The Mobility indicator is significant at the 1% level but indicates that overall non-violent demonstrations are likely to rise by 0.26% with increased mobility. Under Peaceful demonstrations, there is a slight decrease in significance to 5%, but the positive coefficient has only decreased by .02%. The subgroup indicates that an event is likely to increase once restrictions are relaxed, and mobility increases. It is interesting how the decrease in Intervention and Excessive Force events occur. These indicators are significant at the 1% level, showing ever-increasing mobility will decrease events containing government altercations.

Table 5.2: Rate Ratio on Violent Demonstrations

	(1) Riot Violence	(2) Group Violence	(3) Mob Violence
SIP Policy	-0.001087***	-0.001075***	-0.000603***
	(0.000172)	(0.000170)	(0.000034)
COVID-19 Cases	-0.000000	-0.000000	-0.000000**
	(0.000000)	(0.000000)	(0.000000)
COVID-19 Deaths	0.000000	-0.000006***	0.000002
	(0.000007)	(0.000002)	(0.000007)
Cell Phone Mobility	-0.001268***	-0.001309***	-0.002257***
	(0.000265)	(0.000261)	(0.000073)
Observations	254940	254940	254940

Standard errors in parentheses

Clustered-robust standard errors at the county (fips) level.

Lag coefficients suppressed from table output

Data source: ACLED and Harvard Dataverse.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.2 includes Violent demonstration indicators. The first thing to notice is almost all the indicators of this table are significant at the 1% level. As with peaceful demonstrations, SIP policies cause demonstration events to decrease for violent demonstrations. These decreases indicate that even during higher stress and economic downturn, the policy immediately increased the costs of violence and, therefore, decreased potential demonstrations. Daily COVID cases and deaths are not statistically significant in the primary riot model. But when deaths rise there is a significantly negative effect on group violence. Where the pressure of increased case's cause a significant negative effect on Mob violence. Again this shows that all significant indicators are sensitive to the environment surrounded by high COVID cases and death in society.

Unlike the peaceful demonstrations table, the mobility indicators all have decreasing values. These decreasing values indicate a unit increase in mobility has a significant negative effect on violent demonstrations. It suggests that instead of increasing violence through mobility, social behavior is cognizant of mobility restriction and less likely to become violent. This illustrates the increased transit costs felt by the demonstrators. Due to the large area that the US encompasses, the next step is to look at a regional breakdown of the model through mapping and clustering.

5.2 Heterogenous Impact

5.2.1 Geographical Heterogeneity by sIP

Referring back to the state level SIP plots, from the statistical section in Figures A.1 thru A.3 the data shows the implementation of policies per state is different across time. Regional clustering begins to appear using detailed US county-level mapping to aggregate the demonstration in these policies across the US. In Figure 5.1 the aggregate demonstration in the policy can be seen, which illustrates the state of the country at the saturation of its implementation. The map representation shows that not all states implemented the police, but it also shows some counties within states did. Looking at a three-month break down in B.1 thru B.3 the demonstration is slightly more random in the first month. It reaches full saturation in the second month while the central states ease their policies by the third month. The third-month map shows that the nation's demonstration can be broken down into the west, central, and eastern regions.

Figure 5.1: County Level Participation in SIP Policies

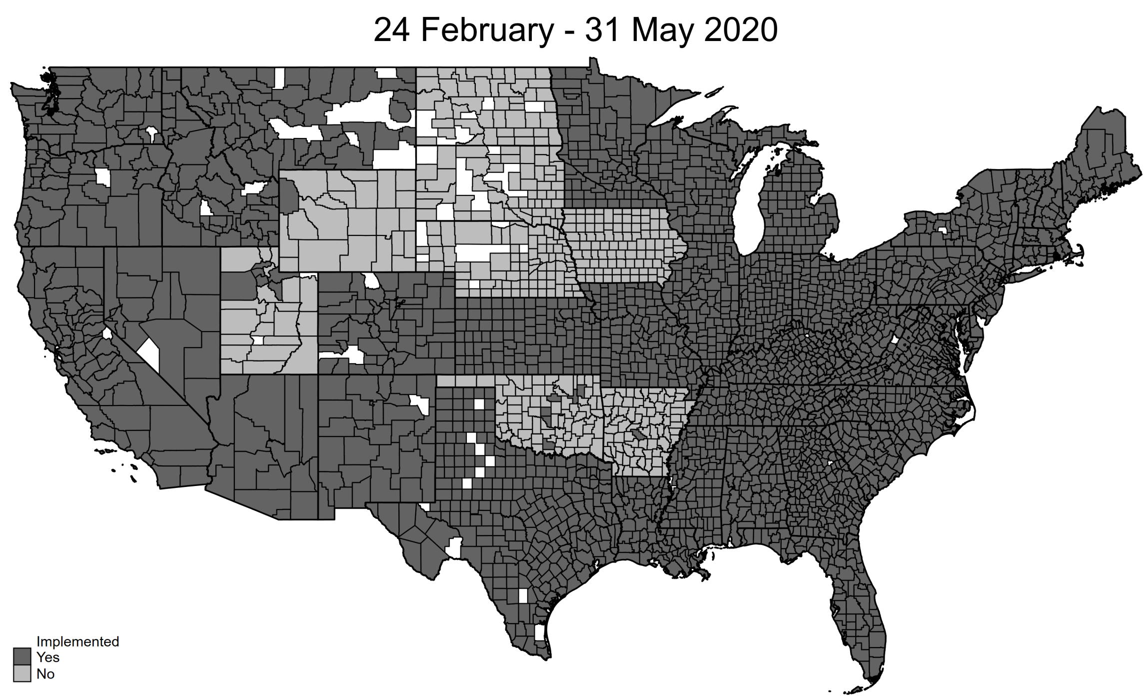
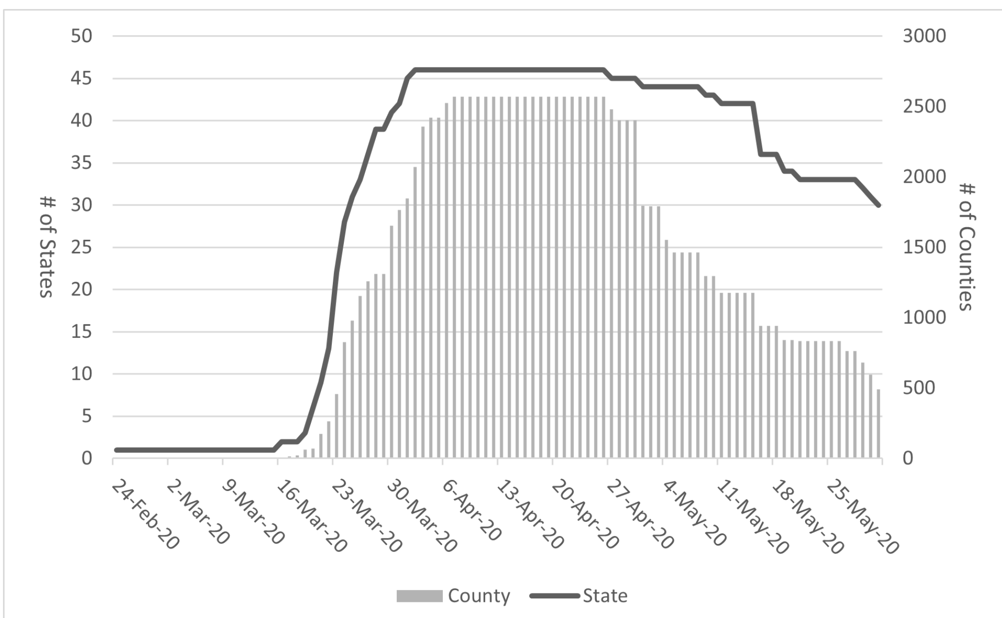


Figure 5.2 shows a more detailed trend of the SIP policy participation from 24 Feb - 31 May 2020. This graph shows increasing demonstration with each additional

state implementation of the policy over time (dark black line). The bar chart under the state curve represents the individual counties' policy implementation. The fast implementation illustrates how quickly and all-encompassing the policy was midway through March. But the graph shows that by the end of April, individual counties began to relax the policy, but still affected many states. This larger gap between the black line and the bar graph indicates the policy may have been initiated in areas that did not initially induce the need for pandemic relief through decreased mobility. This may indicate that blanketed implementation may not be beneficial to social well-being as the US was signaled through SIP policies that things were getting better. However, this was still in the being months of the pandemic.

