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ACEs, Education and Space: The Relationship of Adverse Childhood Experiences and Education Across California Counties

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Education

by

Norbert Negrea

June 2024

Dissertation Committee:
Dr. Robert Ream, Chairperson
Dr. Marsha Ing
Dr. Amos Lee

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The Dissertation of Norbert Negrea is approved:

Committee Chairperson

University of California, Riverside

ACKNOWLEDGEMENTS

This work and the academic years accomplished at UCR would not have been possible without the outstanding mentorship, guidance and efforts from Dr. Robert Ream, Dr. Marsha Ing and Dr. Amos Lee. Dr. Robert Ream's continuous support and push towards excellence and scholastic inquiry during an academic career riddled with significant life experiences (and a global pandemic) highlight his dedication to his students, community and academia. Dr. Marsha Ing's outstanding collaboration and flexibility to co-carry the baton of this dissertation with Dr. Ream was priceless in elevating this work to its utmost potential and eventual completion. Finally, Dr. Amos Lee's warmth and dedication to student success was a guiding light during the strenuous production of this work and the completion of my doctorate of philosophy at UCR.

To my wife Janet Rodriguez, with her endless ocean of support, love, dedication, strength, and clarity to whom I owe my life not just for the achievement of this dream, but of all things good in my life. To my daughter, Liliana, a shining light birthed during this journey towards completion and who has brought me endless joy during the most difficult of times and has become my life motivation. To Reyna and Armando Rodriguez, who have taken me in since adolescence providing guidance, support, love, stability and the most loving grandparents to my shining light of a daughter. To my parents Livia and Sandu Negrea, who continued to hold my worth to a standard beyond our means and ensured that, throughout the immense instability, that my education should come first. And it looks like it finally has, and is finally done.

DEDICATION

Köszönöm Istenem, hogy soha nem engedted, hogy egyedül járjam ezt az életet. Köszönöm anya, hogy mindig hittél az értékemben. Köszönöm Lily, hogy te vagy a legszebb fény ezen a világon, ez a fokozat hozzon még több áldást a jövődre.

Gracias Reyna. Tu amor por mí, mi hija y nuestra familia permanecerá con nosotros para siempre. Gracias Armando por creer siempre que podemos lograr cualquier cosa.

Mi amor, we're done. Yes, I know I did it. But *we* did it. Thank you. Thank you for everything. Te amo con todo mi corazón.

ABSTRACT OF THE DISSERTATION

ACEs, Education and Space: The Relationship of
Adverse Childhood Experiences and Education Across California Counties

by

Norbert Negrea

Doctor of Philosophy, Graduate Program in Education
University of California, Riverside, June 2024
Professor Dr. Robert Ream, Chairperson

When considering issues of education in the United States of America, the vantage point to understanding inequity in education outcomes changes when the scope of an issue is seen from a systemic perspective compared to individual perspective. Research in public health suggests that childhood adversity is often experienced as a serious threat to a child's physical or psychological sense of safety and wellbeing. In order to investigate childhood adversity and education over space, theoretical applications and methods focusing on more macro level systemic vantage points were selected for the current study. Addressing the need for more nuanced research on the relationship between ACEs, space and educational outcomes in secondary schools in California, the proposed study contributes by providing a complex database of expanded ACEs definitions, the creation of an ACE composite variable and then linking them to the educational outcomes of public high school students across California's 58 counties. The primary techniques utilized in analysis focused on geospatial analysis and linear regression. The constructed ACE composite variable was especially suited to the proposed study given that it was explicitly designed to explore the magnitude of

accumulated ACE exposure over a geographic area. Results of the study painted a complex relationship between ACEs, space and education, with particularly interesting findings surrounding the difference between more rural/suburban counties compared to their urban counterparts, including important regional differences between north/central counties and southern counties. Implications on how California can follow suit of other states in the nation to standardize, organize and disseminate statewide ACE data and what kind of policy is feasible within the state to combat the negative population effects of ACE exposure on education outcomes are provided.

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Chapter 1: Introduction

When attempting to understand a problem, the scope of that problem changes depending on the vantage point taken. When considering issues of education in the United States of America, the vantage point to understanding inequity in education outcomes changes when the scope of an issue is seen from a systemic perspective compared to individual perspective (O'Day & Smith, 2016). There is precedent of education systems in the US to put the onus of ongoing education issues on individual students (McGee et al., 2022), which have shown in cases to be problematic (Donovan & Cross, 2002). An individualistic framework ignores the systemic elements that influence education outcomes in the US (Darling-Hammond, 2004; DeVylder et al., 2020; Esses, 2021; Morgan & Amerikaner, 2018; Phelan & Link, 2015).

By incorporating a systemic framework to improve students' education outcomes, researchers expand the typical individualistic notion to address educational performance and intervention on the micro level to the macro level. When it comes to public health, aside from what the name itself suggests, California's Department of Public Health defines the field as one where professionals work to promote healthy lifestyles, remove dangers of the environment and prevent disease for the community and its families (California Department of Public Health, 2023). This macro level framing of the field as a discipline concerned for the "public" can prove advantageous when paired with the field of education insofar as systems of health and education are interdependent, yet typically compartmentalized (Ream, Cohen & Lloro-Bidart, 2014). As the current study argues, understanding the interplay between public health and education on high school

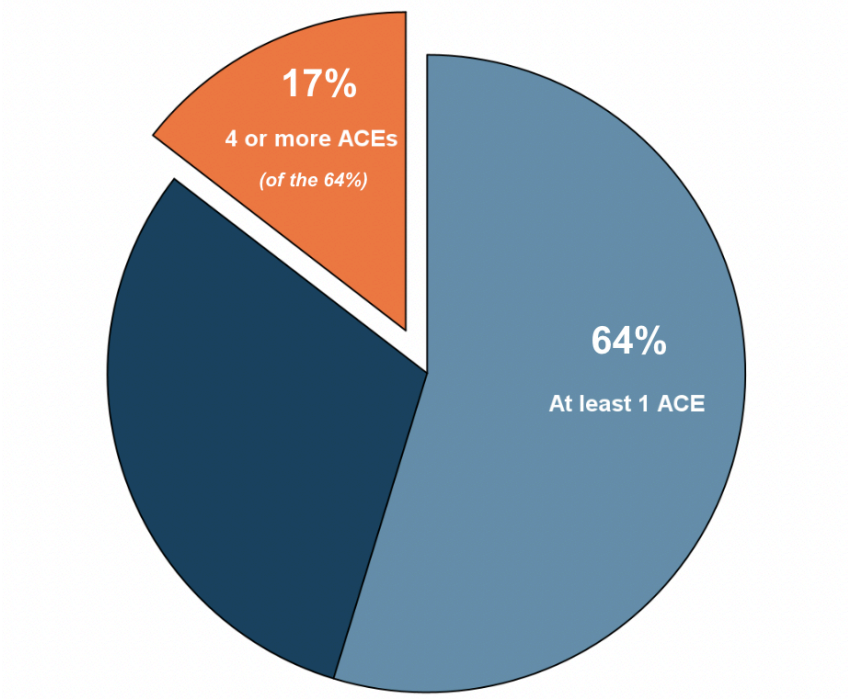
students' educational outcomes on a macro level can provide vital insights on how best to address interventions that can be more effective on a systemic level (Midgley, 2006). It is research that merges the two disciplines, especially as it pertains to differences across population density and spaces (Crouch et al., 2020; Jordan, Kostandini & Mykerezi, 2012), that the current study builds on as momentum in its investigation.

Prevalence of Adverse Childhood Experiences as a Public Health Issue

Research in public health suggests that childhood adversity is often experienced as a serious threat to a child's physical or psychological sense of safety and wellbeing (CDC, 2019; Felitti et al., 1998). Adverse childhood experiences (ACEs) are defined by the Center for Disease Control as potentially traumatic experiences between birth and 17 years of age which hinder a child's sense of safety, stability and or bonding, with physical and or emotional pain that can have long lasting effects for years (CDC, 2019). Indeed, ACEs are widespread in the United States (Murphrey & Sacks, 2019). Nearly half (45%) of U.S. children have experienced at least one adverse childhood experience, while about 1 in 10 have experienced three or more ACEs. According to the National Center for Injury Prevention and Control, Division of Violence Prevention (CDC, 2023), 64% of all adults across the nation reported experiencing at least one ACE and almost 2 out of 10 experiencing 4 or more between 2011 and 2020 (Figure 1).

Figure 1.

Reported Prevalence of ACEs Among US Adults (2011-2020)



Note. Data retrieved from (CDC, 2023)

Adverse Childhood Experiences and Education

Current research combining the fields of public health and education is starting to fine tune some of the variables of utmost importance that policy makers and communities should focus on to increase population health and quality of life. Understanding the trajectory of one's health and quality of life is complex regarding the multitude of influences that can either help or hinder future wellbeing. Yet, research shows that intersectoral efforts at improving the health status of learners can pay dividends in enhanced educational outcomes (Phelan & Link, 2015; Trent et al., 2019). It is therefore crucial for research to continue the investigation of how ACEs impact education, and

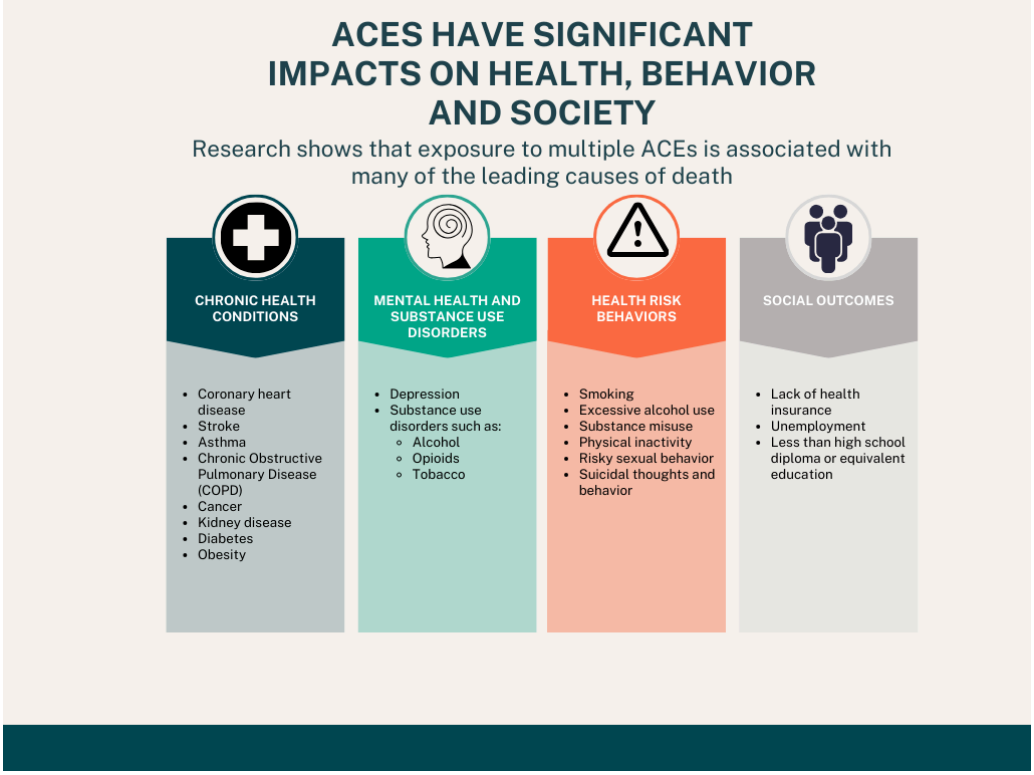
how best to frame the connection between public health and education that can translate to the diverse array of stakeholders and policy makers within a state.

ACEs and Education Equity

Students with ACEs in public education in the United States are more likely to receive inadequate access to health and counseling services, which impacts their educational attainment and future wellbeing (CDC, 2019; Felitti et al., 1998) with long term, widespread impacts on the society's social equity fabric and economy (Figure 2).

Figure 2.

ACEs Can Have Serious Impacts on Education, Health and Societal Outcomes



Note. Information retrieved from (CDC, 2023)

The pillars highlighted in Figure 2 show the vast potential influence of ACEs on an individual's life. Starting from the disproportionate risk of chronic health conditions, mental health and substance use disorders, and exposure to health risk behaviors (CDC, 2023), ACEs are playing a reciprocal role in relation to education–influencing an individual's ability to succeed in education, while in return educational success is impacting one's future health and coping abilities to address ACEs (Phalan & Link, 2015; Wilkinson & Marmot, 2003). Systemic racialization of the differences for marginalized communities in their individual learning experiences (Sleeter, 2001), behaviors (Gregory, Skiba & Noguera, 2010) and abilities (Cartledge & Dukes, 2009) has led to perpetuations of inequity, stalling progress against systemic solutions (Ladson-Billings, 2016; Noguera, 2001) to the larger picture of marginalization in education. It is therefore important to investigate the reciprocal nature of inequality in health and education on a larger scale to better understand the systemic marginalization of students.

As highlighted in Figure 3, the interventions disproportionately placed on externalizing behaviors for individual students of color tend to over discipline and remove students from traditional classroom settings (Nowicki, 2018). This type of identification of students again focuses on person-specific actions, not necessarily tackling the systemic concerns and understanding the potential effects of ACEs on students' experiences in the classroom–which can compromise educational attainment (Cutler & Lleras-Muney, 2006; Goesling, 2007; Kawachi, Adler & Dow, 2010).

Figure 3.

ACEs Layer Onto Racial Inequity Issues In Education, Impacting Future Health

As a preview to the work to come, the current study takes a macro approach to understanding ACEs in its application of theory, utilizing a combination of social determinants of health (Wilkinson & Marmot, 2003) and spatial justice theory (Soja, 2013) to analyze the relationship between ACEs, space and education outcomes for public high school students throughout California. The following review of the literature in the field provides context into the previous seminal investigations on ACEs as measured through participant response sampling, and how recent efforts on the state level are leaning into understanding ACEs from a broader vantage point.

The Growing Body of Research Over ACEs Since 1998

The groundbreaking study that brought significant attention to the phenomena of ACEs was the CDC-Kaiser Permanente adverse childhood experiences study colloquially known as "the ACEs Study" (Felitti et al., 1998). Here, seven categories of "childhood abuse" and "household dysfunction" were linked to severe increases in health risk, disease and early mortality for those who experienced adverse childhood experiences compared to those who did not. Twenty-two years later, Maguire-Jack, Lanier and Lombardi (2020) criticized the original ACEs study for not using a critical lens to ensure that specific categories of adverse childhood experiences, that are disproportionately impacting young people of color, were not left out of the ACE measures and analysis. Their study would use an expanded nine categories for ACEs, which together with Felitti et al.'s work (1998), would be utilized in part for its framework in the investigation and operationalizing of ACEs in the current study.