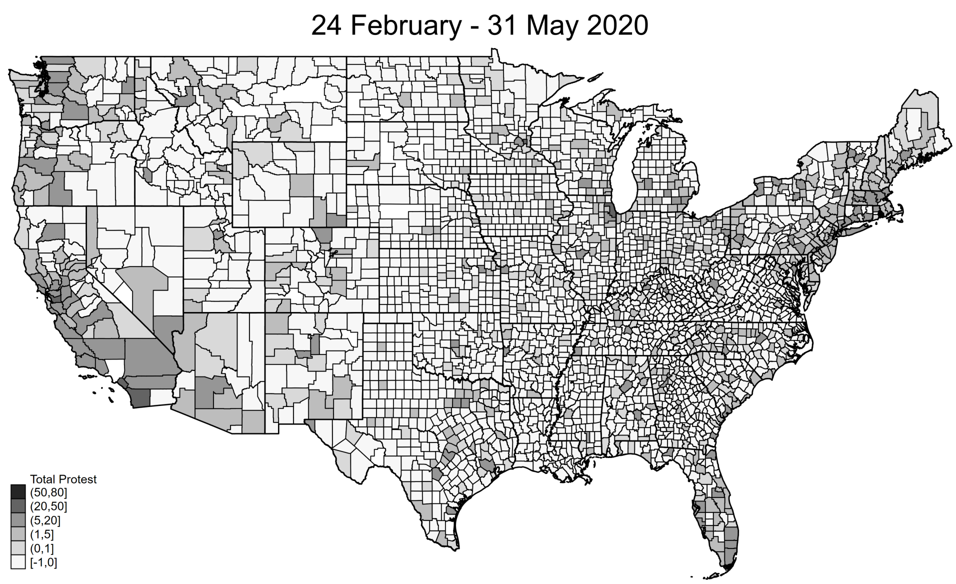
Figure 5.2: Participation in SIP Policies 24 February - 31 May, 2020



5.2.2 Geographical Heterogeneity by Regional

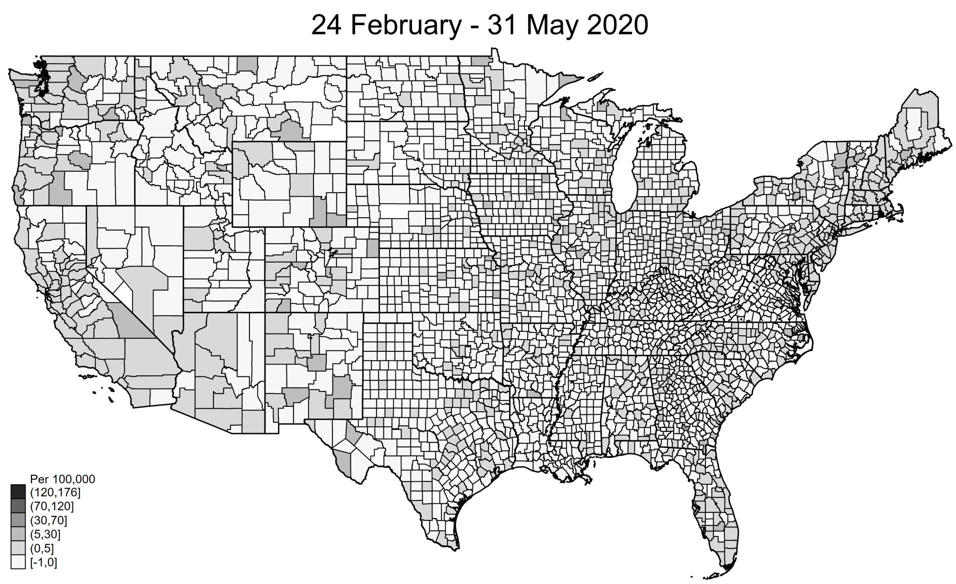
Using the detailed US county-level map to aggregate the application of demonstration demonstration(See Figures 5.3 and 5.5), a regional comparison between the east and west coast areas can be visually identified. In Figure 5.3, it observed that overall participation in non-violent demonstrations between 24 February 2020 and 31 May 2020 had the highest density around the Seattle, San Francisco, Sacramento, and Los Angeles areas for the west coast. Highest demonstration in the northern regions on the east coast where concentrated around New York. High-density urban locations that are more sensitive to economic and policy impacts tended to have higher demonstration rates. A monthly breakdown can be seen in Figures B.4 thru B.6).

Figure 5.3: County-Level Map: Non-Violent Demonstration



However, adjusting per capita in each county means a more even distribution across regions. In Figure 5.4 demonstrations have been adjusted per capita and then represented at the mean US county level. If looking at any participation level above 70 events per 100,000 people, there is only one county at this level. Richmond, Vergina, has a population of 9,077 for 2020 with an above-average demonstration events level of 16. Whereas Los Angeles did have more demonstrations at 86 events but had a population of over 9.97 million. The per capita adjustment gives a better visualization of county-level behavior when population changes occur.

Figure 5.4: County-Level Map: Non-Violent Demonstration per Capita



Note: County population source: (Bureau, 2022).

Table 5.2.2 consists of five regressions to include three states with the highest number of events for the data set. And two models that cluster counties that had at least one demonstration event with those that had no occasion. Until software technology allows for a Zero Inflation Poisson for panel sets, this is the method of choice. The first thing to notice is the difference in directionality between the west coast states (WA CA) and east coast state (NY). Washington, California, and New York are significant at the 1% level and have high likelihood values. However, Washington and California indicate an increased likelihood of demonstration, whereas New York reveals a decrease when implementing SIP policies. The mobility indicators mirror this directionality for the states. On the west coast, the effect of increased mobility will increase demonstrations while increased mobility in New York will still see a decline.However, only California shows a significant effect from mobility.

The fourth and fifth column in Table 5.2.2 reflects the counties with at least one demonstration event (SZiP > 0) or no events (SZIP $= 0$) during the timeframe of the dataset. Clustering these counties helps identify the differences in behavior between participating regions and non-participating areas. Not only are SIP policies significant at the 5% for counties with non-violent demonstrations but at 1% levels for those without. When clustering there is an increase in the coefficient for the participating counties by a magnitude of 0.3%. Additionally, when daily deaths increase, they have a 5% statistical significance. Daily Deaths have not been a highly significant indicator for the main regression until now. But when deaths per day rise, social behavior will increase demonstrations in the regions that are more prone to participate in demonstrations.

Column four indicates that even though these areas do not participate in demonstration during this data frame, SIP policies still influence their behavior. Even though the coefficients are small it is significant due to the fact that the negative change is representative of a shift from zero. When the control indicators increased, the public would decrease their participation in demonstrations. The separation of the clustered groups allows for stronger coefficients and primary indicator interpretations.

Table 5.3: Rate Ratio on Peaceful Demonstrations: by State & County

	(1) WA	(2) CA	(3) NY	(4) QZIP > 0	(5) QZIP = 0
Non-Violent					
SIP Policy	0.0153***	0.0423***	-0.0242***	-0.0052**	-0.0005***
	(0.0058)	(0.0116)	(0.0077)	(0.0022)	(0.0000)
COVID-19 Cases	0.0001	0.0002	-0.0000	0.0000	-0.0000**
	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
COVID-19 Deaths	0.0009	0.0021	0.0002	0.0002**	-0.0000***
	(0.0015)	(0.0019)	(0.0002)	(0.0001)	(0.0000)
Cell Phone Mobility	0.0074	0.0343**	-0.0338	0.0218***	-0.0022***
	(0.0132)	(0.0170)	(0.0219)	(0.0052)	(0.0000)
Observations	3192	4788	5124	64764	190176

Standard errors in parentheses

Clustered-robust standard errors at the county (fips) level.

Quasi Zero Inflation Poisson (QZIP)

Lag coefficients suppressed from table output

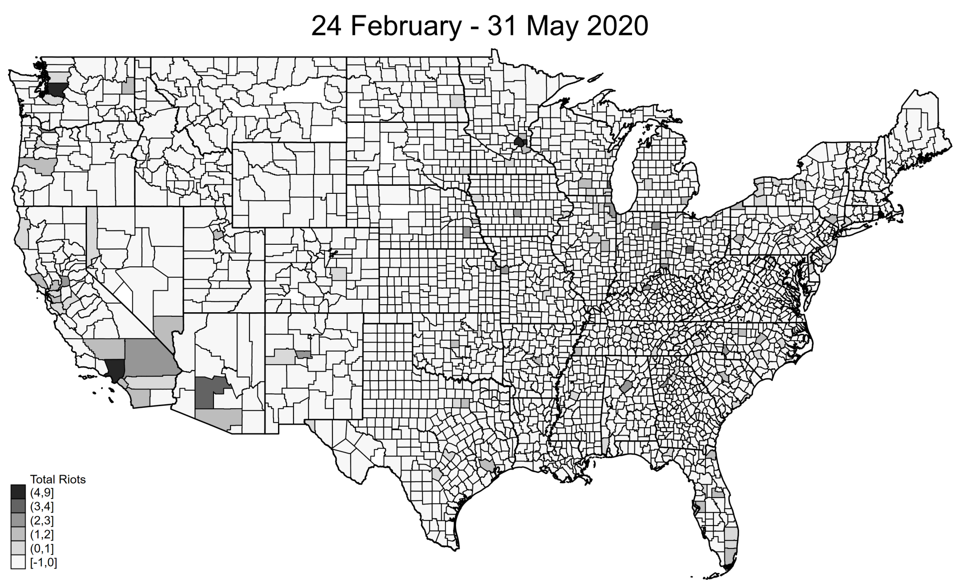
Observations are location specific.

Data source: ACLED and Harvard Dataverse.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Figure 5.3 the data shows concentrated regions with higher participation in riot activities. These all have accumulative violence greater than four and include LA (Los Angeles, CA), King (Seattle, WA), and Hennepin (Minneapolis, MN) counties. These counties are approximately two thousand miles apart, so their geographic locations are not driving for violent participation in demonstrations. However, the urban density influences the effect of peaceful demonstrations. A monthly breakdown can be seen in Figures B.7 thru B.9).

Figure 5.5: County-level Map: Violent Demonstration

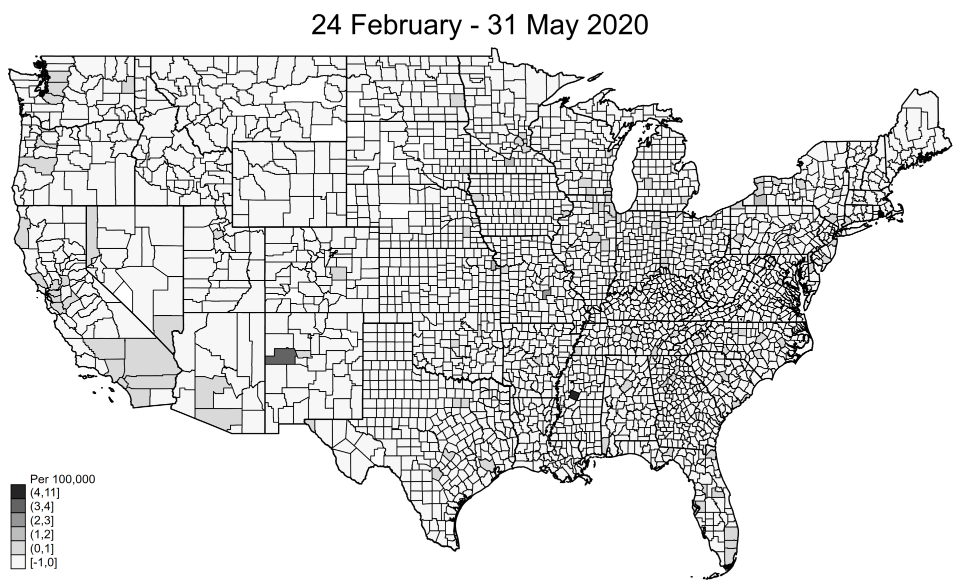


Again, adjusting per capita in each county means a more even distribution across regions. In Figure 5.6 violent demonstrations have been adjusted per capita and then represented at the mean US county level. If looking at any participation level above three events per 100,000 people, there are three counties[3] These counties only

[3]The three counties are Cibola(NM, 26,462 3.78), Holmes (MS, 16,808, 5.95), and Richmond (VA, 9077, 11.02), (county, state, population, events per capita).

have one violent event but also smaller populations. Again, Los Angeles did have more violent demonstrations at nine events but had that higher population of over 9.97 million. While per-capita adjustment gives a better visualization of county-level behavior, it may be a less efficient process with smaller occurrences in the dataset.

Figure 5.6: County-level Map: Violent Demonstration per Capita



Note: County population source: (Bureau, 2022).

Looking at the histogram of each state (See Figure A.4 thru A.6), the related SIP policies for these areas show violence began to pick up at the end of May. All three state graphs give a different interpretation. In California, the SIP policy is still in place, but violence increases. Washington sees a smaller spike due to the specific county that has increased activity while keeping its SIP policy in place. In contrast, Minnesota has ended its SIP policy, seeing a spike in violent participation. The indicator seen here is the event pushing demonstration that drove the change in behavior, which outweighs the SIP policies' opportunity cost.

One of the main driving factors for the spike in Minneapolis (MN) towards the end of May was the killing of George Floyd (20 May 2020). The additional increases in violent demonstrations may indicate the spillover effect in the other two locations. Taking a closer look at the landscape by dividing the observations into three different time periods, the data shows that most violent demonstrations happen around George Floyd's death (See Figures B.7 thru B.9).

Riot indicators were processed through the model at the same levels as the Non-Violent demonstrations (See Table 5.4). The first thing to notice is there is no longer a clear difference between coastal states.Washington shows SIP negatively affecting demonstrations, it is not statistically significant, whereas California is positive but it too is not statistical significant. Whereas, New York has a negative and .1% significance level for sip implementation. This regression also shows that as cases increase demonstrations decrease. However, mobility effects show that lowering mobility will increase demonstrations while easing mobility will decrease demonstrations.

The fourth and fifth column in Table 5.4 reflects the counties with violent events (QZIP > 0) or no events (QZIP $= 0$). Clustering these counties helps identify the differences in behavior between participating regions and non-participating areas. Not only are SIP policies significant at the 5% for counties with violent demonstrations but at 1% levels for those without. When clustering there is an increase in the coefficient for the participating counties by a magnitude of 0.3%. Column four allowed for excluding counties within states that did not observe any violence. Cases and Mobility do increase participation for areas with observed violent events but decreases for those without violent events. However, daily deaths do not significantly influence demonstrations in either group. But there are significantly stronger coefficients and primary indicator interpretations when clustering the two groups.

Table 5.4: Rate Ratio on Violent Demonstrations: by State & County

	(1) WA	(2) CA	(3) NY	(4) QZIP > 0	(5) QZIP = 0
Riot Violence					
SIP Policy	-0.0006	0.0010	-0.0074**	-0.0023***	-0.0006***
	(0.0008)	(0.0009)	(0.0031)	(0.0007)	(0.0001)
COVID-19 Cases	-0.0000	0.0001	-0.0000	0.0000*	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
COVID-19 Deaths	-0.0001	-0.0001	-0.0001*	-0.0000	0.0000
	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Cell Phone Mobility	-0.0003	0.0017	-0.0171**	0.0025*	-0.0022***
	(0.0023)	(0.0024)	(0.0086)	(0.0014)	(0.0001)
Observations	3192	4788	5124	64764	190176

Standard errors in parentheses

Clustered-robust standard errors at the county (fips) level.

Quasi Zero Inflation Poisson (QZIP)

Lag coefficients suppressed from table output

Observations are location specific.

Data source: ACLED and Harvard Dataverse.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Sensitivity Analysis

To test the performance of the model, Table 5.5 includes five regressions to compare the strength and validity of SIP policy effects on demonstrations. Regression one is an OLSregression without the Poisson addition. The SIP indicator is negative and significant at the 5% level. The controls are both positive and statistically significant for this model. However, the coefficient is harder to interpret at a decrease of 0.0013 events per day when SIP policies get implemented. The control indicators are positive and statistically significant.

The Poisson regression model (2) indicates the same error distribution but different interpretations due to the data's "count" nature. The SIP indicator is still negative and significant at the 1% level. When SIP policies get implemented, there is approximately a 0.2% increase in demonstrations event participation per day. Again the control indicators are positive and statistically significant. But in the third model, when the control indicators get removed, the coefficient is doubled, showing that their indicators help control biases. But SIP coefficient is still negative and significant at the 1% level.

Regression Four removes all counties with zero participation in demonstration events, which is a quasi ZIP approach. The SIP indicator is negative, but the coefficients rate ratio has increased to approximately 0.5%. The coefficient shows the directionality is still constant but has a greater magnitude with decreased statistical significance at 5%. The controls have also increased but are still positive and statistically significant. When the control indicators get removed (See model five), the coefficient doubles showing that the controls indicators were controlling for biases, but the directionality is still negative.

Table 5.5: Sensitivity Analysis Using OLS, Poisson, and Adjusted Models

	(1) OLS	(2) Poisson	(3) P.SIP	(4) QZIP	(5) QZ.SIP
Non-Violent					
SIP Policy	-0.00132**	-0.00195***	-0.00233***	-0.00520**	-0.00824***
	(0.00054)	(0.00054)	(0.00049)	(0.00218)	(0.00177)
COVID-19 Cases	0.00000	0.00000		0.00001	
	(0.00000)	(0.00000)		(0.00001)	
COVID-19 Deaths	0.00003**	0.00002		0.00020**	
	(0.00001)	(0.00001)		(0.00010)	
Cell Phone Mobility	0.00481***	0.00263***		0.02181***	
	(0.00103)	(0.00102)		(0.00520)	
Observations	254940	254940	254940	64764	64764

Standard errors in parentheses

Clustered-robust standard errors at the county (fips) level.