In between these two seminal studies, the state of California had conducted research to illuminate the public health concern of ACEs with their "Let's Get Healthy" collaborative that produced an ACEs choropleth map based off of county boundaries (Let's Get Healthy California, 2016). This report was significant for two reasons: first, it already laid the groundwork for utilizing the expanded ACEs categorizations of neighborhood violence and discrimination that Maguire-Jack et al solidified as crucial for investigating the clustering patterns of ACEs in respect to race and ethnicity; second, it incorporated ACEs data into geographic analysis by displaying ACEs distribution over California counties. The importance of utilizing counties as units of analysis stems from

the “essentials for childhood initiative (efC)” led by the partnership at the California Department of Public health, which aims to address ACEs as a public health issue that can be addressed through research provided to stakeholders and policy makers. This conclusion is also built into the structure of the current study as it attempts to center research implications around the geographic jurisdiction of county lines, pushing for a more systemic understanding of ACEs.

In the years between the two seminal studies, there have been positive strides in communities taking initiative to try and integrate the science of ACEs and trauma-informed care into the neighborhoods that various health and non-health organizations served. One such initiative that proliferated during this gap was the Mobilizing Action for Resilient Communities Initiative (MARC) from 2015 to 2017 (Westat, 2019). The initiative aimed to strengthen ties between ACE focused networks across the country and fuel change regionally and nationally against the concerns that ACEs bring to various communities around the US.

Fourteen existing networks across thirteen states were a part of the MARC Initiative and evaluation[1]. These networks were evaluated on their relationships to one another and the greater effort to facilitate regional and national change regarding ACEs and trauma. Two key takeaways pertinent to the current study are that this large scale

[1] The networks included: 1) Alaska Resiliency Initiative, 2) Healthy Environments And Relationships That Support (HEARTs) in Albany, New York, 3) Vital Village in Boston, Massachusetts, 4) ACEs Collaborative in Buncombe County, North Carolina, 5) Resilience Network of the Gorge in Columbia River Gorge, Oregon, 6) Illinois ACEs Response Collaborative, 7) Resilient KC in Kansas City, Missouri, 8) Elevate Montana, 9) Philadelphia ACEs Task Force (PATF), Pennsylvania, 10) San Diego Trauma Informed Guide Team (SD-TIGT), California, 11) Sonoma County ACEs Connection, California, 12) Peace4Tarpon in Tarpon Springs, Florida, 13) Children’s Mental Health Collective Impact (CMHCI) in Wisconsin, and 14) Whatcom Family & Community Network/Walla Walla Community Network in Washington.

initiative and evaluation resulted in increased ACEs and trauma informed practice in K-12 partnerships, as well as two different cases of specific legislation introduced in local governments to address ACEs and increase funding. This type of momentum that has been building during the gap between the two seminal studies is even more reason why California stands to benefit by considering how ACEs impact education across the state and what inferences can be drawn to address the interrelated health and educational needs of youth in the most populous state in the Nation.

Conceptual Framework and Theory From the Field

An ecological framework for understanding how to expand beyond an individualistic notion of trauma, to that of a population or community phenomenon, was offered up by the Prevention Institute and Kaiser Permanente in the report "Adverse Community Experiences and Resilience: A Framework For Addressing and Preventing Community Trauma" (Pinderhughes, Davis & Williams, 2015). The report promotes the importance of understanding trauma as a collective, community and population experience as highlighted by the quote from Dr. George Albee: "No epidemic has ever been resolved by paying attention to the treatment of the affected individual" (p. 7). Recommendations urge researchers and policy makers to incorporate the study of collective, community trauma to build out results and solutions that tackle the widespread issue of childhood adversity as it continues to influence the home, school, neighborhood, and the entire ecology of individual wellbeing. The current study therefore builds upon the call from Pinderhughes et al. (2015), as well as geospatial scholarship (Boterman et al., 2019; Garo, Allen-Handy & Lewis, 2018; Smith, Parr & Muhidin, 2019) and equity

scholarship (Heard-Garris et al., 2021; DeVylder et al., 2020), to move forward with investigating adverse childhood experiences on a population level to advance understanding to the fields of education and public health.

Yet despite extensive research on ACEs and chronic health problems (Merrick et al., 2018; Shonkoff, Garner, 2012), and the extended twenty two year timeline between the Felitti et al (1998) and the Maguire-Jack (2020) study, research has only just begun to probe the link between ACEs, space and children's educational experiences (Chafouleas, Pickens & Gherardi, 2021; Hinojosa et al., 2019; Metzler et al., 2017; Perfect et al., 2016; Thomas, Crosby, & Vanderhaar, 2019). Addressing the need for a more ecological approach to research on ACEs and educational outcomes by accounting also for geographic space, the current study contributes by investigating ACEs, high school academic outcomes and county specific geography to deepen understanding of the geography of opportunity (Tate, 2008) and possible implications for policy and practice.

The Current Study

The current study aims to explore the exposure of adverse childhood experiences across California counties, investigating its relationship to education outcomes of public school students in California counties in the context of their future health and wellbeing. Addressing the need for more nuanced research on ACEs' relationship to education outcomes over space in California through a broader systemic vantage point, the proposed study contributes by providing a complex database of expanded ACEs definitions linked to the educational outcomes of public high school students across California's 58 counties. As research reviewed on geospatial analysis would suggest

(Boterman et al., 2019; Garo, Allen-Handy & Lewis, 2018; Smith, Parr & Muhidin, 2019), understanding the regional differences in population density and educational opportunity such as through the categorizations of rural, suburban and urban are important when considering the relationship between constituents and their county level systems of power (California State Association of Counties, 2024; Percival, Johnson, & Neiman, 2009).

As a preview of the work to come, the current study utilizes a combination of social determinants of health (Wilkinson & Marmot, 2003) and spatial justice theory (Soja, 2013) to analyze the relationship between ACEs and education outcomes for public high school students throughout California. In regards to the guiding questions that will structure the analyses, this study addresses two overarching questions:

1. What is the incidence of ACEs across counties in California?
2. What is the relationship between ACEs and educational outcomes?
    a. (RQ2A) Specifically, what is the relationship between ACEs and high school graduation?
    b. (RQ2B) Specifically, what is the relationship between ACEs and high school suspension?
    c. (RQ2C) Specifically, what is the relationship between ACEs and high school expulsion?

To investigate these two overarching research questions (and sub questions), data was used from sources including the Population Reference Bureau, Prison Policy Initiative, U.S. Census Bureau, Federal Bureau of Investigation's Uniform Crime

Reporting System and the California Department of Education. The primary techniques utilized in analysis focused on geospatial analysis and linear regression. The constructed ACE composite variable was especially suited to the proposed study given that it was explicitly designed to explore the magnitude of accumulated ACE exposure over a geographic area. Paired with the guidance from research suggesting the importance of the outlined education outcome variables (Rumberger, 2007), the dependent variables and ACE composite are analyzed together and in this act merge the two disciplines of public health and education. By analyzing this relationship at the population level and across space (counties), the current study adds to the body of research attempting to promote policy intervention that raises awareness of how public health and education are interconnected (Ream, Cohen & Lloro-Bidart, 2014) and how the influences of ACEs in education outcomes should be addressed on a larger scale, rather than focused on individual interventions.

Potential Contributions to ACEs Research from Current Study

Much has been written about multiple forms of marginalization and disparities in educational outcomes across racial, ethnic, and socioeconomic groups (Anderson, 2007; Carter et al., 2017). However, less well understood is how this type of systemic marginalization plays out over space for a population. This study focuses on the health status of learners from a population level vantage, particularly geography in the form of a county (Hillman, 2017; Tate, 2008).

The current study explores the relationship of ACEs concentration and distribution with education outcomes across the state of California to better understand

the magnitude and direction of the role that ACEs play in students' educational outcomes. Previous studies and reports on California ACE exposure continue to utilize data that is operationalized from individual respondent data (Let's Get Healthy California, 2016; Felitti et. al., 1998; Maguire-Jack et. al., 2020), which can be a concern regarding the under-reporting of abuse for reasons of difficulty, denial or fear of losing custody (McElvaney, 2015). It also continues to frame the issue of ACEs as "one person's problem," rather than what ACEs really are–a public health concern (Pinderhughes, Davis & Williams, 2015). By utilizing county population level data to connect the vital research conversation on ACEs exposure, geographic space (including rural, suburban and urban distinctions) and educational outcomes in California, the current study builds upon nearly twenty three years of ACEs research and adds specifically to the focus on California's public health and education concern on a macro level compared to traditional individualistic research of the phenomena.

Summary of Research Findings

A brief summary of the findings from the current study shows that the geospatial analysis and linear regression points to a complicated picture of how ACEs across California counties relate to education outcomes in secondary schools. The geospatial analysis points to more rural and suburban counties of concern where exposure is higher proportionally compared to their urban county counterparts. The prevalence of ACEs (as operationalized and measured by the ACE composite), showed highest in the following counties: Shasta (17/30); Yuba and Humboldt (14/30); San Joaquin, Sacramento, Kings, Alameda (13/30); Tehama, Monterey, Los Angeles, Kern, Fresno and Del Norte (12/30).

The results of research question 2, discussed much more in depth in Chapters 4 and 5, revealed inconclusive direct connections between ACEs and education outcomes across California counties. How this contributes to the body of research, and future implications for analysis, are discussed in Chapter 5.

Overview of Dissertation

The study is separated into five chapters: introduction, overview of key literature and theoretical framework, research design, results and discussion. Chapter two discusses theoretical perspectives of investigating ACEs, the theories guiding the current study and conceptual framework, while reviewing pertinent literature and seminal articles from the field. Chapter two dives into the theoretical framework that incorporates social determinants of health (Wilkinson & Marmot, 2003) and spatial justice theory (Soja, 2013) to see how reviewing the issues of ACEs in the context of the jurisdictions of California counties can lend an important layer of analysis to the discussion of ACEs and education in secondary schools. Chapter two also outlines research regarding interpreting the differences between the rural and urban spectrum as it pertains to the variables of the current study, as well as grounding the understanding between how this geographic categorization can be a useful tool in understanding population differences across space. Chapter three reviews the research design as it pertains to methodology, focusing on geospatial analysis and linear regression, the operationalization of the eight ACE categories and the creation of the ACE composite. Chapter four reveals the results of the study, including the final data projections and tables including pertinent information regarding the geospatial analysis and the linear regression results. Chapter five brings it

all together to discuss what meaningful changes can be done to ensure that research and practice addressing adverse childhood experiences in California is improved.

Chapter 2: Theory & Literature

Having briefly illustrated the magnitude and persistence of adverse childhood experiences (ACEs), this chapter shifts focus to a more in-depth review of theoretical interpretations of understanding ACEs, including the two theories present in the current study's conceptual framework. Chapter two also presents the conceptual framework, along with pertinent literature in the field of ACEs as it pertains to measurement, consequences, causes and potential solutions to addressing ACEs.

Theoretical Interpretations of ACEs

Research regarding the phenomena of adverse childhood experiences continues to shift in regards to how the field understands and frames the concern. Here, this section will review the building blocks of the theoretical interpretations and research that eventually leads to the current study's theoretical perspectives influencing the research questions and subsequent analyses.

The Origins of ACEs from Understanding Health Disparities

The theoretical beginnings of adverse childhood experiences in Western research is traced back to the 1960's with the concept of "health gradients" and their impacts on people of different social statuses (Osmick & Wilson, 2020). Health gradient theory explained that those with higher socioeconomic status were predicted to have better health outcomes compared to those with lower socioeconomic status. The Whitehall study from 1967 was seminal in this theoretical understanding of health gradients, focusing on British civil servants in their working years to determine the impacts of their occupations on mortality (Wigger, 2011). Although relatively narrow in focus in

operationalization regarding a particular occupation and theoretically with socioeconomic status, this study analyzed group level differences in the community to better understand what could be interpreted as a public health concern amongst a working class subgroup. A few decades later during the 1980s, the field advanced in research scope in the United States.

In the mid 1980's, the US Department of Health and Human Services created a task force on Black and Minority Health, submitting a report that was the first of its kind regarding the state of US health among different racial/ethnic groups (Heckler & Margaret, 1984). Findings suggested that there was a continuous disparity of mortality and illness disadvantaging Black and minority communities in the US compared to their white counterparts. The study was a great example of understanding public health disparities in the US, and laid the groundwork for what the next decade would produce in respect to understanding ACEs. It is here that in the 1990s, Michael Marmot and Richard Wilkinson's work on social determinants of health began to take shape.

Theoretical Stance of the Current Study

The current study employs a union of two theoretical perspectives—social determinants of health (Wilkinson & Marmot, 2003) and spatial justice (Soja, 2013)—in order to best understand the phenomena of ACEs as it pertains to space and education. These two theories, in combination, guide the investigation into the pertinent literature on the measure, causes, and consequences of ACEs, which also guides the final research questions and research design of the current study in order to contribute to the field of ACEs research.

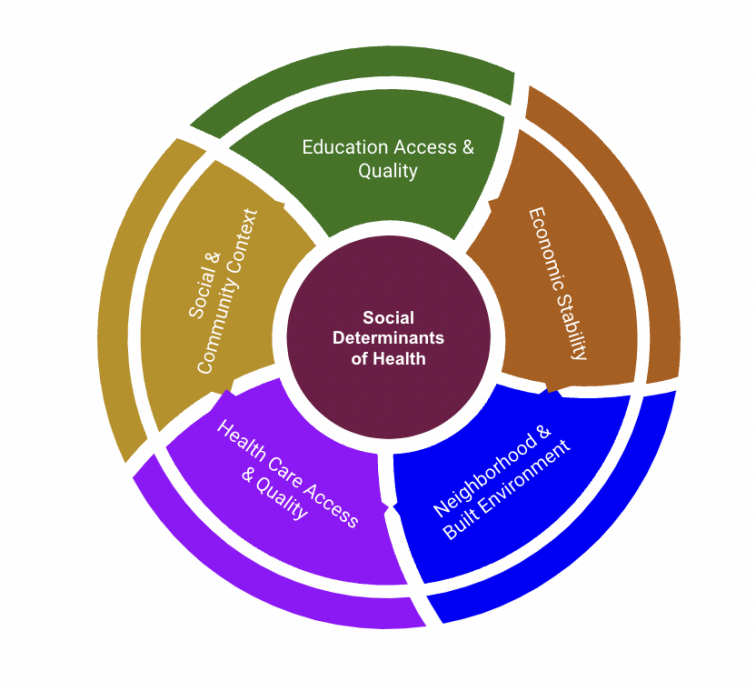
Social Determinants of Health

Considering the impact of the created environment on a population's health and wellbeing, social determinants of health (SDOH) provides a crucial theoretical foundation into investigating ACEs in the current study. Originally a response to the growing body of public health knowledge that framed "developing" nations from "developed" ones, social determinants of health, in its basic definition, states that "people who are less well off have substantially shorter life expectancies and more illnesses than the rich" (Wilkinson & Marmot, 2003, p. 7). The body of literature that has substantiated this claim is massive and part of multiple large scale public health priorities both nationally and internationally (CSDH, 2008; Healthy People 2030, n.d.).

The current model of social determinants of health is defined by the US Department of Health and Human Services as "the conditions in the environments where people are born, live, learn, work, play, worship, and age that affect a wide range of health, functioning, and quality-of-life outcomes and risks" (Healthy People 2030, n.d.). The categories emphasized by the theory can be separated into five major domains: economic stability, education access and quality, health care access and quality, neighborhood and built environment and finally social and community context, per Figure 4.

Figure 4.