Quasi Zero Inflation Poisson (QZIP)

Lag coefficients suppressed from table output

Data source: ACLED and Harvard Dataverse.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The five models in Table 5.5 have a consistent negative directionality of SIP on non-violent demonstrations. While the magnitude of each model is dependent on the controls and observations within the model, they are all statistically significant above the 5% level.

Not only did participation in demonstrations vary, participation in SIP policies varied, creating a quasi-experimental environment. In Table 5.6 column one represents the primary regression model output observed in Table 5.1. Column three represents the clustered regression model when using the quasi zero inflationary process Table 5.3 for the participation group. Columns two and four represent counties that implement SIP policies and will represent the difference between SIP effects and other mechanisms inherent in the demonstration process.

When controlled for non-participants in the SIP policies, there is a 0.006% decrease in the ratio from the original effects of 0.195% to 0.189%. While this is a small amount, it shows other unobservable influences within the non-implemented counties. These indicators could be changes in social norms, decreased migration patterns[4], or event-driven factors themselves. When clustering by counties with demonstration participation and policies implementation (see column four), there is an increase in the effect on the demonstration by 0.029%. This marginal change is a small effect but could indicate additionally unseen influences in the model. These differences could be due to the demographics or regional [5] effects of demonstrators.

[4]The slowing of human migration in the US could impact mobility and show indications of an economic downturn. 60% of domestic moves in the US were within counties with population ages between 20-29 of those most likely to relocate (Fry & Cohn, 2021).

[5]These differences could include urban densities vs. rural, demographic per event, and participation numbers instead of event-driven. Due to the pandemic impact, lower participating numbers could lower overall event data.

Table 5.6: Robustness Check of SIP Policies on Demonstrations

	(1) All	(2) SIP = 1	(3) QZIP > 1	(4) QSIP = 1
Non-Violent				
SIP Policy	-0.00195***	-0.00189***	-0.00520**	-0.00549**
	(0.00054)	(0.00055)	(0.00218)	(0.00222)
COVID-19 Cases	0.00000	0.00000	0.00001	0.00001
	(0.00000)	(0.00000)	(0.00001)	(0.00001)
COVID-19 Deaths	0.00002	0.00002	0.00020**	0.00022**
	(0.00001)	(0.00002)	(0.00010)	(0.00011)
Cell Phone Mobility	0.00263***	0.00297**	0.02181***	0.02022***
	(0.00102)	(0.00125)	(0.00520)	(0.00555)
Observations	254940	215880	64764	60396

Standard errors in parentheses
Clustered-robust standard errors at the county (fips) level.
Quasi Zero Inflation Poisson (QZIP)
Lag coefficients suppressed from table output
Data source: ACLED and Harvard Dataverse.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

While controlling for SIP perticipaton at the counties level through fixed effects, demonstrations are very heavily impacted by social norms. But these finds do show that there may be other control mechanisms influencing demonstrations.

Due to the short time span and the daily reporting nature of the dataset, additional controls are not added at this time. Different economic, demographic, and trend indicators should be added in more extended datasets to increase fidelity for future research and modeling approaches. The quasi-experimental findings of the significant estimates are only marginally different from the main result. The consistant findings show that the main effects are mostly felt through SIP policies during the COVID-19 pandemic, and it is seen through the mechanism of mobility and individual behavior shifts.

SECTION 6: DISCUSSION

6.1 Inequality and Demonstrations

Section two stressed the importance of equality through the pursuits of demonstrations throughout our history. These pursuits of demonstrations have continued during the pandemic, with even more emphasis on issues such as climate change, police brutality, and racial equality. When policies meant to help society become problems at the national level, the government needs to understand how it affects all possible behavioral shifts. SIP may have a more even effect on a nation with a more homogenous social makeup. When the US sees a large ethnic fractionalization causing a heterogeneous environment, the government should note how this may cause the policy's intent to fall short of the needs in a state or region (Glaeser, 2005).

Demonstrators push to make changes when the division of wealth and inequality spreads, which can be difficult. Primarily because of how different the wealthy and the poor influence political change. Since the poor rely on voting and demonstrations to push change, this can be tricky as sometimes peaceful demonstrations may not work, but violence can drive supporters away. In contrast, the wealthy use their membership in special interest groups or lobbying activities to fight for what more affluent society members want (Glaeser, 2005). In this case, it may be up to the highest bidder rather than social needs, leading to an unequal socioeconomic environment. Unequal influence on the democratic process is why the results of our research are significant in understanding the short-run effects of blanketed policies.

6.2 Policy Implications

Section five shows that during the exogenous effects of the pandemic and subsequential SIP policy implementation, the participation in demonstrations lessened through the decreases in events. Demonstrations are a way for a society to increase its social capital through "features of social organization, such as trust, norms, and networks that can improve the efficiency of society by facilitating coordinated actions" (Wallis *et al.*, 2004). Equation C.1 (Hall & Jones, 1999) represents a production function where y_i represents country output per worker [1]. Using Joe Wallis's addition of a social capital scaler (Reference equation C.2)), a better represented human capital function indicates the influences of social capital (when all other observations are held constant)(Wallis *et al.*, 2004). The equation can describe the divergence in productivity in the US if country output is replace with state or county level output.

A visual way to see how social capital impacts economic outcomes through the pursuit of livelihood capital assets is seen in figure C.1 (Chhibber, 2000). The institutional environment consists of both formal rules provided by state legal systems and informal norms societies build through networking. A collaborative environment means that states must follow established rules set through the political process of social norm drivers. This balance drives incentives, along with technology, to efficiently control transaction costs[2] of the process on an industry. However, if formal rules get implemented that negatively impact informal rules (normative behavior), it

[1]Standard production function where Y_i = Total output, K_i = Stock of physical capital, L_i = Labor, H_i = Stock of human capital, A_i = Measure of Technology (Hall & Jones, 1999).

[2]The transactions costs could include cost of restructuring, set up of a new business, or even bribes.

could destroy social capital (Chhibber, 2000). Therefore, there is a need for states to produce formal rules that efficiently represent informal rules and support social capital needs.

When formal rules are inefficient, demonstrations are a way for individuals to pursue change to increase social capital. While social capital is a non-tangible value, it can be affected by individual, cultural, and historical influences. These elements get used to generate a ranking value through a Social Capital Index (SCI). It measures the well-being and stability of a population (Chisadza *et al.*, 2021). By utilizing SCI database this research output could be used as a scalar for some of the subindices of the index. The influences of demonstrations could be seen through the subindices of civic engagement, voting rates, confidence in institutions, and violence rates. These smaller sub-effects could have a larger cumulative effect on the SCI index. And through this extended research, demonstration influences could be seen on social capital trends.

This research shows a consistent decreasing effect of policies that suppress demonstration participation through higher transit costs. These effects lead to fewer demonstrations events for society to pursue efficiency in social capital. Depending on the SCI in a county, the impact of policy implementation can lead to higher social capital costs. While the results and research look at short-term behavior effects, the question is, could long-term trends in demonstrations and political policies change social capital in a complex economic environment?

While this model does show significant impacts of SIP policies on immediate individual behavior, more extensive modeling will need to be done to identify the long-term effects of the pandemic. Annual data that can cluster heterogeneity effects concerning time may give a better picture of the trends in demonstration participation. These clustering techniques could include comparing weekdays to weekends, national events to local events, or types of events to identify the distribution and magnitude demonstrations play on social capital.

6.3 Long-Run and Global Relationship

While the expectation in the US is to see an initial decrease in demonstrations due to policy implementations, events like the death of George Floyd can cause spikes in social participation. Looking forward to future research, the question will be if the participation rate would have been greater without the policies and pandemic environment. Looking at dashboard from the ACLED site[3], there is the initial spike in quarter two of 2020 leading up to the demonstrations for civil justice. But there is an almost linear decreasing trend for the next two years even with additional social and global events occurring, including the current global crises in Ukraine. Yet, protests and riots are lower than they have been since the implementation of the SIP policies in the US. The decreasing trend in demonstrations could indicate the persistence of the policy and pandemic influence on social behavior change and its impact on pursuing well-being goals (ACLED, 2021).

The long-run effects stress why it is essential to understand large-scale policies' impacts. The diminishing consequences on the social environment in the US are similar to the outcomes seen in the Sub-Saharan report (Basedau & Deitch, 2021). When observing global behavior, the research found that areas with conflict-poverty cycles would see a more prolonged effect through the pandemic environment (Berman *et al.*, 2021). While violence does tend to be more prevalent in US demonstrations than those of the global community (Haynes & Wintz, 2016), when demonstrations

[3]https://acleddata.com/dashboard//dashboard: Date from 1 January 2020 to 1 February 2022, Event types (Protests, Riots), Region – US)

decrease, then violence at the demonstration events tend to decrease proportionately. This study shows an extension to the previous literature and that other similar socioeconomic countries can be modeled and observed through these modeling processes.