The Five Major Domains of Social Determinants of Health

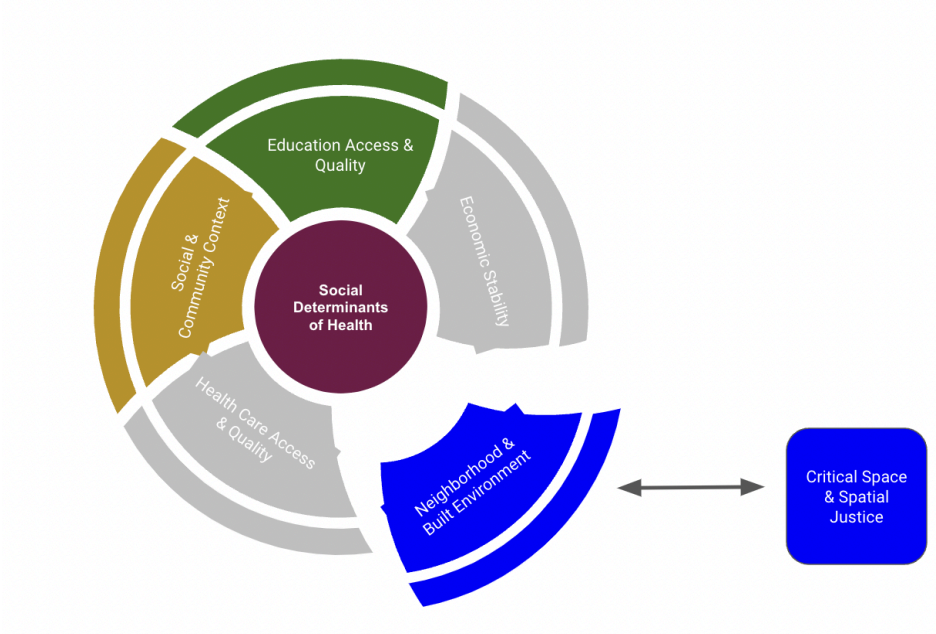


Note. Adapted resource from Healthy People 2030, n.d.

Although each of these domains are important for understanding the whole picture regarding how health and quality-of-life outcomes are affected in an individual and community, the current study aims to focus specifically on the domains of "social and community context," "neighborhood and built environment" and "education access and quality" (Figure 5).

Figure 5.

Three Specific Domains of SDOH Being Investigated, With Ties to Theory



Note. Adapted resource from Healthy People 2030, n.d., additional reference to Spatial Justice (Soja, 2013)

Honing In On Specific Domains Pertaining to Current Study

Social & Community Context. One particular domain of SDOH that is a focal point of the current study is *social and community context*. The conceptual basis of this domain focuses on how elements out of people's control, such as the safety of their neighborhoods, experiencing discrimination, or the incarceration of a caregiver, can have a negative impact on an individual's health and safety. It is the accumulation of these "elements out of one's control" that people experience which ties in the concept of adverse childhood experiences.

The current study aims to understand how the accumulation of adverse childhood experiences, as a product of the social and community context, plays a role in how the environment influences health and quality-of-life for communities at the county level.

Education Access and Quality. For the current study, the SDOH domain of *education access and quality* is another critical component of investigation. ACEs such as discrimination or the potential negative cognitive impacts of stress on brain development, can hinder students' ability to persevere through school and graduate from high school and college (Healthy People 2030, n.d.). As the research evidence and models grounded in SDOH reveals, individuals with higher levels of education are more likely to experience healthier and longer lives (Healthy People 2030, n.d.).

The current study therefore aims to investigate ACEs and the domain of *education access and quality* to determine the association between ACEs and educational attainment, and what implications can be drawn regarding the broader impact to community health and quality-of-life concerns.

Neighborhood and Built Environment. The third and final domain from the SDOH model that will be investigated is the *neighborhood and built environment*. This particular domain is special, as it will be the outstretched hand that ties together SDOH and the theory of "spatial justice" (Soja, 2013), as illustrated in Figure 5. Healthy People 2030 emphasizes that where someone physically lives, and their neighborhood rates of violence, for example, can have serious impacts to a person's and community's health and safety. An extensive body of research also emphasizes that racial and ethnic

minorities are at a higher probability of living in communities facing these concerns of health and safety (Esses, 2021; DeVylder et al., 2020; Phelan & Link, 2015).

The current study therefore aims to investigate *neighborhood and built environment* not just through potential exploration in the operationalization of variables pertaining to ACEs, but also space itself as a geographic variable included in the investigation. In order to add depth to the concept of built environment and its pertinence to the study, the theoretical combination of critical space and spatial justice is reviewed.

Critical Space and Spatial Justice

Soja's theoretical concept of spatial justice (Soja, 2013) creates a pathway of investigation into the relationship of ACEs concentration and distribution by space within the state of California, understanding that policy decisions and education are intimately tied to the types of judiciary delineations and their structures present (California State Association of Counties, 2024). The influence that local jurisdictions have, such as counties in California, can directly impact the policies, administrative processes, funding and services available to students within that geographic space (Percival, Johnson, & Neiman, 2009). Therefore, investigating the geographic distribution of ACEs concentration in relation to the educational outcomes of high school students within the space of a county will further operationalize the tenets of Soja's theory of space and the importance of analyzing geographies critically.

Soja explains how the "exogenous geographies," or the range of "generated geographies" that pertain to power divisions on the scale from the local to global, define and provide the context of injustice within a geographic space. From the gerrymandering

of electoral districts, to South African Apartheid, spaces and policies are contorted and manipulated according to varying bodies of power that exert their authority over defined jurisdictions (Boterman et al., 2019; Burke & Schwalbach, 2021; Heard-Garris et al., 2021).

To explain how the outcomes of exogenous geographies are made manifest, Soja also explains the "endogenous geographies" that are the decisions and processes that determine where things are placed within a space. When public goods are met with inefficient or marginalizing processes, the population within that geographic space suffers the consequences of the exogenous geography. The opposite also holds true–that when marginalization is combatted, the exogenous geography therefore plays a role in empowering the population it once affected.

The spatial justice framework aims to shed light on the often sidelined aspect of human experience–spatiality and geography. Aside from the societal and temporal, the geographic element of human experience and knowledge is vital to any investigation. It is also incomplete, as the current study will argue, without the lens of investigating how the processes entailed in endogenous geographies contribute to our exogenous geographic outcomes.

Therefore, building upon Soja's theoretical insight, the current study operationalizes California counties as exogenous geographies–a critical spacial unit of analysis for investigating the distribution of ACEs and their impact on educational outcomes.

Connecting "Geographic Space," Education and ACEs

The investigation of educational inequality within a geographic context has seen fruit in recent years. For example, Garo, Allen-Handy and Lewis (2018) build from critical spatial analysis theories (Goodchild & Janelle, 2004; Soja, 2013) to show how various forms of trauma are impacting marginalized Black suburban and urban communities in their educational endeavors in Charlotte, North Carolina. The study uses geospatial analysis to show how race, poverty and violence are spatially correlated within their geographic location, how aggregation of these variables impact trauma vulnerability for Black children and families, and finally what those implications are for Black male secondary school students. Utilizing geographic information systems (GIS), the study created a Trauma Vulnerability Index (TVI) which depicted the spatial realities of Black children and families compared to their white counterparts in their geographic location of Charlotte neighborhoods.

Regarding their justification for inquiry, the study explains how neighborhood exposure to various forms of violence and poverty disproportionately impacts Black communities (Federal Interagency Forum on Child and Family Statistics (FIFCFS) 2013; Vorasi & Garbarino, 2000) and impacts a child's development, externalizing behaviors and the negative implications of trauma exposure such as increased fear, terror and despair (Buffington, Dierkhising & Marsh, 2010). Understanding trauma exposure in places where communities are situated can assist in understanding how trauma permeates to other elements of the environment, such as the communities' systems of education. The impacts of trauma on post-traumatic stress disorder (PTSD), anxiety, depression,

aggression, dissociative behavior and poor physical health (Flannery, Wester & Singer, 2004; Rasmussen, Aber & Bhana, 2004; Thompson & Massat, 2005) can be great barriers to a community's success in education, especially when those needs for services and support are not met.

Utilizing geospatial analysis has shown to be an important method in understanding how to contextualize inequity. One such study conducted in Australia analyzed the differences in fifth grade student outcomes in standardized testing while incorporating geospatial variables of urban versus rural communities, as well as differences in socioeconomic status (Smith, Parr & Muhidin, 2019). The findings pointed to more rural areas having less school access and quality of education outcomes compared to their suburban counterparts, with clustering of educational advantages per a region's wealth. By understanding the ways in which inequity in education varies across space and populations, this study provides crucial insight for educators and policy makers on how to proceed with specific interventions across the county.

The crucial insight that is gained from geospatial analysis also underscores the importance of understanding social contexts and the communities within a given space. Boterman, Musterd, Pacchi and Ranci (2019) focused on school segregation on a national and local level and how it can influence the social context of educational outcomes. The study incorporated multiple analyses on the spread of segregation throughout the country and across varying population densities, with a specific eye on urban areas, ultimately tying in the important relationship between issues of segregation and policy on student outcomes. The findings of the study emphasized how the literature on US cities continued

to point towards highly segregated schools in the urban center, where resources were skewed towards more affluent neighborhoods and schools which serviced more white students. It is this conclusion, that space, allocation policies and education are intimately connected in student outcomes, that aids in the direction of the current study's conceptualization of the issue of ACEs.

Population density and education are crucial elements in the current study's understanding of how to best connect public health, space and education together in the context of California. Rumberger's (2007) research highlighted important variables ripe for investigating education inequality in California. To begin, the article emphasizes the importance of California as a microcosm of the concerns regarding perpetual racial and ethnic inequality of academic achievement in the US, given that the majority of California's public education students are students of color (California Department of Education, 2024). To address these concerns, which impact the majority of public education students in the state, it is important to understand what types of "inputs" (factors impacting academic achievement) are affecting the "outputs" of academic achievement. It is from this article that the education outcomes of high school graduation is operationalized as a critical variable for investigating education inequity in California, as Rumberger emphasizes its importance in determining the future for California's students as adults.

In respect to high school graduation's inverse, studies have shown that suspension and expulsion can dramatically hinder a students overall academic success and future opportunity (Mendez, Knoff & Ferron, 2002). Some studies document how suspensions

are influential to a student reaching their “tipping point” of eventual expulsion (Smith et al., 2021), and how student suspensions are correlated with student drop out (Lee et al., 2011). The influence on student drop out, and the possible removal from school, also corroborates with the work by Rumberger (2007) regarding crucial variables of academic achievement to investigate when trying to understand the differences in achievement for California’s students.

When investigating data from the National Longitudinal Survey of Youth on two cohorts from 1979 and 1997, Jordan, Kostandini and Mykerezi (2012) were able to produce results that showed similar rates of high school graduation and drop outs when controlling for various demographic and environmental variables. Aside from the fact that recent research has shown that residential segregation (Gibbons et al., 2020), including California (Kucsera, Siegel-Hawley, & Orfield, 2015), continues to exist and influence health (Phelan & Link, 2015), Jordan et al’s (2012) results also pointed to important differences across historically marginalized communities of color in regards to graduation rates when they considered where a respondent lived. Although the rural, suburban and urban differences were not as significant in their analysis when controlling for environmental variables, Black and Hispanic students' results indicated they experienced more “problematic schools” and “disadvantaged areas” (p. 5). Here the work of Jordan et al points to the importance of still analyzing academic achievement across the spatial distinctions, especially when considering the built environments where students attend school.

To contextualize the current study's understanding of exogenous geographies (Soja, 2013), the categories of rural, suburban and urban play a role when reviewing ACEs, space and education in California. Understanding the operationalization of more rural versus more urban spaces (colloquially deemed the "rural problem") has seen dramatically different interpretations over the last 100 years in the US (Biddle & Azano, 2016), and continues to perpetuate somewhat problematic racial differences still to this day (Tieken, 2017). Current research has shown crucial differences between these categorizations of space in ACEs exposure (Crouch et al., 2020) and academic achievement (Rumberger, 2007). It is for this reason that the current study finds it fruitful to contextualize the regional differences in respect to ACEs, space and education across California's large and diverse state of 58 counties through the understanding of which counties are deemed rural, suburban and urban.

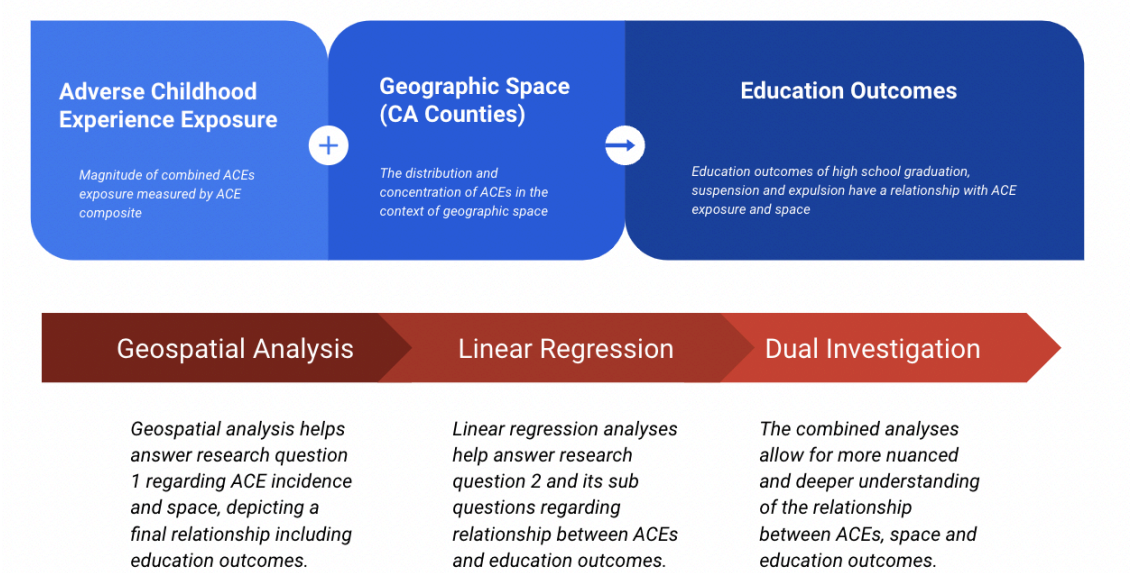
It is through this review of pertinent literature in the field guided by the theoretical lenses of SDOH and spatial justice theory, along with the exemplar studies analyzing geographic space in the context of understanding social phenomena, that the current study utilizes the following conceptual framework.

Conceptual Framework of the Current Study

In order to investigate three crucial domains of SDOH including 1) social and community context, 2) education access and quality, and finally 3) neighborhood and built environment in relation to critical space, the following framework serves as the conceptual basis for this study and provides guidance into the research plan (Figure 6).

Figure 6.

Conceptual Framework



The blue elements of the figure in the upper portion of the framework outlines the investigatory relationship of the three primary variables: ACEs, space, and education outcomes. ACEs and space are independent variables that are anticipated to influence the dependent variable of education outcomes. In order to investigate these relationships, the bottom red portion of the framework outlines the analytical approach taken in the study.

In order to understand and answer the first research question pertaining to the incidence of ACEs over the defined geographic space, I used geospatial analyses to best investigate the phenomena. The second research question, along with its sub questions, pertain to how ACEs are related to education outcomes in the sample under investigation. For this question, linear regression analyses fit to determine the magnitude and direction of the relationship, if any. Finally, combining the results of the two analytic methods

provides a nuanced and deeper understanding of how ACEs, space and education interact and what implications can be drawn.

The momentum for the current study builds upon the theoretical lenses and conceptual framework provided, and pivots now into pertinent research in the field of ACEs as it relates to measurement, consequences, causes and potential solutions.

Review of Pertinent Literature in the Field on ACEs

Measuring ACEs

When considering how ACEs have been operationalized and analyzed in research, the seminal work of the Adverse Childhood Experiences (ACE) Study (Felitti, et al., 1998) is highly cited as laying the groundwork for studies to come. Published in 1998, the ACEs Study surveyed clinic patients from San Diego's Kaiser Permanente location starting in the year 1996. The study focused on the sampling from the San Diego location, administering the sub survey with a focus on participant level responses. The total population utilized for the study's analyses was 8,056, with almost 80% being white, a mean age of 56.1 years of age (ranging 19-92), and a hefty skew towards graduation from college at 43%. Logistic regression analyses were conducted to examine the relationship between ACEs and health risk outcomes.

ACEs were initially defined by survey responses to seven categories: psychological abuse, physical abuse, contact sexual abuse, exposure to substance abuse, mental illness, violent treatment of mother or stepmother, and criminal behavior in the household. In terms of consequences, health risk outcomes included: smoking, severe obesity, physical inactivity, depressed mood, suicide attempts, alcoholism, any drug

abuse, parental drug abuse, a high lifetime number of sexual partners (50+), and a history of having sexually transmitted disease. The results of this original study suggested a "graded" relationship between exposure to multiple ACEs and the magnitude of risk for negative health outcomes. Individuals with higher cumulative[2] ACEs exposure were "4- to 12-fold increased health risks for alcoholism, drug abuse, depression, and suicide attempt; a 2- to 4-fold increase in smoking, poor self-rated health, ≥50 sexual intercourse partners, and sexually transmitted disease; and a 1.4- to 1.6-fold increase in physical inactivity and severe obesity." (p. 245). This groundbreaking ACEs study shaped the current framework of understanding how trauma at a young age can impact future health and wellbeing. While the demographics of study participants were not representative of communities of color that are disproportionately impacted by ACEs (Healthy People 2030, n.d.), it did highlight the prevalence and repercussions to future health that trauma has in our society.

Changes in Operationalization

Building on Felitti and colleagues' research, others have shifted focus to investigate the relationship of race and ethnicity to ACEs.

Maguire-Jack and colleagues (2020) provided critical insight into the differences experienced between race and ethnic groups regarding ACEs. The study utilized data from the National Survey of Children's Health (NSCH) from 2016 to determine if significant differences in the incidence and consequences of ACEs were present across racial/ethnic groups. Their study sample included 43,711 children ages 0-17 categorized

[2] Cumulative ACE exposure, as utilized in the current study, refers to the exposure of multiple categories of ACEs. This is pertinent as it relates to the current study's ACE composite variable, described later, as a combination of the eight ACE categories analyzed.

as either Latinx, non-Latinx White, or non-Latinx Black. Results of the study revealed differences of experiencing ACEs across racial and ethnic groups (and total ACE exposure); with a significant higher probability of exposure to mental illness and parental drug and alcohol use in non-Latinx White children, and a significant higher probability of exposure to discrimination for Latinx and non-Latinx Black children. Youth of color were disproportionately more likely to have multiple ACEs (Centers for Disease Control and Prevention, 2019; Maguire-Jack, Lanier & Lombardi, 2020) compared to their White counterparts, with Black children at age one having had comparable ACEs exposure to White children at age ten (45% compared to 43%, respectively).

The study concluded that in previous studies of at-risk youth populations (Fagan & Novak, 2018; Garcia et al., 2017), non-Latinx White students experienced higher exposures to multiple ACEs, compared to other racial and ethnic groupings. Yet, the study revealed that those comparisons differed when considering a nationally representative sample that isn't distinguished as "at-risk." The results show that non-Latinx White children are at a lower probability of experiencing ACEs, let alone multiple ACEs when compared to their Latinx and non-Latinx Black counterparts. Some similarities drawn between all groups studied is that household and childhood poverty are experienced across the board for those who experienced ACEs. The correlation has been well documented (Osmick & Wilson, 2020; Wigger, 2011; Wilkinson & Marmot, 2003), and even more so for single-parent households. Policies that attack poverty and assist with single-parenting can effectively assist all youth experiencing ACEs, but it is

absolutely critical to build systemic solutions that are addressing racial and ethnic inequalities to ACE exposure which can lead to health and behavior risks that perpetuate racial and ethnic inequality for future generations.

Maguire-Jack's research expanded on and criticized the lack of critical analysis for ACEs and communities of color in Felitti et al. (1998). Focusing on a more representative sample that incorporated the diverse experiences of communities of color, Maguire-Jack et al (2020) expanded on the ACEs categories to include traumatic experiences of neighborhood violence and racial/ethnic discrimination to secure a more holistic look at trauma for youth in the US. This work moved the needle forward in creating the clearest picture of the impact of ACEs on young people and their future health and wellbeing, while providing a call to action: "...although there are evidence-based treatments that have been shown to be effective in reducing substance use problems (Substance Abuse and Mental Health Services Administration, n.d.), reducing rates of exposure to discrimination, neighborhood violence, and parental incarceration requires a more significant cultural and policy shift" (Maguire-Jack et al, 2019, p. 7).

Both of these highlighted works on ACEs measurement focused on participant level data and analysis. Conclusions and insights were drawn in respect to understanding the phenomena of ACEs, guiding the field for decades. Yet, the two studies of Feletti et al (1998) and Maguire-Jack (2020) missed the opportunity to provide guidance on how to understand and measure ACEs across geographic spaces at a larger vantage point–a key component to which the current study aims to contribute to the discussion.

Consequences of ACEs

Exposure to adverse childhood experiences can have lasting impacts on almost all elements of an individual's life (CDC, 2021). Whenever protective factors are not present in combating the negative effects of ACEs, they can impact life outcomes such as one's physical and mental health, increased exposure to risky behaviors, exposure to infectious and or chronic diseases and one's opportunities for education, occupation and income. These impacts on a person's life due to ACE exposure can have serious long term effects. For example, intergenerational exposure to risk factors such as caregiver substance abuse can have a cyclical effect that perpetuates the higher probability of ACE exposure in children and later generations (Anda et al., 2002). Adults who reported having ACEs had higher risks of alcoholism and depression, which in turn, is a risk factor for ACEs in their children.

Alongside the importance of health and mortality concerns regarding the consequences to ACEs, the current study is also interested in its impact on educational outcomes. ACEs and its biological byproduct of "toxic stress" (excessive exposure to high or prolonged levels of stress hormones) can have lasting impacts on the brain and behavioral adaptation, leading to potential hindrances in development and learning (Franke, 2014). These biological and behavioral imprints of ACEs on an individual can have severe implications for academic success and education outcomes, especially in education systems that are not built to support the wide-ranging needs accompanying exposure to ACEs (Agnafors, Barmark & Sydsjö, 2021). As the consequences of ACEs

on individuals and communities have become apparent through research over the years, the field has also identified important causes and protective factors as well.

Causes of ACEs

There are many researched "risk factors" that can increase the probability of a child experiencing an adverse childhood experience (CDC, 2024). Some of those risk factors include individual factors such as caregivers with substance abuse disorders, mental health disorders, high levels of economic stress and less education. Some family risk factors include experiences of incarceration and social isolation (CDC, 2019; Maguire-Jack et al, 2020; Wilkinson & Marmot, 2003). Finally, some risk factors as measured within the space of a community are higher rates of neighborhood violence, limited educational and economic opportunities and frequent experiences of food insecurity (CDC 2019; CDC 2024). What is equally important in understanding the "causes" of ACEs, or variables that increase probability of exposure, are buffers that are also part of counteracting the risk factors.

Protective factors that are also listed by the Center for Disease Control based off their authoritative guides (CDC, 2024) include individual, family, and community protective factors.

The individual protective factors include caregivers who create safe and positive relationships with their children, can meet basic needs of food, shelter, education, and health care, and those that have a college degree or higher. Family protective factors are manifested in families that have strong social support networks and those having outside of the family caring adults as role models or mentors. Finally, neighborhood and

community protective factors include access to stable housing, high-quality preschool, safe childcare and access to education programs, as well as access to health care and financial support (Benzies & Mychasiuk, 2009).

Reviewing the individual, family, and community risk and protective factors, it is critical to keep in mind that the current study addresses a baseline need of understanding the scope and magnitude of ACEs in the context of geographic space in California counties. This research is also designed to advance understanding of ACEs in relation to education, which can be a protective factor against the probability of experiencing ACEs. It is here that this review turns to outlining some of the solutions to the larger baseline picture of scope and magnitude that have been developing over the last few years across the nation and in California.

Solutions to ACEs

One of the first surveys in the US to address the need for expanded ACEs investigation came from the Philadelphia Expanded ACEs Survey (Cronholm et al., 2015). Additional items included areas such as neighborhood violence, racism and involvement in foster care. The efforts in Philadelphia cascaded into expanding the knowledge, awareness and usage of the expanded categorizations in various networks and into the eventual involvement in the MARC initiative (Philadelphia ACEs Project, 2023). The work done in Philadelphia, and the eventual investigation by Maguire-Jack et al. (2020) regarding the expanded categorizations, investigating racial inequity in exposure, clustering and sampling, provides an important framework of how to investigate ACEs in California.

California's Efforts on Collaborative ACEs Solutions

California has begun to make strides on how they communicate resources regarding ACEs through the PACEs Connection network (PACEs Connection, 2023). This online community focuses on network development and communication of various resources to those attempting to address the issues of ACEs in their localities. Both of California's ACEs initiatives highlighted in the MARC Initiative (Westat, 2019), in San Diego and Sonoma County, utilize this resource to share out their progress and communicate to the broader ACEs prevention networks. Although moving forward in communicating resources amongst the network of health professionals, California does not have the years of coordinated, expanded ACEs surveying data nor integrated policies that are specifically addressing the concerns of ACEs across its rural, suburban and urban spaces as they pertain to education.

Summary

The literature review above is designed to illuminate the logic that undergirds this investigation. First, SDOH (Wilkinson & Marmot, 2003), Spatial Justice and Critical Space (Soja, 2013) provide the theoretical lenses that frame the investigation of how ACEs are connected to education and space. Second, the measure of ACEs has changed since the late 1990's and movements have pushed to incorporate expanded categories that include the importance of ACEs disproportionately impacted by communities of color–encapsulating a clearer picture of the impacts of ACEs in the US and California, yet still relying methodologically on participant level response data. Third, ACEs are widespread and are associated with poor health and school performances (CDC, 2023;

CDC, 2019). Research on protective factors have shown to mitigate some of the effects of ACEs, and coordinated efforts piloted by state initiatives (such as Pennsylvania) have shown to harness policy and practice actions to boost those protective factors since the mid 2010's. High school dropout and barriers to academic achievement greatly hinder a students future health and success (Rumberger, 2007), which have shown to have differentiated outcomes across communities depending on their neighborhoods locations, be it more rural or more urban (Jordan, Kostandini & Mykerezi, 2012). It is the hope that research such as the current study, and the research design and chapters to come, can illuminate the strategies, methods and limitations to analyzing this complex health phenomena of ACEs on a larger scale as it pertains to space and academic achievement. The next chapter outlines the research methodologies utilized to tackle the current investigation.

Chapter 3: Research Design

The current study utilizes data from all 58 counties in California to build upon previous literature on ACEs, space and education. California serves as a case study of how to elevate the research and practice of understanding the impacts of ACEs on education across jurisdictions that are home to predominantly students of color (California Department of Education, 2024). Chapter three outlines the research design for this study by starting with a description of the sample and data sources. To check the quality of the county-level data included in this study, data for each of eight ACE categories is described and a visualization of the eight categories is presented separately in the form of a chloropleth projection map. These eight categories were then used to create a single ACE composite. After describing the process to create the ACE composite, this chapter concludes with a rationale for the county-level linear regression models used to investigate associations between the ACE composite and each of three educational outcome variables.

Sample

The state of California is divided into 58 counties (Figure 7). Counties are spatially outlined boundaries that separate geographic areas within the state and play two crucial roles: first is to organize and provide municipal services like roads, emergency services, and libraries, and the second is for delivering state services such as foster care, public health care and elections (California State Association of Counties, 2024). Each county also has a County Office of Education (COE) which assists in numerous aspects, both fiscally and administratively, to ensure the quality of education within the districts of

each county and the students they serve (Merced Office of Education, 2024). The fiscal and administrative importance of powers vested in counties, especially as it pertains to public education, are therefore important spatial elements of the county level unit of analysis and the focus in the current study.

Figure 7.

Map of California's Counties, 2018

The sample for this study includes data from all 58 California counties (Table 1). Data from the US Census Bureau for 2018 for the 58 counties was utilized to be commensurable to the majority of data sources which were collected for the same calendar year. California's 58 counties have been divided into three helpful categorizations from California's State Association of Counties (2024), ranging from rural, to suburban and urban. The descriptive statistics reveal that California's population

density ranges significantly, showing great diversity between urban, suburban and rural counties. For example, in regards to demographic diversity, the average non-white population across the state's 58 counties is nearly 50%, with highs in Imperial County at 89% and lows in Sierra County at 12%. This type of diversity in the overall population representation on average across the state emphasizes the importance of California as a case study for understanding how to address ACEs as a public health concern, given, again, the concerns of higher cumulative ACE exposure probability in communities of color (Maguire-Jack et al., 2020).

Table 1.
Select Descriptive Statistics of County Sample (n = 58)

	2018
Total Population Range	(1,146-10,098,052)
Total Population Mean	674,979.00
Total Non-White Population Mean	45.74%
Highest Percent Non-White Population	Imperial County (89.03%)
Lowest Percent Non-White Population	Sierra County (12.39%)

Note. Sourced from US Census Bureau. (2023).

Data Sources

Data for this study were collected from several sources. This section describes how the ACE composite and three education outcomes were operationalized from these different data sources. I first describe each of the eight categories that were used to create the ACE composite. In this description, I clarify the data source each category was

retrieved from, pertinent information regarding the category itself and, if relevant, differentiation between the current operationalization of the category and those of the seminal studies reviewed in Chapter 2. I then describe how the ACE composite was created from these eight categories, through the process of chloropleth mapping. The mapping process is discussed further in regards to the shapefiles utilized for the projection, and the type of analysis being conducted.