SECTION 7:
CONCLUDING REMARKS

The research in this study used comprehensive data from two sources to evaluate the linkage between SIP policies and demonstration events. Using over 254.9 thousand observations while controlling for mobility and Covid death, the model used Poisson county by day fixed effects to estimate the rate ratio of the likelihood of SIP policies affecting demonstrations. Since the model used a 14-day lag approach, the study showed an overall negative 14-day effect of 2.7% on Non-Violent demonstrations and an overall negative effect of 1.5% on Riot Violence. The sensitivity testing shows that the controls help to keep the model unbiased as well as showing the primary indicator of SIP as consistently negative and only marginally affected. This study explored the heterogeneity inherent in the vastness of the US geographical layout to include differences in states, regions, and urban concentrations.

While this research has shown a stable modeling approach, its acknowledged that more sophisticated models may better fit the data. A Zero-inflated Poisson Regression Modal may be a viable choice in the future, but the research had limitations to this approach. First, while there are statistical software packages for Stata[1] to use Zero-inflated methods on sectional and time-series data, there is no coding at this time for panel data. During the scope of this research, the Zero-inflation method for panel

[1]stata is the software used to data analysis for this study.https://www.stata.com/

sets was ambiguous on its importance over a fixed-effect model. But with that said, the data does have a large amount of non-players (zeros) in the set, and it may be worth comparing a regular Poisson and a Zero-inflation model to find a better fit. In the end, it may still be up to the data influence, structure, and overall questions being asked.

It is also beyond the scope of this study to analyze the data at the organizational and event level. This is due to the variability within the data and time limitations. The variability of organizations, and their demonstration pursuits, include 2,905 different groups. The data for this set only observes a total of 2,450 non-Violent demonstrations. This study does point out the need for a more extensive data set to look at the effects of a great range of observations and levels. This study primarily focuses on the effect SIP policies have on the US during the initial implementation period.

The importance is easily viewed through the scope of the Sustainable Livelihood Framework (Bohle, 2009). Society is balancing the four critical dimensions of sustainability (economic, environmental, social, and institutional sustainability) by efficient use of five livelihood assets[2] represented by a pentagon in Figure C.2 (Bohle, 2009). Policies, institutions, and processes manage these Livelihood assets. Still, if the outcomes are seen as inequitable or misaligned with societal well-being goals, then one of the pursuits of the Livelihood Strategies would be the use of demonstrations. If this were suppressed, this would not only move the arrow that influences the assets from outcomes of adjustment to the government control level, but it would also increase the vulnerabilities in the environment. This study shows why it's essential to identify influence of policies on social environments and their effect on social well-being through demonstrations.

[2] The five livelihood assets are: Human, natural, financial, physical, and social capital.

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APPENDIX A:

GRAPHS

Figure A.1: Protest With SIP Policy Implementation: Section 1

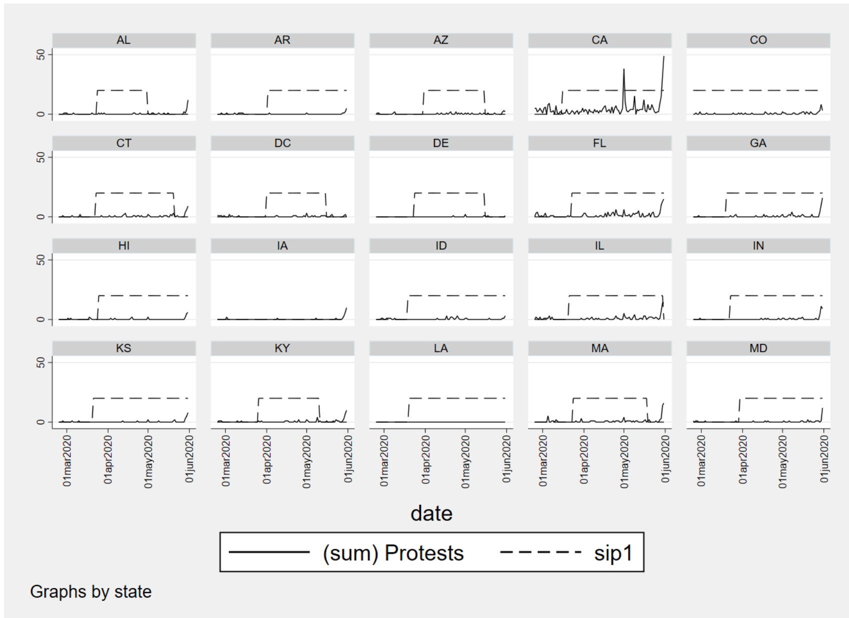


Figure A.2: Protest With SIP Policy Implementation: Section 2

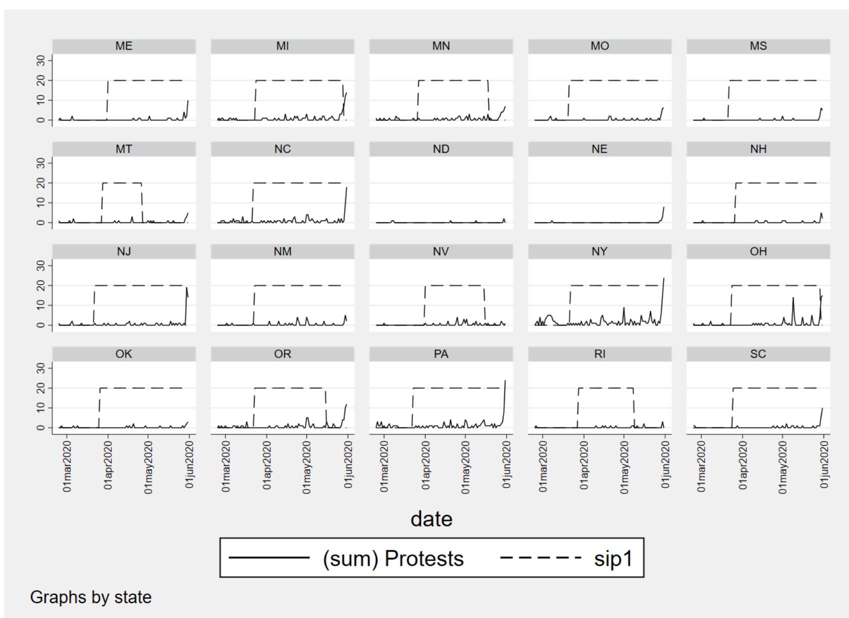


Figure A.3: Protest With SIP Policy Implementation: Section 3

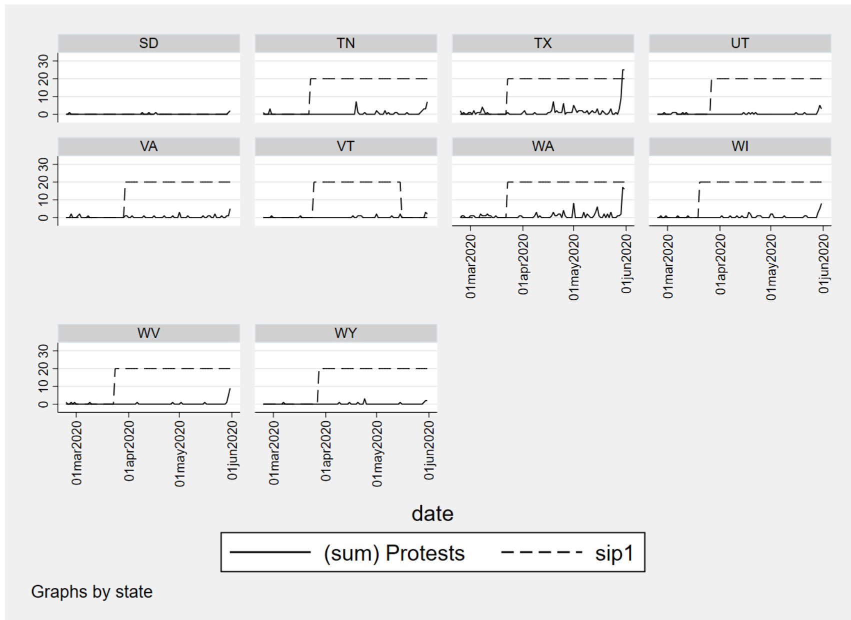


Figure A.4: Riots With SIP Policy Implementation: Section 1

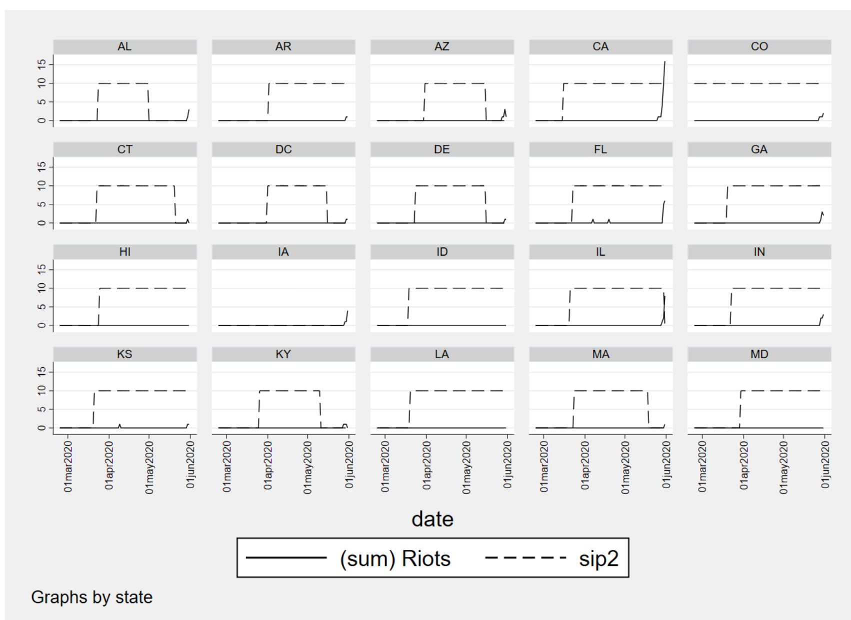


Figure A.5: Riots With SIP Policy Implementation: Section 2

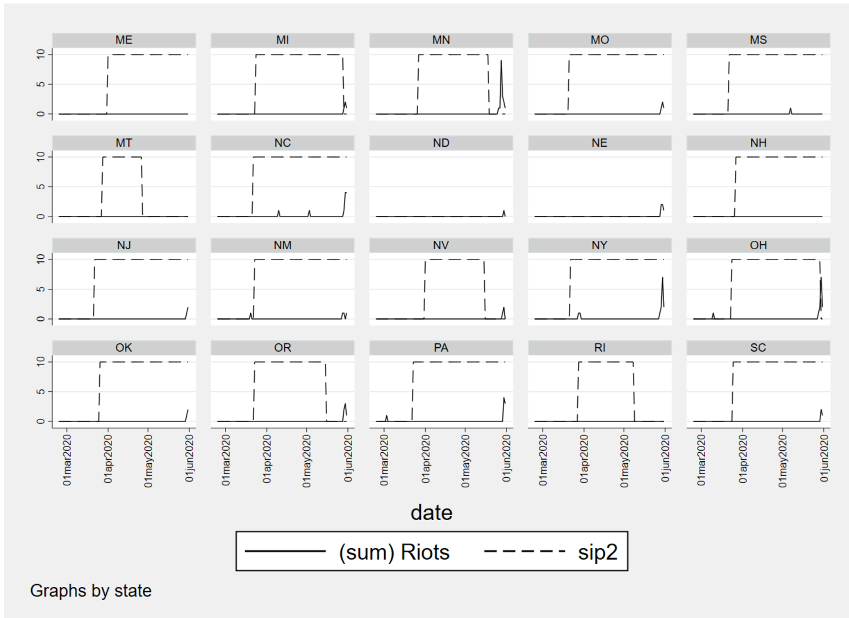
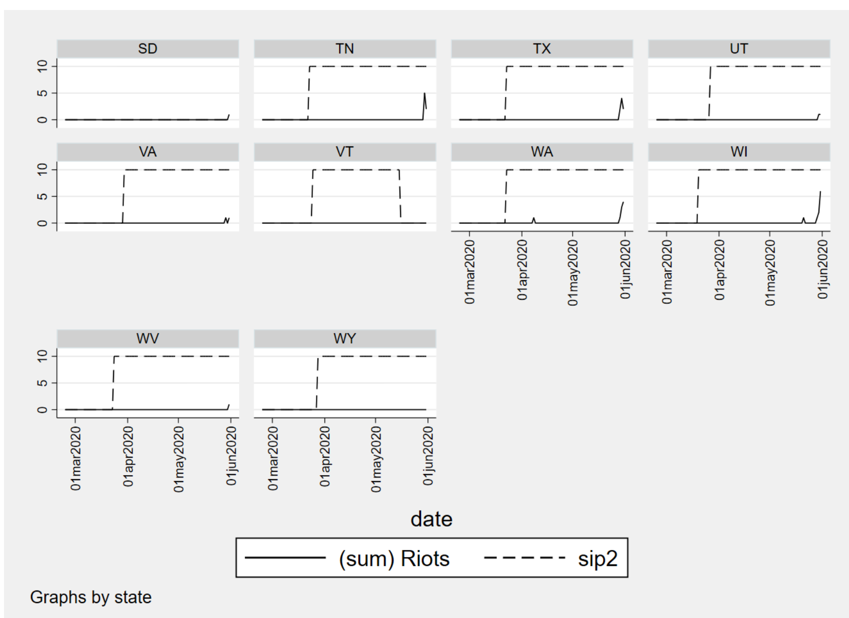


Figure A.6: Riots With SIP Policy Implementation: Section 3



APPENDIX B:

GEOGRAPHIC MAPS

Figure B.1: County Level SIP Implementation - Period 1

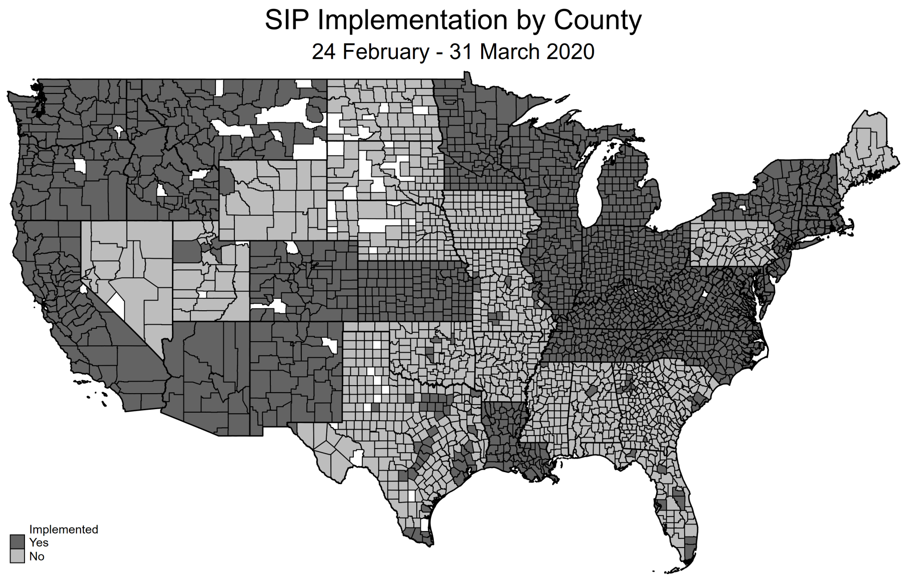


Figure B.2: County Level SIP Implementation - Period 2

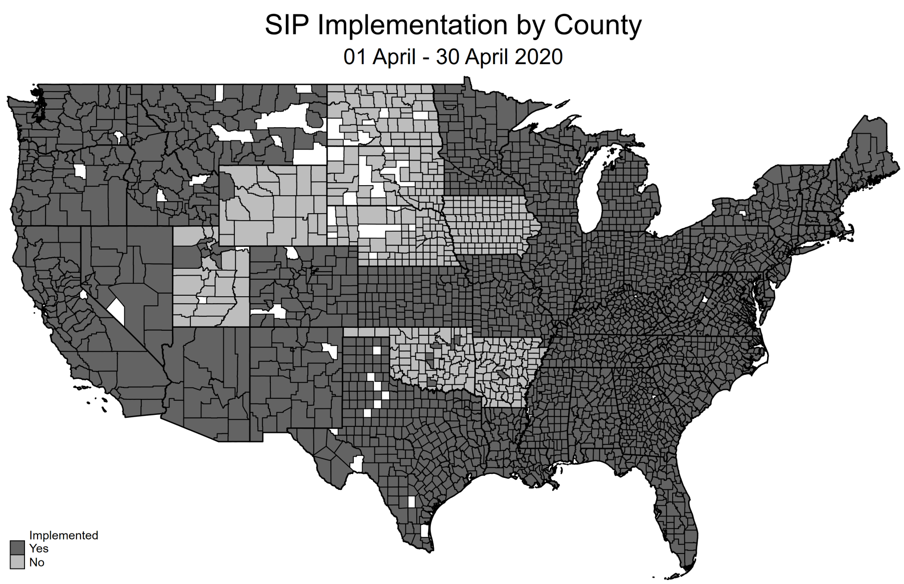


Figure B.3: County Level SIP Implementation - Period 3

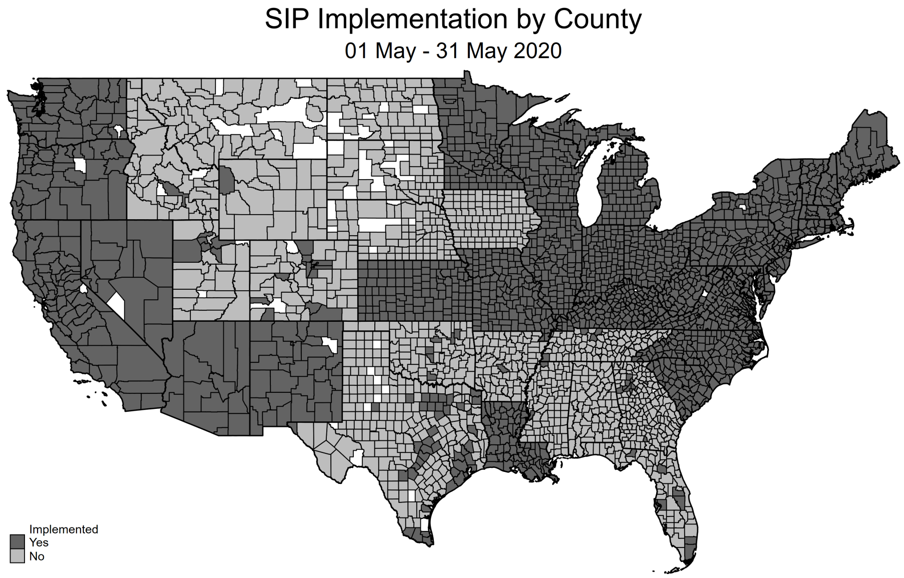


Figure B.4: Participation in Non-violent Demonstration - Period 1

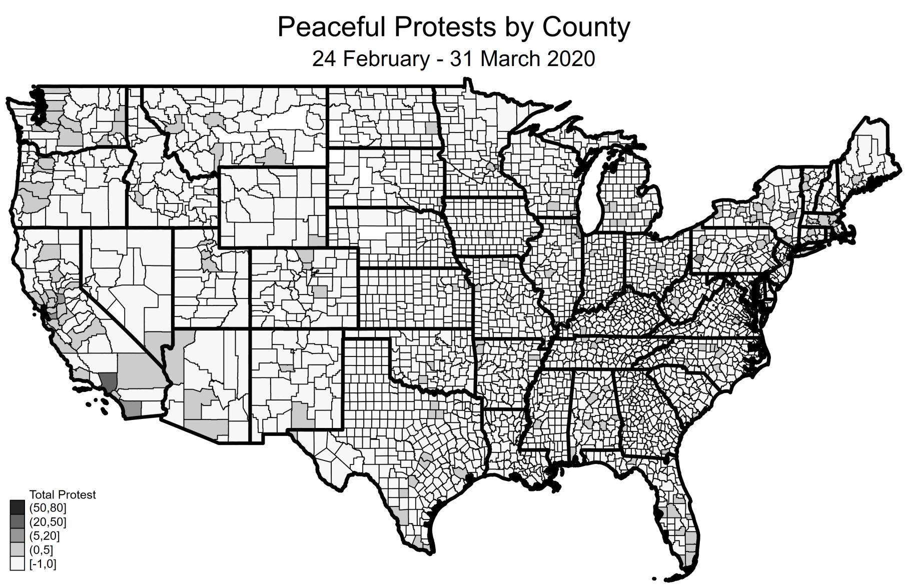


Figure B.5: Participation in Non-violent Demonstration - Period 2

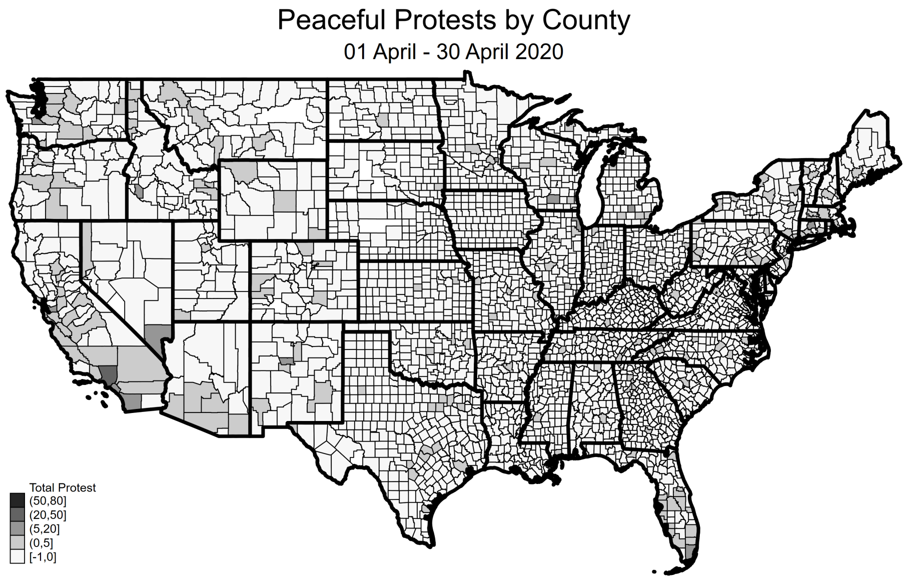


Figure B.6: Participation in Non-violent Demonstration - Period 3

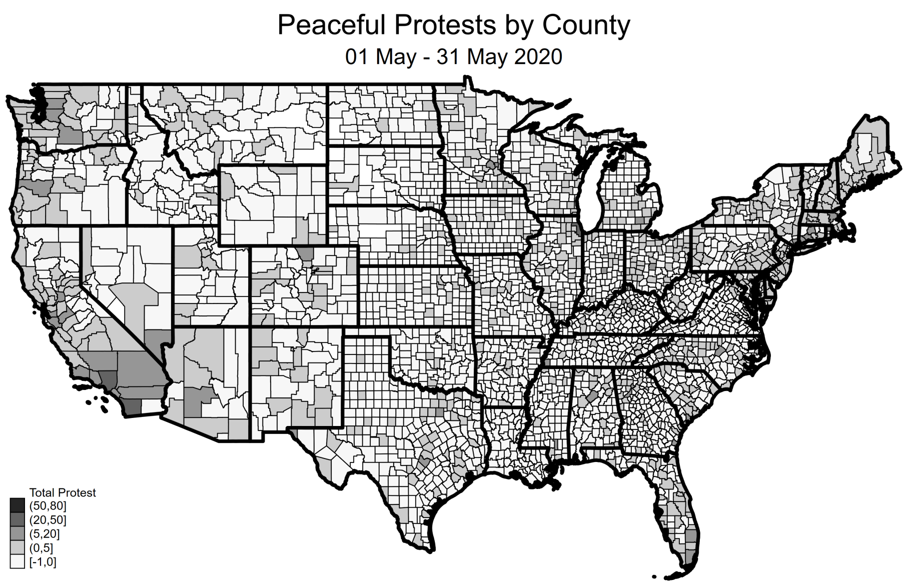


Figure B.7: Participation in Violent Demonstration - Period 1

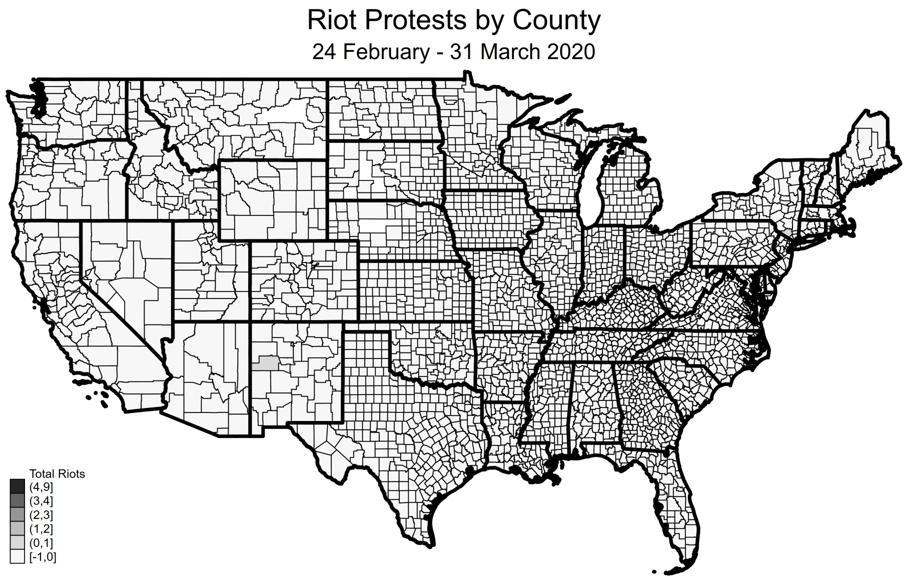