Adverse Childhood Experience Categories

Two seminal ACE's studies (Felitti et al., 1998; Maguire-Jack et. al., 2020) operationalized their variables based on survey responses from individuals, ranging from the original seven constructs to the expanded nine constructs (Table 2). As described in Chapter 2, the conceptualization of ACEs from Macquire-Jack and colleagues (2020) is the most current regarding operationalizing neighborhood violence and discrimination. While the current study aimed to gather as much representational data related to all of the constructs, two specific decisions had to be made. First, the constructs of parental death and extreme economic hardship were not included in the study in order to focus on the primary concepts from Feletti's 1998 constructs and the expanded social justice informed categories (neighborhood violence and discrimination). Data regarding "substance abuse" and "mental illness" were not available. These two ACE constructs are important to the discourse (Anda, Whitfield, Felitti, Chapman, Edwards, Dube & Williamson, 2002) but unfortunately could not be incorporated into this study. The current study defines adverse childhood experiences through the operationalizations of eight categories.

Table 2.
Comparison of ACE Categories Across Studies to Current Study

General ACE Category	Feletti et al. (1998)	Maguire-Jack (2020)	Negrea (2024)
Physical Abuse	X		X
Emotional Abuse	X		X
Sexual Abuse	X		X
Incarceration	X	X	X
Domestic Violence	X	X	X
Marital Disruption		X	X
Neighborhood Violence		X	X
Discrimination		X	X
Exposure to Substance Abuse	X	X	
Extreme Economic Hardship		X	
Mental Illness	X	X	
Parent/Guardian Death		X	

The eight ACE categories included in this study represent county-level data as compared to individual level data. The county-level data represents all counties in the state of California, thus capturing the entire population of the state and moving beyond the measuring of ACEs in terms of individual responses. In addition, this county-level data allows for considering ACEs in terms of the created geographies (Soja, 2013) which could lead towards policy decisions that are beyond what happens locally for a particular student in a particular classroom; but decisions that could impact all students in a particular county or particular geographic region (Brewer & Smith, 2008). Thus, the operationalization of ACEs in terms of counties and not individuals is a unique contribution of the current study that builds upon the discourse and conceptualization of ACEs as a regional and statewide public health concern.

Physical Abuse. The Center for Disease Control and Prevention (CDC) defines physical abuse as "the intentional use of physical force against a child that results in, or has the potential to result in, physical injury" (Leeb, Paulozzi, Melanson, Simon & Arias, 2008, p.14). Examples include "hitting, punching, beating, stabbing, biting, pushing, shoving, throwing, pulling, dragging, dropping, shaking, strangling/choking, smothering, burning, scalding and poisoning." For this study, data from the California Child Welfare Indicators Project (CCWIP; Webster et al., 2023) was cleaned and separated by category of maltreatment by Population Reference Bureau's (PRB) kidsdata.org sub branch (Population Reference Bureau, 2023). The California Child Welfare Indicators Project is the primary source in which the PRB's kidsdata.org gathers their data, which is a partnership between University of California, Berkeley and California's Department of Social Services. The project provides crucial outcomes data for public entities and researchers to utilize.

Under the PRB kidsdata.org data report for "Substantiated Cases of Child Abuse and Neglect by Type of Maltreatment," the specific category of maltreatment utilized for physical abuse was "physical abuse." An important footnote provided by the data source is that maltreatment is an unduplicated count per child within county and in the state, yet is uniquely counted in different counties if the child experiences maltreatment while moving between counties in the same time span. What this means is that if a child moved from one county to another county within the same state, the child would be counted more than once. This does not allow for inferences about child-level incidences across the entire state; but does allow for inferences about the counts of incidences within each

county. This does not allow for comparisons for any given county relative to the state incidences; but does allow for county-to-county incidences, a central feature of this study.

To measure physical abuse, Felitti and colleagues (1998) utilized two survey items that focused on retrospective self reports of adults and if, when growing up, a parent or adult in the household did "push, grab, shove, or slap" the respondent and whether it was hard enough to "leave a mark" or had them "injured." The sample size from the study was 8,056 from San Diego's Kaiser Permanente Health Appraisal Clinic. Respondents were recruited after receiving a standardized medical evaluation, with the ACE supplemental survey mailed to them a week later. Their survey response rate was 70.5%.

The data included in this study differs from the Felitti et al. 1998 data by including county level reports from the California Department of Social Services, not a convenience sample of self-reported survey responses. Research has indicated that survey respondent data that attempts to collect sensitive data, such as abuse (Barr et al., 2017) and other forms of maltreatment (Mathews et al., 2020), can lead to crucial underreporting of these occurrences in survey data (Kepple, Freisthler & Johnson-Motoyama, 2014). Focusing on more standardized forms of data collection that reflects the entire sample can push the conversation closer to understanding the magnitude of adverse childhood experiences when compared to individual level data reporting. This is why the county-level-distinction holds for all subsequently operationalized ACE categories below.

Emotional Abuse. The CDC defines emotional abuse (or psychological abuse) as "intentional caregiver behavior that conveys to a child that he/she is worthless, flawed, unloved, unwanted, endangered, or valued only in meeting another's needs" (Leeb et al., 2008, p.16). It is described further as being either continual or episodic, including behaviors such as blaming, belittling, degrading, intimidating, terrorizing, isolating, confining, and behaviors that can be harmful or damaging to a child and their developmental needs. For this study, the PRB's (2023) kidsdata.org sub branch's data was utilized. Under the report for "Substantiated Cases of Child Abuse and Neglect by Type of Maltreatment," the specific category of maltreatment utilized for emotional abuse was "emotional abuse."

By comparison, the Felitti et al. (1998) study utilized survey items that were focused on "psychological" abuse, with a respondent reporting if they experienced a parent or adult in the household often or very often "swear at, insult, or put you down" and who's actions made them "afraid" they'd be "physical hurt." The current study's operationalization differs here, similar to the other categories of abuse, in that they are substantiated reports rather than relying on the survey respondent's recollection.

Sexual Abuse. The CDC defines sexual abuse as involving "any completed or attempted sexual act, sexual contact with, or exploitation (i.e., noncontact sexual interaction) of a child by a caregiver" (Leeb et al., 2008, p.14). This includes examples such as the pressure or forcing the child to engage in sexual acts (such as fondling, penetration, and exposure). Similarly to the two other measures of abuse, the PRB's (2023) kidsdata.org sub branch's data was utilized. Under the report for "Substantiated

Cases of Child Abuse and Neglect by Type of Maltreatment," the specific category of maltreatment utilized for sexual abuse was "sexual abuse."

Felitti et al. (1998) operationalized "sexual abuse" where if an adult or anyone over 5 years of age in the household "touch or fondle you in a sexual way," "have you touch their body in a sexual way," "attempt oral, anal, or vaginal intercourse with you" and or "actually have oral, anal, or vaginal intercourse with you." As the final operationalization of abuse, the current study again relies on the substantiated claims instead of survey respondent reports.

Incarceration. The Prison Policy Initiative (PPI) defines the incarceration variable rate used in the study as "the number of imprisoned people divided by the total population and then multiplied by 100,000. It allows ready comparison of the frequency of imprisonment between each county of different population sizes" (Prison Policy Initiative, 2023). Felitti et al (1998) operationalized their category of "household dysfunction" sub category "criminal behavior in household" as a response to the item if any "household member" has gone to prison. The Maguire-Jack (2020) operationalization: a "parent served time in jail," narrowing the participants' responses to just their defined parents. The current study recognized that incarceration data is complex, acknowledging that a person is not always held in an institution from where they were living.

Data from the Prison Policy Initiative (2023) reflects the validation of multiple data sources from California state matched to census Federal Information Processing

Series (FIPS) Codes in the 2020 census[3]. The specific data used for operationalizing incarceration for this study was "Imprisonment Rate Per 100,000." This operationalization attempts to capture the county-level implications of imprisoning their local populations, which differs from the two seminal studies' individual reporting of a familiar unit experiencing incarceration.

Domestic Violence. The current study utilized the data source OpenJustice from the California Office of the Attorney General (California Department of Justice, 2023) to operationalize Domestic Violence as the rate per 1,000 adults by county for domestic violence-related calls for assistance. OpenJustice is described as "a transparency initiative led by the California Department of Justice that publishes criminal justice data so we can understand how we are doing, hold ourselves accountable, and improve public policy to make California safer." California Penal Code 13700 defines domestic violence as "abuse committed against an adult or a minor who is a spouse, former spouse, cohabitant, former cohabitant, or person with whom the suspect has had a child or is having or has had a dating or engagement relationship" (California Legislative Information, 2023). OpenJustice as a data source corroborates with the legal definition from CA Penal Code 13700 by including "different types of domestic relationships" that are subject to "varying interpretations by law enforcement agencies," which aids in the current studies comparison across counties (Bonta, 2023).

Comparatively, Felitti et al. (1998) study defined domestic violence as a "household dysfunction" that was sub categorized as "Mother treated violently." The

[3] Although the PPI data's year of report does not match that of some other ACEs data sources, its robust combination of California incarceration information and parsimony aids in the overall utility of the current study's research.

study operationalized domestic violence narrowly to include only if a mother or stepmother had been "pushed, grabbed, slapped, or had something thrown at her," "kicked, bitten, hit with a fist, or hit with something hard" "repeatedly hit over at least a few minutes" and or "threatened with, or hurt by, a knife or gun." The current study's operationalization, as described, expands domestic violence to not be only narrowly defined as "mother" but either of the defined partners in the marriage.

Divorce or Marital Disruption. The current study utilized the US Census Bureau's (2023) Table B12006: marital status by sex by labor force participation. In order to have the most inclusive definition, the responses for "separated," "widowed" and "divorced" were combined. The operationalization of the category is similar to two items present in Maguire-Jack (2020) that account for "parent died" and "parent divorced/separated."

This expanded definition from the Maguire-Jack (2020) operationalization of "parent divorced/separated" allows for more inclusivity to varying types of "marital disruption" that can cause varying types of disruption within a household. Therefore, this study built off of Maguire-Jack's work and then calculated the percentage by dividing the combined categories by the total population ever married over 16 years of age.

Neighborhood Violence. The current study utilized the Federal Bureau of Investigation's (FBI) "Uniform Crime Reporting System" (UCR) (Federal Bureau of Investigation, 2023) that provides the reported offenses for violent crimes from the sheriff's office or county police department by California county. The rate per 1,000 residents was calculated by taking the total violent crimes reported in a county in 2018,

dividing it by the county population, and multiplying by 1,000. The CDC defines neighborhood violence, or community violence, as when "violence happens between unrelated individuals, who may or may not know each other, generally outside the home. Examples include assaults or fights among groups and shootings in public places, such as schools and on the streets" (CDC, 2024).

Maguire-Jack (2020) operationalized this ACE variable as "victim/witness of neighborhood violence." Here, the current study's operationalization includes various forms of reported violence within a community, including a broader swath of the county population in the category.

Racial Discrimination. The current study utilizes the Department of Justice's Open Justice database table 6 titled "Events, Offenses, Victims, and Suspects by County and Jurisdiction" from 2018 (Becerra, 2018). Here, the specific subcategory of "victim" of a "hate crime" on a county's population level was utilized to operationalize racial discrimination.[4] The sources operationalization of "victim" includes entities outside of a human being, including businesses, religious organizations, etc. It is due to this operationalization that a rate could not be calculated, and that counts were retained.

This contrasts to operationalizing "discrimination" as "the child was treated or judged unfairly due to race or ethnic group" (Maguire-Jack, 2020, p. 3). What this operationalization aims to do is include various forms of discrimination in order to contextualize the built environment inside the geographic space of a county. This aim is

[4] Note, this data does include "anti-white" as a form of racial discrimination, which would not be included under the umbrella of racism. The researcher still deemed it proper for use given that the overall sub category accounts for 5% or less of all reports for hate crimes.

consistent with the unit of analysis (counties), which differs from that of the individual level within Maguire-Jack's survey respondent data.

Education Outcome Variables

Based off of the work referenced earlier on the importance of understanding the education outcomes of high school graduation and the drivers that interrupt that pursuit (Jordan, Kostandini & Mykerezi, 2012; Rumberger, 2007), the following education outcome variables were utilized in the investigation of the current study.

High School Graduation. High school graduation rates were obtained from the California Department of Education's DataQuest database. The specific data used was from the "Four-Year Adjusted Cohort Graduation Rate," representing the percent of high school graduates in the 2018-19 cohort of 9-12 graders who graduated in that academic year per county (California Department of Education, 2023). The "adjustment" accounts for students who transfer in and out of the cohort group, such as students entering the cohort after ninth grade or who emigrate out of the state. The reason for selecting this particular variable is because it excludes "general equivalency diploma, certificate of completion, certificate of attendance, or any other similar or lesser credential, such as a diploma based on meeting Individualized Education Program (IEP) goals" which are pathways that leave students less academically prepared and likely to successfully complete post-secondary education (Reed, Hurtt, Kurlaender, Luu & Merritt, 2023).

High School Suspension. High school suspension was obtained from the California Department of Education's DataQuest database (California Department of Education, 2023). The specific report used was "Suspension Rate" provided by California

County. This variable represents the total unduplicated count of students suspended in the 2018-2019 academic year of 9-12 graders divided by the cumulative enrollment for 9-12 grade per county. Note, this variable leans conservative, given that students can receive multiple suspensions, which increases the suspension rate. Yet, for the purposes of this study regarding consistency in reporting of education outcomes, no adjustments were made. Although our BIPOC students are more likely to receive multiple suspensions to their white counterparts (Mendez, Knoff & Ferron, 2002), the study moved forward with the operationalization on a more conservative estimate to establish a baseline of the relationship between the variables in question before recommending a more nuanced review of a particular outcome variable.

High School Expulsion. High school expulsion was collected using California Department of Education's DataQuest database (California Department of Education, 2023). The specific report used was "Expulsion Rate" provided by California County. This variable represents the total unduplicated count of students expelled in the 2018-2019 academic year of 9-12 graders divided by the cumulative enrollment for that academic year for grades 9-12.

ACE Category Prevalence and Magnitude In CA Counties

To create the ACEs composite used in the subsequent analyses of the map projections and linear regression, each individual ACE category was first analyzed separately through geospatial analysis across the space of California's counties. This projected mapping process is an analytical process that led to the investigation of RQ1 regarding incidence of ACEs across California's counties, and then subsequently with the

ACE composite variable utilized in RQ2 for the relationship of ACE incidence and education outcomes.

Shapefiles Used to Create Geographic Projections

To support the creation of visual representations of the geographic space, a 2018 TIGER/Line shapefile (the data file that builds out the geographic projection in ArcGIS) was utilized. These data files for the projection come from the US Census Bureau, which contains annual files from 2006 up to the year 2023 (US Census Bureau, 2023). The US Census Bureau's TIGER/Line shapefiles produced their first data file in 1989 (US Census Bureau, 2018), and has continuously updated their data working with federal and state entities to ensure accuracy.

Chloropleth Mapping

Chloropleth mapping is a type of geospatial analysis method that allows for the analysis of complex data and communication of complex issues in a visual and digestible fashion (Kurland & Gorr, 2012). Geospatial analysis involves spatial data and variables to investigate phenomena across various geographies. This method of investigation has been shown to produce useful application across disciplines, including health (Wang, 2020), education (Garo, Allen-Handy & Lewis, 2018), and public policy (Furtado & da Silva, 2021). The software utilized for this analysis is ArcGIS (Kurland & Gorr, 2012), or Arc "Geographic Information Systems."

In order to begin the initial analysis, a TIGER/Line shapefile was utilized for the projection from the US Census Bureau, which contains files up to the year 2023 (US Census Bureau, 2023). Shapefiles are available from 1992, although not for every

calendar year. More recently there have been annual updates, starting from the year 2006. The shapefile provides the structure of a defined geographic space, in the case of this study, the state of California and the 58 county boundaries.

The particular type of geospatial analysis that will be conducted is chloropleth mapping, or more colloquially "heat mapping" (Kurland & Gorr, 2012). This analysis allows for a phenomena to be displayed and analyzed by degree of magnitude across a specified geographic space. There are two primary benefits of such a method: first, this approach allows for a variable's magnitude to be analyzed and displayed for broad audience review; second, it projects the variable's magnitude over a specified geographic area. The chloropleth mapping of the individual ACEs categories will build upon each other in the creation of an ACE composite, which will be utilized to address the second overarching question of the relationship between ACEs and educational outcomes.

Chloropleth Projections for the Eight ACE Categories

The next section describes and reviews the analysis of the eight ACE categories' chloropleth map projections across California's 58 counties. The descriptive statistic for each ACE category is summarized in Table 3.

Table 3.
Summary of Descriptive Statistics for ACEs Categories

Variable	Sample	Min	Max	Mean	Median	Standard Deviation
Emotional Abuse	58	0.000	0.200	0.024	0.010	0.037
Sexual Abuse	58	0.000	0.168	0.0317	0.0320	0.034
Physical Abuse	58	0.000	0.235	0.043	0.043	0.046
Domestic Violence	56	3.100	44.100	7.989	7.100	5.718
Incarceration	58	80.000	666.000	308.793	278.500	133.697
Marital Disruption	58	0.202	0.376	0.282	0.270	0.041
Discrimination	58	0.000	470.000	21.276	4.000	63.161
Violence	57	0.098	10.471	1.799	1.280	1.846

Symbology for all chloropleth analysis projections followed a “heat ramp” scheme, in which the details utilized for each projection in the analysis is summarized in Table 4. Table 4 also organizes the categories by number of class breaks, which is the structure for reviewing the following sub sections. Class breaks, in regards to the standard deviations used for analysis, are assigned to each category by the software based on the range of a variable’s distribution, which is unique and tied to the distribution of each variable being projected. The class breaks are meant to also maintain proportional integrity to have a logical differentiation between each class, which means the value differences in standard deviation are the same between class break 1 and 2 as it would be for class breaks 2 and 3 and so forth (accounting for tail end differences).

Table 4.
Summary of Symbology Schemes for Chloropleth Analyses[5]

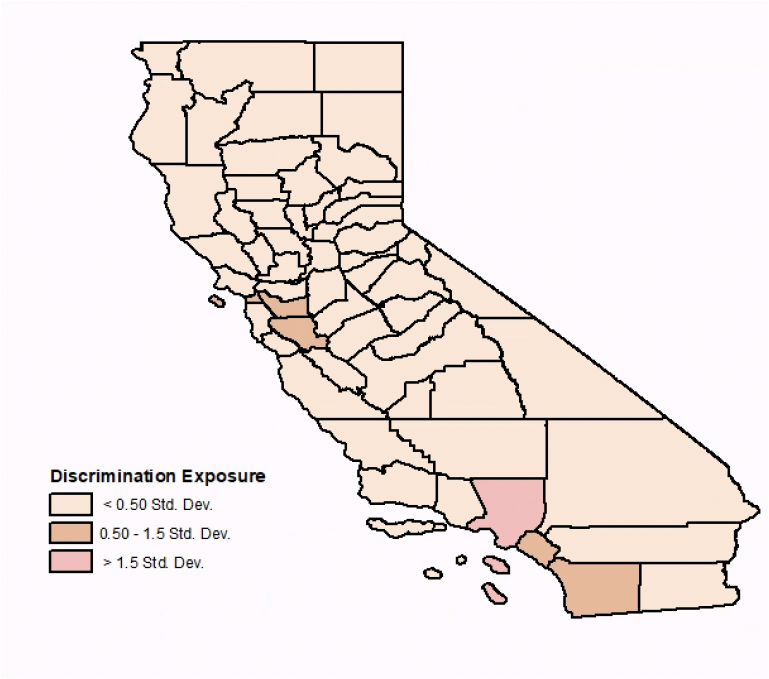
Variable(s)	Class Break 1	Class Break 2	Class Break 3	Class Break 4	Class Break 5	Class Break 6
Discrimination	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	NA	NA	NA
Domestic Violence	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	(RGB) = 255, 127, 127	NA	NA
Emotional Abuse	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	(RGB) = 255, 127, 127	(RGB) = 230, 0, 0	NA
Sexual Abuse	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	(RGB) = 255, 127, 127	(RGB) = 230, 0, 0	NA
Physical Abuse	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	(RGB) = 255, 127, 127	(RGB) = 230, 0, 0	NA
Marital Disruption	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	(RGB) = 255, 127, 127	(RGB) = 230, 0, 0	NA
Violence	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	(RGB) = 255, 127, 127	(RGB) = 230, 0, 0	NA
Incarceration	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	(RGB) = 255, 127, 127	(RGB) = 230, 0, 0	(RGB) = 156, 0, 5
ACE Composite	(HSV) = 31, 16, 100	(HSV) = 23, 35, 94	(RGB) = 255, 190, 190	(RGB) = 255, 127, 127	(RGB) = 230, 0, 0	(RGB) = 156, 0, 5

Projection Analyses With Three Class Breaks. The following projection analyses have three class breaks. All 58 counties in the sample were present for this projection. The chloropleth projection of incarceration when set to class break values of 1 standard deviation resulted in 3 class breaks. With the 3 class breaks, the scoring applied to each county for their ACE composite was therefore 0 at the "lowest exposure" (i.e. lowest standard deviation class) and 2 at the "highest exposure" (i.e. highest standard deviation class).

California Counties Exposure to Discrimination.

Figure 7A.

California Counties Exposure to Discrimination, 2018



The results from the class breaks show an extremely uneven distribution, with the majority of cases in the first and lowest class break. This particular variable, which is mentioned in the limitations, is the only variable that is a "count" variable due to data availability. Given the results, only one county occupied the highest class break which was Los Angeles.

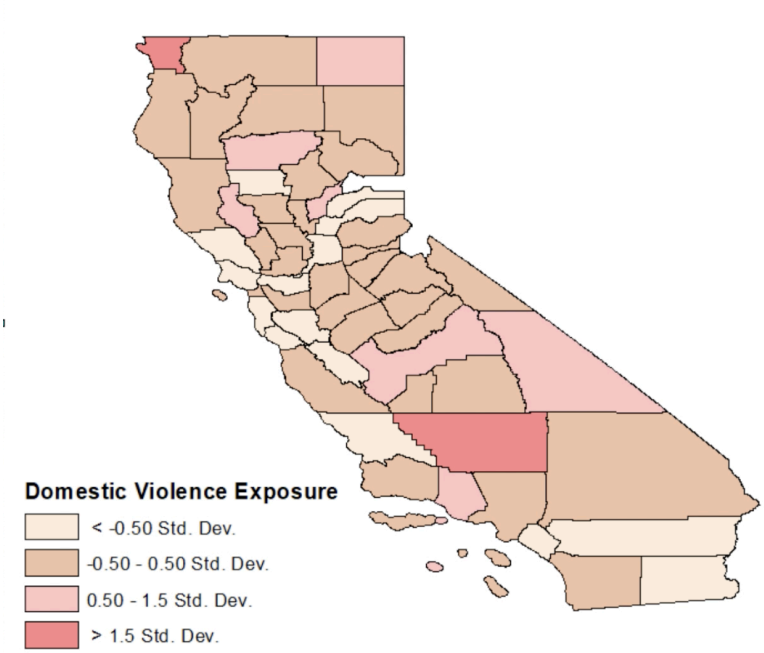
Projection Analyses With Four Class Breaks. The following projection analyses have four class breaks. With the 4 class breaks, the scoring applied to each county for their ACE composite was therefore 0 at the "lowest exposure" (i.e. lowest standard deviation class) and 3 at the "highest exposure" (i.e. highest standard deviation class). For domestic violence, 56 counties were included in the projection. Two counties

(Sierra and Alpine) were excluded because their data was redacted in the report due to being below the threshold of 20 cases. As will be explained later in the chapter, this does not end up causing a difference in their ACE composite assignment given that the two counties would have occupied the lowest standard deviation class break.

California Counties Exposure to Domestic Violence.

Figure 8.

California Counties Exposure to Domestic Violence, 2018



Two counties have data that reported below the redacted threshold of 20 domestic violence calls, which were Sierra and Alpine county. The data for these two counties are therefore not available for analysis in the current projection.

The results from the class breaks show that a majority of the cases land in the second class break, with 33 counties. The distribution for domestic violence differs from

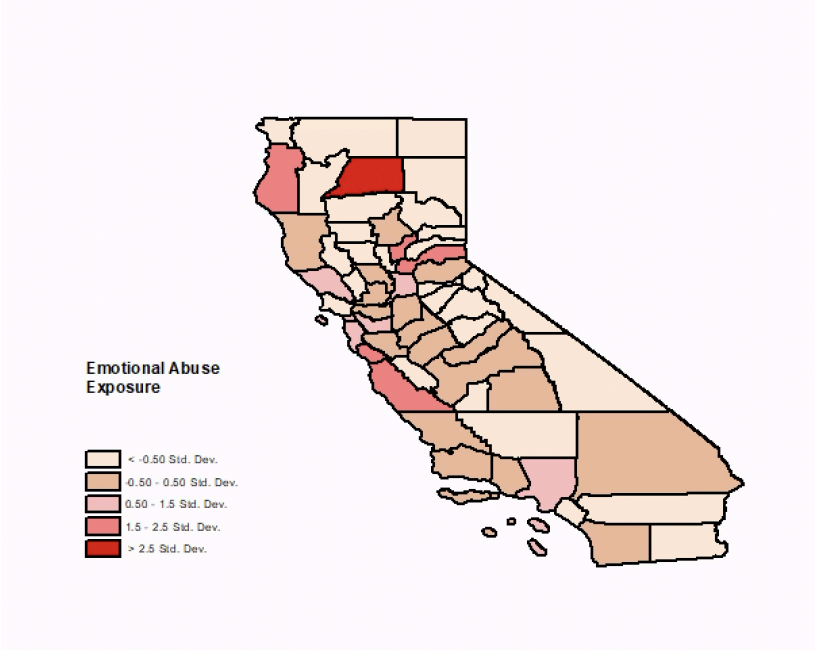
physical, sexual and emotional abuse by having more cases in their largest two distributions, the highest exposure class including Del Norte and Kern counties.

Projection Analyses With Five Class Breaks. The following projection analyses have five class breaks. With the 5 class breaks, the scoring applied to each county for their ACE composite was therefore 0 at the "lowest exposure" (i.e. lowest standard deviation class) and 4 at the "highest exposure" (i.e. highest standard deviation class). For emotional abuse, sexual abuse, physical abuse and marital disruption, all 58 counties in the sample were included in the projection. For violence, San Francisco's data was not reported by the source leaving 57 counties included in its projection.

California Counties Exposure to Emotional Abuse

Figure 9.

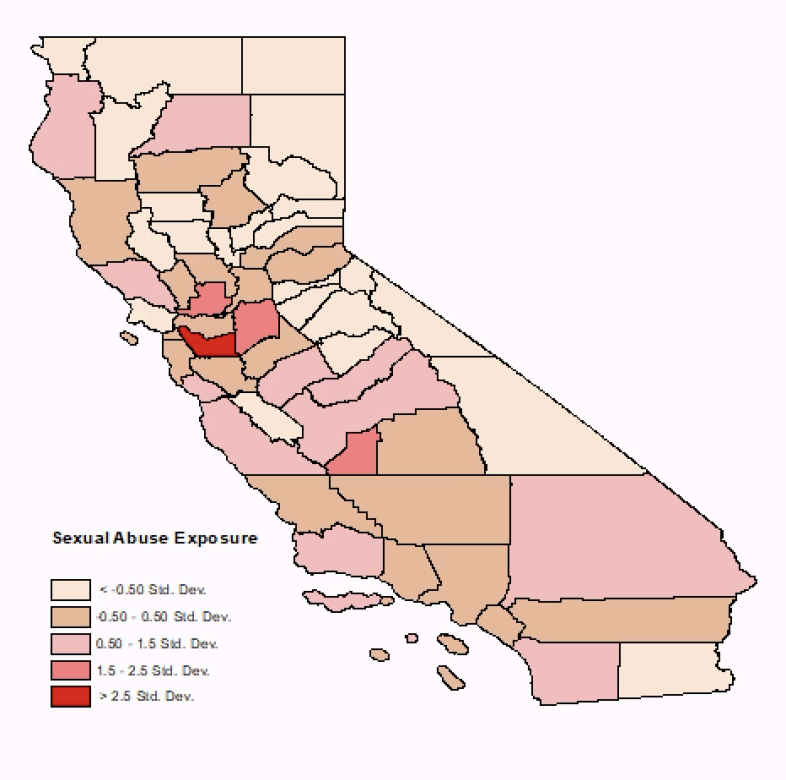
California Counties Exposure to Emotional Abuse Ages 0-17, 2018



The results from the class breaks reveal larger representation on the lower end of the distribution, with over half (46) of the cases in the first two classes. Twenty-eight counties occupied the lowest class of standard deviations at < -0.5 SD, such as Alpine, Orange and Riverside. Only 1 county occupied the highest class of standard deviations at > 2.5 SD, which was Shasta.

California Counties Exposure to Sexual Abuse

Figure 10.
California Counties Exposure to Sexual Abuse Ages 0-17, 2018

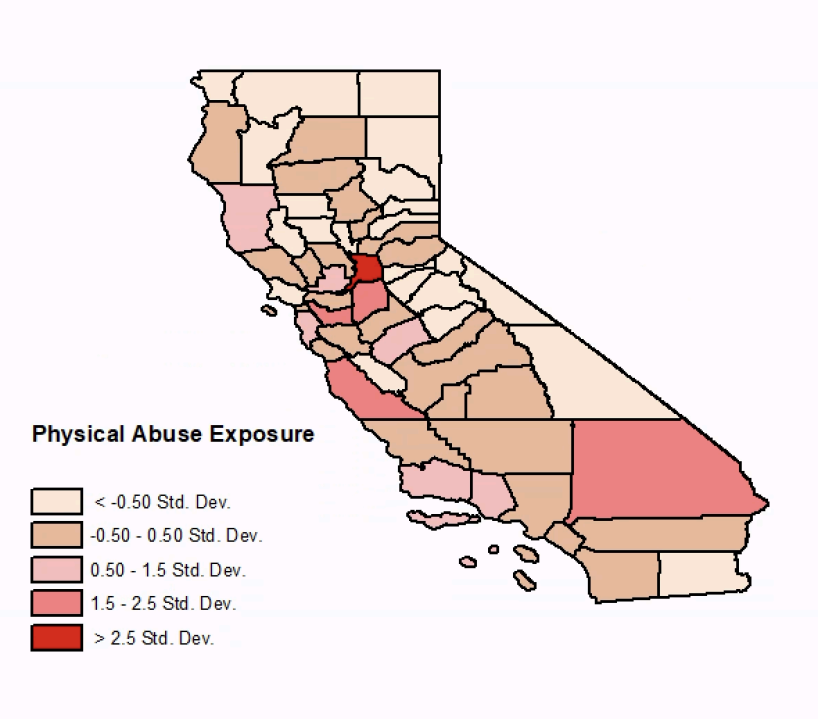


The results from the class breaks reveal larger representation on the lower end of the distribution, with 23 counties being in the lowest exposure class and 20 counties in the second class. The distribution for sexual abuse had more counties occupying mid tier

classes compared to emotional abuse. Sexual abuse exposure resulted in only one county in the highest exposure class, which was Alameda.