Figure B.8: Participation in Violent Demonstration - Period 2

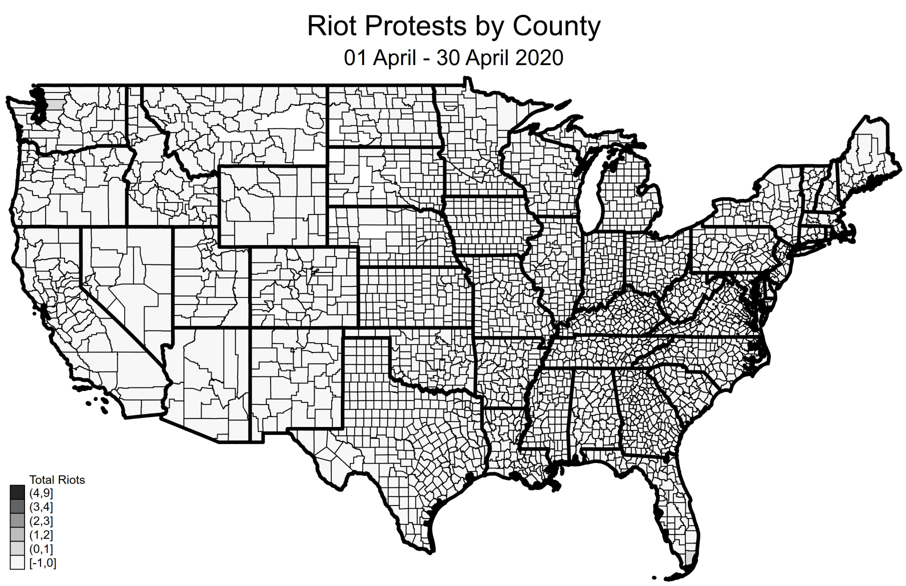
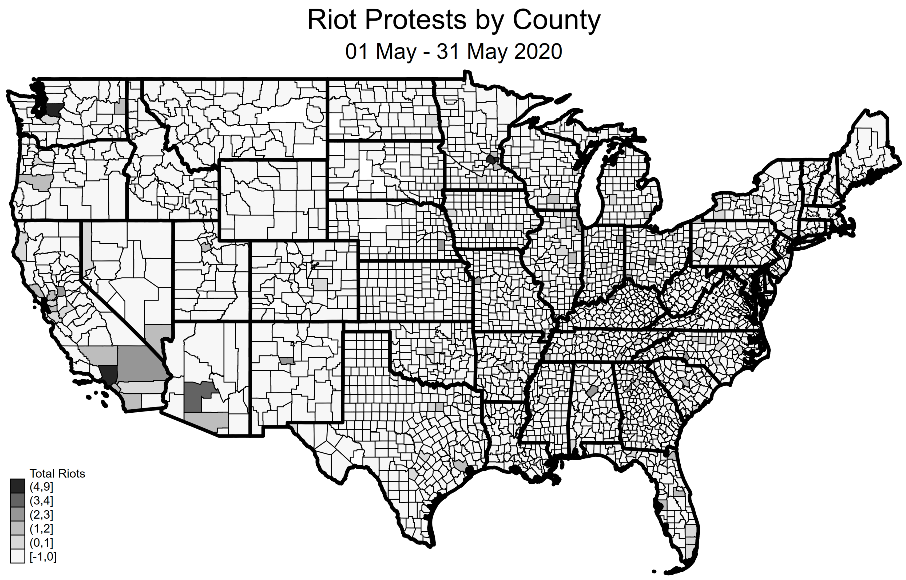


Figure B.9: Participation in Violent Demonstration - Period 3



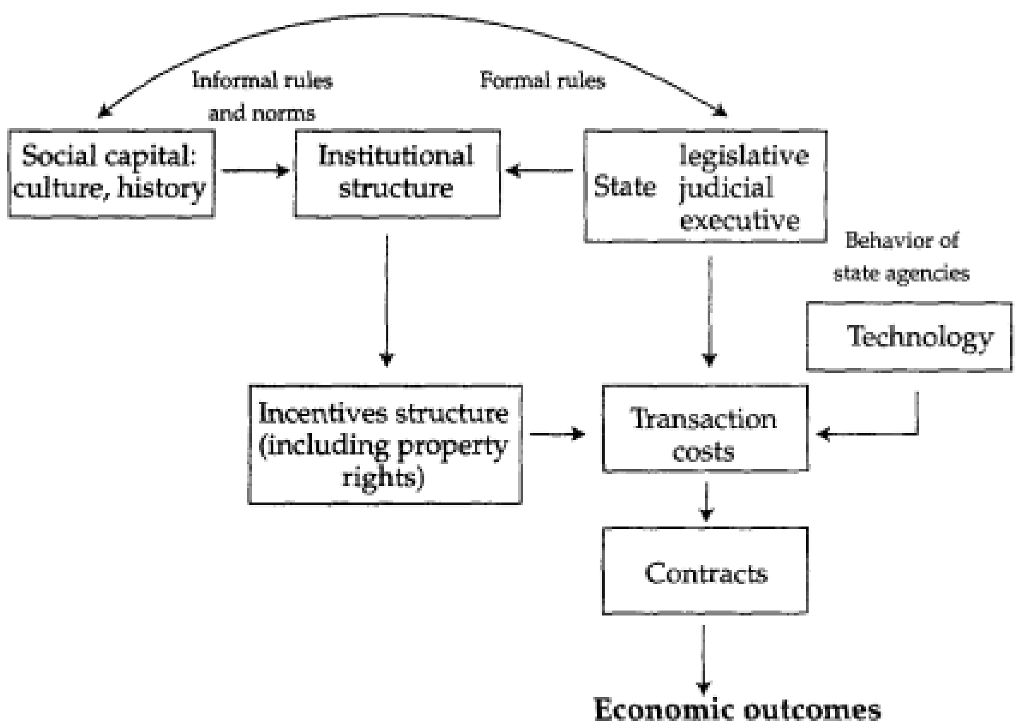
APPENDIX C:

CONCLUDING REFERENCE MATERIAL

$$y_i \equiv \left(\frac{K_i}{Y_i}\right)^{\frac{a}{1-a}} \left(\frac{H_i}{L_i}\right) A_i \tag{C.1}$$

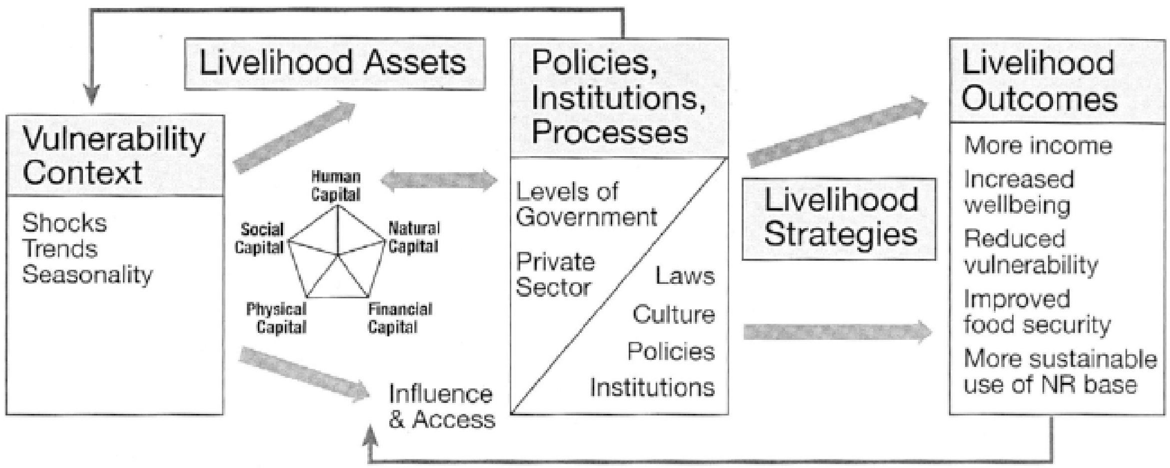
$$y_i \equiv \left(\frac{K_i}{Y_i}\right)^{\frac{a}{1-a}} \left(\frac{H_i}{L_i}\right) A_i S_i \tag{C.2}$$

Figure C.1: State, Institutions, and Economic Outcomes



source: (Chhibber, 2000)

Figure C.2: The Sustainable Livelihood Framework. Original: DFID (1999)



source: (Bohle, 2009)