California Counties Exposure to Physical Abuse

Figure 11.
California Counties Exposure to Physical Abuse Ages 0-17, 2018

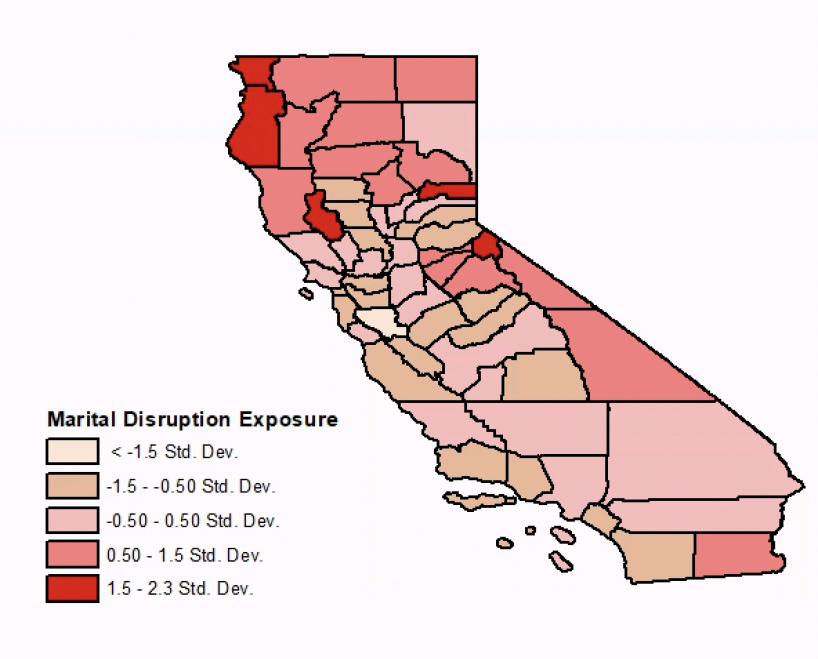


The results from the class breaks reveal larger representation at the lower end of the distribution, with 47 cases occupying the first and second classes. The distribution for physical abuse had less counties occupying mid tier classes compared to sexual abuse. Physical abuse exposure resulted in only 1 county in the highest exposure class, which was Sacramento.

California Counties Exposure to Marital Disruption

Figure 12.

California Counties Exposure to Marital Disruption, 2018

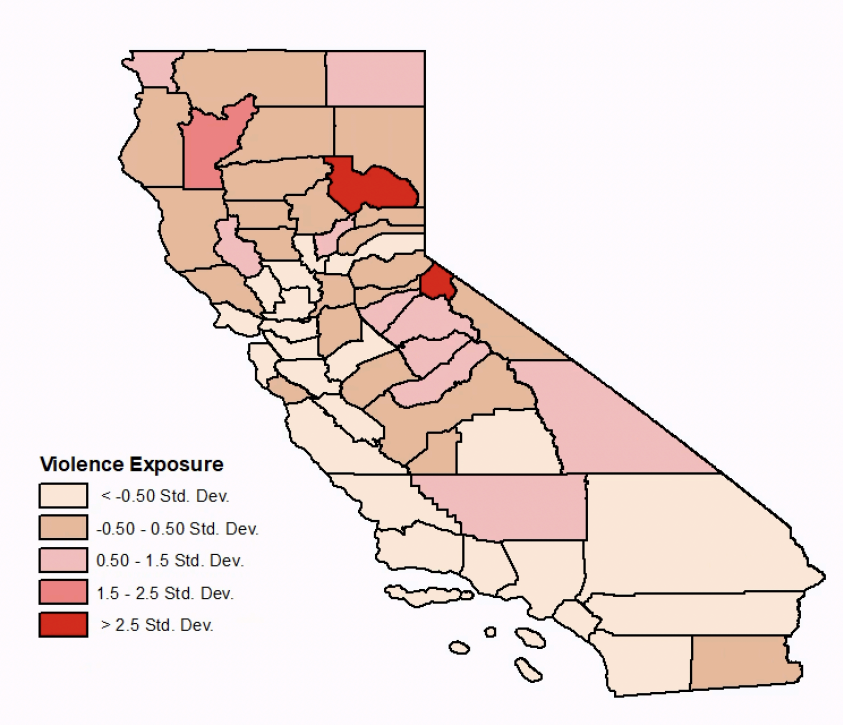


The results from the class breaks show a more even distribution, but with less concentration into a particular class. The variable of marital disruption has the most cases in their highest exposure class, with $n = 5$. Those 5 counties are Sierra, Lake, Humboldt, Del Norte and Alpine.

California Counties Exposure to Violence

Figure 13.

California Counties Exposure to Violence, 2018



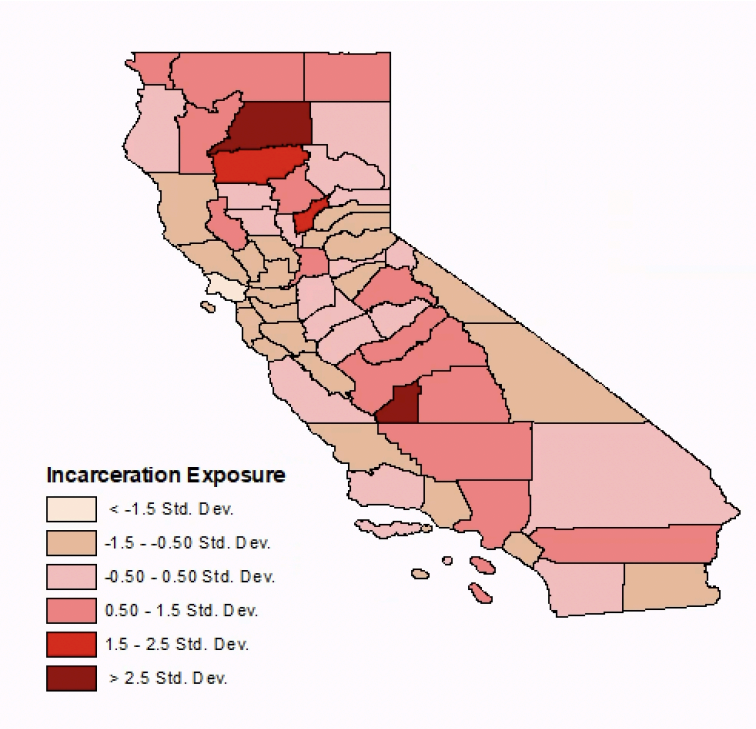
The results from the class breaks revealed another large representation in the lower end of the distribution, with 44 cases occupying the first and second class evenly. The highest exposure class break contained the counties of Plumas and Alpine.

Projection Analyses With Six Class Breaks. The following projection analyses have six class breaks. With the 6 class breaks, the scoring applied to each county for their ACE composite was therefore 0 at the "lowest exposure" (i.e. lowest standard deviation class) and 5 at the "highest exposure" (i.e. highest standard deviation class). For incarceration, all 58 counties in the sample were present for the projection.

California Counties Exposure to Incarceration

Figure 14.

California Counties Exposure to Incarceration, 2020



The results from the class breaks show a more even distribution, with cases landing more so in the middle class breaks than at the extremes. Tehama and Yuba county occupied the second highest class break, with Kings and Shasta having the highest exposure class break.

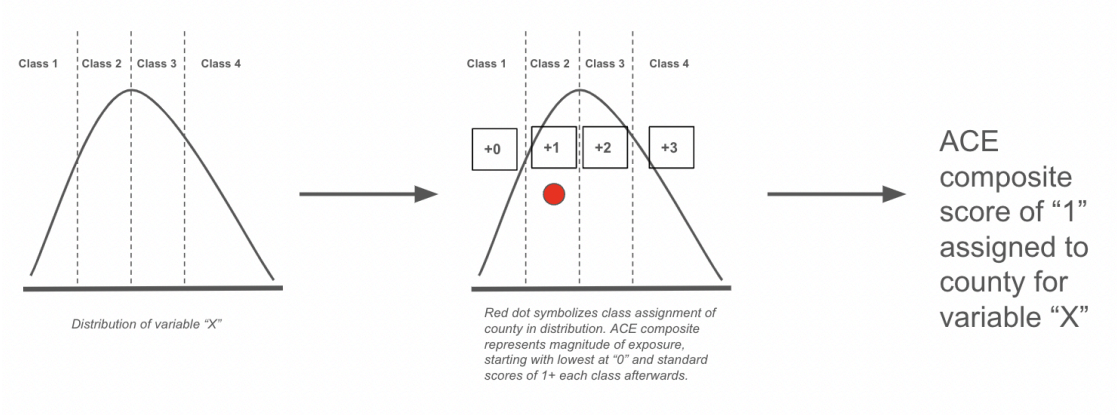
Creating the ACE Composite

In order to best answer the initial research question regarding the incidence of ACE exposure across California counties, the author created a composite variable of the accumulated ACE categories: the ACE composite. The process of creating the ACE composite is described below.

Each of the eight ACEs category chloropleth projection maps is based off the "class breaks," or the categorization of a variable's distribution which then corresponds to a particular symbol or color on the map to depict variation. Once a variable is uploaded into the ArcGIS system, the variable is then categorized into class breaks by equal standard deviations of one. Since class breaks are determined based on the variance of a variable's distribution, there is also a range of class breaks that resulted from the analysis. To best standardize the scoring of a county's resulting class break over the eight different individual ACE variables, an ACEs composite is assigned based off of their class. An example of this process can be found in Figure 15 below.

Figure 15.

Example of ACE Composite Assignment



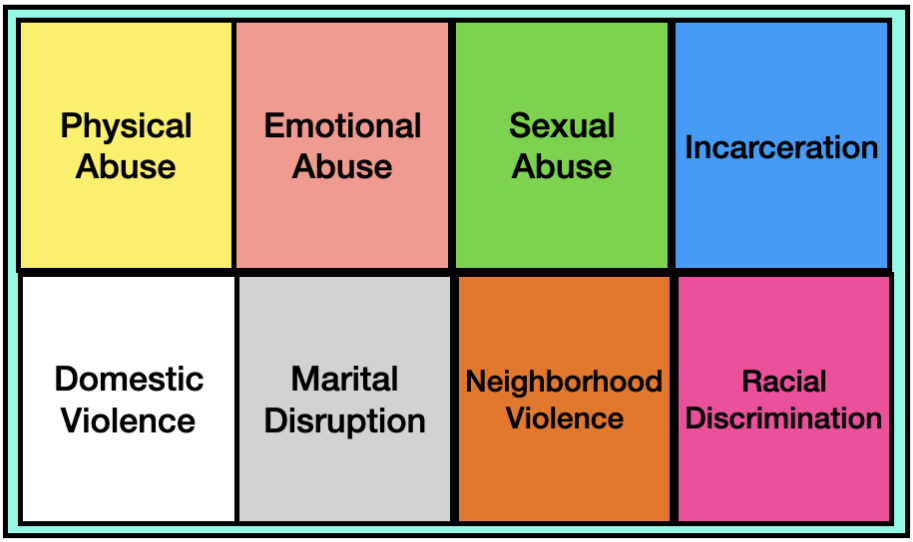
Once all the chloropleth projection analyses were completed for all eight ACE categories and each individual ACE composite was assigned to each county, the scores were summed to create a final total ACE composite for each county (Figure 16). The final total ACE composite represents the cumulative magnitude of exposure to the adverse childhood experiences measured, allowing for the researcher to determine a

conclusion to the first overarching question regarding incidence across California's counties. It also creates a variable that allows for the second overarching question to be investigated regarding the relationship between ACEs in a geographic space (counties) and education outcomes.

Figure 16.

Total ACE Composite Represents the Summation of All Individual ACE Categories

|----------ACE COMPOSITE ----------|



Category Trends: ACE Composite Database

When reviewing the eight categories across the 58 counties, there were a few noticeable trends. Counties who occupied the lowest class breaks in a category distribution tended to do so more often in subsequent categories. There were less pronounced trends for those who occupied the highest class breaks, where distribution

was much more randomized, with the majority of scores falling somewhere in the middle of the distribution.

Some additional descriptions of the database are that incarceration and marital disruption witnessed the most cases of the sample entering the highest class breaks, meaning higher incidence and exposure of those adverse childhood experiences. The category with the most cases occupying the lowest class break belonged to discrimination, which, due to the data limitation regarding data availability and operationalization, makes sense. Finally, the categories with the most cases occupying the middle of their class break distribution were domestic violence and neighborhood violence. The further investigation into the composite variable and related statistical analyses are described below.

Regression Analysis

Ordinary least squares (OLS) regression analysis was used to address the overarching research question on the relationship between ACEs and education outcomes. Regression analyses are inferential statistical tests (Kaye & Freeman, 2011), that are used to determine conclusions surrounding the relationship between two or more variables. Here, utilizing regression analyses was a good match regarding research question two and investigating the relationship between ACEs and each education outcome.

Bivariate Correlations to Determine Strength of Relationship

Initial analyses to prepare for the OLS regression included descriptives and bivariate correlations to determine the strength and direction of the relationships before

attempting a regression model. The results were as follows: ACE composite and high school graduation ($r = 0.01$, $p = 0.91$), ACE composite and high school suspension ($r = 0.25$, $p = 0.06$) and ACE composite and high school expulsion ($r = 0.23$, $p = 0.08$). The hypothesized direction of the relationship matched for the impact that ACEs would have on suspensions and expulsions, which would be positive–meaning more ACEs is related to higher suspensions and expulsions. Although the results of these three correlations were insignificant, I decided to conduct all three regression models to better understand the explanatory nature of the ACE composite while also adding nuance to the implications drawn in conjunction with the geospatial analyses. The following models show how the relationship of the ACE composite will be explored for each of the three education outcomes.

County Level High School Graduation = $\beta_0 + \beta_1$(ACE Composite) + Error

County Level High School Suspension = $\beta_0 + \beta_1$(ACE Composite) + Error

County Level High School Expulsion = $\beta_0 + \beta_1$(ACE Composite) + Error

The β_0 in each formula is measuring the intercept of what the education outcome (graduation, suspension or expulsion) percent would be for a county if there were no cumulative ACE exposure (and error was constant). The slope value of β_1 measures the change in the education outcome variables per unit increase in a county's ACE composite. Finally, the error term is a constant term that represents the difference

between the expected and predicted values in the model. The models outlined above are meant to serve as further contextualization of the geospatial analyses conducted on the ACE composite and academic outcomes across the California counties in the sample.

Checking Assumptions for Regression Analysis

Prior to conducting regression analyses, data must be checked to see if they meet assumptions underlying the analyses (Fox, 1997). These assumptions (linearity, normality, homogeneity of variance, independence, errors in variables, model specification) were examined for each of the three regression models described above.

Unusual or Influential Data Points

ACE Composite. To identify any unusual or influential data points, descriptive statistics were carried out and a boxplot was created (Appendix A). Descriptive statistics suggested that there were no outliers among the 58 counties. Similarly the boxplot revealed no outliers in the variable's distribution.

High School Graduation. Four outliers were initially identified: Sierra (100%), San Francisco (64%), Nevada (46%), Mono (46%) and Inyo (41%). These outliers were checked to determine if there were any data entry errors. After none were identified, data from previous academic years were reviewed. Data included in this study was consistent for the previous two academic years for these four counties. For example, Sierra's graduation rate was 100% in 2016 and 2017, which was consistent with the 100% in 2018. Given this consistency in the data across these previous years, all four counties were not considered outliers and were retained in this study.

High School Suspension. With the boxplot for high school suspension, two cases were initially identified as outliers: Modoc (13%) and Sierra (0%). Similar to high school graduation the outliers were checked to determine if there were any data entry errors. In addition, previous academic years were reviewed to determine if the data included in this particular year were similar or different. Data from the year analyzed in the study was consistent with the county trends for high school suspension from the last two academic years. Given this consistency, Modoc and Sierra county data for high school suspension were not considered outliers and both counties were retained in the analysis.

High School Expulsion. The boxplot analysis for high school expulsion initially identified one outlier, Kings County (0.9%). Kings' data was reviewed for previous academic years to see if the trends held similar for the one utilized in the study. The data review revealed that Kings' data was consistent in trends over the last two academic years. Given this consistency, King county data for high school expulsion was not considered an outlier and was retained in the analyses.

Normality of Error Distribution

Normality of error distribution assumes that the residuals of the actual and predicted data is distributed evenly across a dataset. Violation of this assumption is problematic because if there are extreme outliers in a distribution or non-normal distribution, this violates the assumption of the regression analyses and can impact the outcomes and interpretations of an analysis.

ACE Composite and High School Graduation. The results of the fitted plot revealed scattered deviation from zero, while the plot of the residuals revealed inconsistent deviations from the fitted line at both tail ends (Appendix A). The error distribution of ACE composite and high school graduation was not normally distributed. This is an initial signal that there may be a non-normal or non-linear distribution. The counties most apparent in skewing the linearity are Inyo (-0.43), Mono (-0.37), Nevada (-0.37), Sierra (0.17), Mariposa (0.11) and Modoc (0.10). Modoc county is the only one listed here that is above the mean ACE composite (10), while all other counties were below the mean–Nevada being one of the lowest in the sample (4).

ACE Composite and High School Suspension. The results of the fitted plot and plot of residuals does not reveal any sort of systematic pattern which suggests that there is a normal distribution. Although normally distributed, two cases stood out in the plot–Modoc (0.064) and Sierra (-0.06). Modoc is above the mean for ACE composite (10) and Sierra lies just below it (7).

ACE Composite and High School Expulsion. The results of the fitted plot and plot of residuals revealed deviation from plot and line, signaling a non-normal or non-linear distribution. The two counties contributing to this nonlinearity are Del Norte (-0.003) and Kings (0.006). In respect to their ACE composite, Del Norte (12) and Kings (13) are some of the highest ACE composite, neary 4 and 5 points above the mean for the sample.

Interestingly enough, Modoc and Sierra counties show up in both high school graduation and high school suspension when considering cases contributing to the

nonlinearity. Both counties have relatively different overall ACE composite and some of the differentiations between their respective ACE composite and their influential education outcomes data will be discussed further in Chapters 4 and 5.

Homoscedasticity

Homoscedasticity refers to the differences in error between the actual and expected values of a variable. Violation of this suggests that some values are significantly different from what would be expected. In order to check for homoscedasticity, the Breusch-Pagan test was utilized. This tests the null hypothesis that there is no difference in the expected and predicted error values. The alternate hypothesis is that there is a difference in the expected and predicted error values. If the null hypothesis is rejected, then I have evidence to conclude that there is heteroscedasticity.

ACE Composite and High School Graduation. There is evidence to indicate that there is heteroscedasticity for high school graduation ($p < .0001$) and high school expulsions ($p < .05$) but not for high school suspensions ($p = .60$). This suggests a violation of the heteroscedasticity assumption for high school graduation and high school expulsions.

ACE Composite and High School Suspension. The results of the regression mode of ACE composite and high school suspension resulted in a p value of 0.60394, which fails to reject the null hypothesis and accept that homoscedasticity is present.

ACE Composite and High School Expulsion. The results of the regression model of ACE composite and high school graduation resulted in a p-value of 0.042592, rejecting the null hypothesis and accepting that heteroscedasticity is present.

Linearity

The assumption of linearity assumes that an increase in one variable will impact the value of the other, depicting a linear relationship between an independent and dependent variable. Having non-linear relationships with analytical models is an issue if running a simple linear regression, which assumes that the relationship is linear. In order to check for linearity, scatterplots were created to conduct visual tests between the independent variable and the dependent variable pairs (Appendix A). All plots of the ACE composite and the education outcome variables revealed a linear pattern, which suggests that this assumption is met for all three education outcome variables.

Model Specification

It is important that thoughtful consideration is given to the type of analytical model a study undergoes with the research questions presented. Given the parsimonious nature of the models and limited number of variables included in this analyses, no other models were explored for the analysis.

Issues of Independence

Issues of independence deal with whether the impact of one event occurring impacts the chances of another one occurring. For the purposes of the current study, all of the data included in this study are independent of each other. None of the data included in this study is nested, since it only includes counties within one state. Since county is the unit of analysis, there is no violation of independence. Neither students nor districts are investigated in the analysis so there are no concerns of data being nested. As mentioned above, the issue of county to county comparison is not in violation of the data collection

of students who are counted across counties within the same academic year, as this only pertains to county to state comparisons. Counties do not overlap in terms of geographic boundaries and the data is assumed to be unique for each particular county. Moreover, given how the data was collected (see above), there are no concerns about violations of the independence assumption.

Summary of Research Design

The database of the eight categories was carefully curated to describe the incidence of ACEs across all 58 California counties. These eight categories were combined to create a single ACE composite. The next chapter describes the results of the analyses to better understand the relationship between the ACE composite and three education outcomes (high school graduation, suspension and expulsion). The results addressing the current study's research questions are presented through the two specific methodological approaches of the linear regression models and the final projection analysis. Further explanation on the importance of these two specific methods and their results are discussed more in depth chapter 4.

Chapter 4: Results

Chapter four includes the results of research question 1 (ACE incidence and magnitude across CA counties) and research question 2 (relationship between ACE exposure over space with education outcomes at the secondary level). The chapter is organized by research question. First, geospatial analysis was conducted to address the question of ACE incidence and cumulative ACE incidence across California counties through chloropleth mapping. Next ordinary least squares regression was conducted to address the question of the relationship between ACE exposure and the education outcomes of high school graduation, suspension and expulsion. The chapter concludes with a synthesis of the results from both research questions.

Research Question 1: Visualizing and Investigating the Incidence of ACEs Across California Counties

To address the first question, chloropleth map projections were created and analyzed to determine the incidence of ACEs across a geographic space (counties). The California State Association of Counties' (2024) categorizations of "rural," "suburban" and "urban" counties were utilized (Table 5). These categorizations match the discourse and theory of larger scale conversations of ACEs in public health, and the importance of built environments in exposure and prevention (Let's Get Healthy California, 2016; Pinderhughes, Davis & Williams, 2015; Soja, 2013).

Table 5.

California Counties By Category: Rural, Suburban or Urban

Rural Counties	Suburban Counties	Urban Counties
Alpine	Butte	Alameda
Amador	Imperial	Contra Costa
Calaveras	Kern	Fresno
Colusa	Marin	Los Angeles
Del Norte	Merced	Orange
El Dorado	Monterey	Riverside
Glenn	Napa	Sacramento
Humboldt	Placer	San Bernardino
Inyo	San Luis Obispo	San Diego
Kings	Santa Barbara	San Francisco
Lake	Santa Cruz	San Joaquin
Lassen	Shasta	San Mateo
Madera	Solano	Santa Clara
Mariposa	Sonoma	Ventura
Mendocino	Stanislaus	
Modoc	Tulare	
Mono	Yolo	
Nevada		
Plumas		
San Benito		
Sierra		
Siskiyou		
Sutter		
Tehama		
Trinity		
Tuolumne		
Yuba		

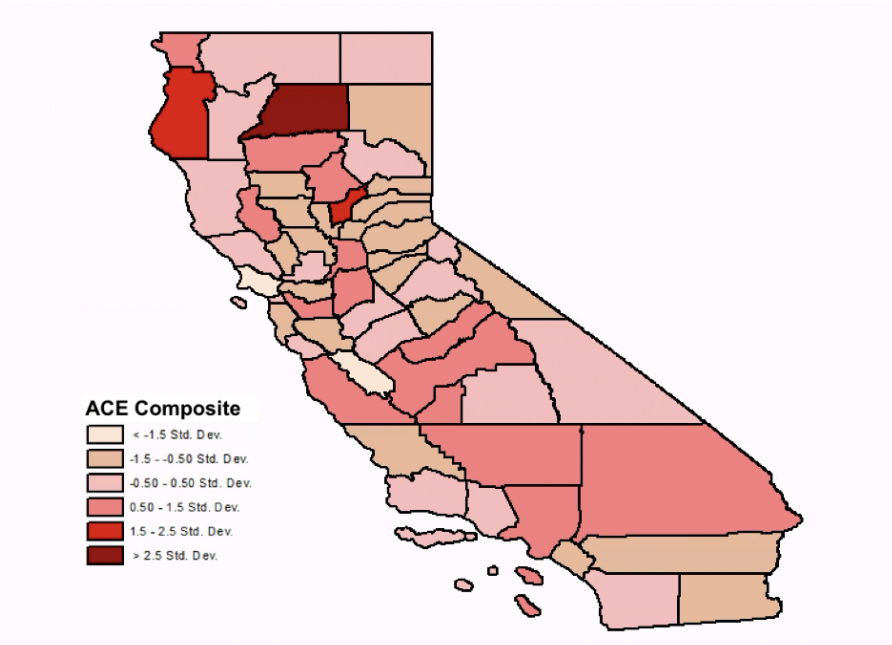
Note. Sourced from California State Association of Counties. Retrieved from https://www.counties.org/carousel-wo-title-46 on April 30, 2024.

California Counties ACE Composite

The ACE composite consists of the combination of eight ACE categories across the 58 California counties. The chloropleth projection of the ACE composite was used to create a "heat mapping" symbology, where "darker red" spaces symbolize higher cumulative ACE exposure and "lighter sand colored" spaces symbolize lower cumulative ACE exposure. The ACE composite ranged from a low ACEs exposure score of 0 to high ACEs exposure score of 30. The chloropleth projection of the ACEs composite was set to class break values of 1 standard deviation, which resulted in six class breaks. As discussed in chapter 3, the class break assignment takes into account equal value ranges in order to maintain logical succession in regards to standard deviation, while considering the total variation within a variable. The standard deviation value difference between class 1 and class 2 (1 standard deviation) is the same as the standard deviation value difference between class 2 and class 3 and so on. With the six class breaks, the "lightest" colorations symbolize counties with lower ACE composites, while the "darkest" colorations symbolize counties with higher ACE composites (Figure 17).

Figure 17.

California Counties' ACE Composite By Class Break



Results of the chloropleth analysis revealed that the average ACE composite was 8.71. The median ACE composite was 8.50 and mode was 10. The maximum value was 17 (Shasta county) and the minimum value was 4 (Marin county, San Benito county).

Table 6.

ACE Composite Class Break Assignment Across California Counties, Highlighted by Rural, Suburban or Urban Categorization

Class Break 1	Class Break 2	Class Break 3	Class Break 4	Class Break 5	Class Break 6
San Benito	Imperial	San Diego	San Bernardino	Humboldt	Shasta
Marin	Riverside	Ventura	Los Angeles	Yuba	
	Orange	Santa Barbara	Kern		
	San Luis Obispo	Inyo	Kings		
	Mono	Tulare	Fresno		
	Mariposa	Santa Cruz	Madera		
	Calaveras	Stanislaus	Monterey		
	Amador	Merced	Alameda		
	El Dorado	Tuolumne	San Joaquin		
	Placer	Alpine	Sacramento		
	Nevada	Solano	Lake		
	Sierra	Sonoma	Tehama		
	Lassen	Mendocino	Butte		
	Glenn	Trinity	Del Norte		
	Colusa	Siskiyou			
	Yolo	Modoc			
	Sutter	Plumas			
	Napa	San Francisco			
	Contra Costa				
	Santa Clara				
	San Mateo				

Note. This table represents the class break distribution of CA counties based off their ACE composite. Counties are also color coded to represent their categorization provided by the California State Association of Counties' (2024) with blue = rural, orange = suburban and purple = urban.

The majority of California's counties (32) fall in the middle 3rd and 4th class breaks (Table 6). Three counties occupy the highest 5th and 6th class breaks, while 23 counties occupy the 1st and 2nd class breaks. The majority of California's counties have

a moderate exposure to ACEs–with the counties of Shasta, Yuba and Humboldt having the highest exposure. In regards to regional trends and the categorizations provided by the California State Association of Counties, geographically the rural counties in the northwest have a clustering of the counties in the 3-5 class breaks. The urban counties in the southeast have clusterings of class breaks 3-4, while the mixture of suburban and urban central California region has more diversity of class breaks and a heavy representation of the 2nd class break.

Some of California's largest urban counties, such as Los Angeles, San Diego, Orange and Riverside, are not present in the highest class breaks of 5 and 6. In fact, none of the categorized urban counties occupied class break 5 and 6. Instead, those class breaks were occupied by rural and suburban counties. In respect to the proportion of county category occupying higher class breaks, 65% of suburban counties occupied class breaks 3 or higher, compared to 64% of urban counties and 56% of rural counties.

Investigating the Relationship Between ACEs and Education Outcomes

To address the second research question regarding the relationship between ACEs and education outcomes in a geographic space defined here as California counties, linear regression was utilized. Three separate regression models were carried out to determine the magnitude and direction of the association between the ACE composite and the three education outcomes of high school graduation, suspension and expulsion (Table 7). Results of the linear regressions are provided below.

Research Question 2A. The Relationship of the ACE Composite and High School Graduation

The null hypothesis that was tested is that there is no relationship between the ACE composite and high school graduation. The alternate hypothesis is that there is a significant relationship between the ACE composite and high school graduation. There was no significant relationship between ACE composite and high school graduation, $t(57) = 0.11$, $p = .92$, and the overall model was also not significant, $F(1, 55) = 0.01$, $p = 0.92$ which suggests that there is no support for a linear model. While the data fail to reject the null hypothesis, the insignificant overall F-statistic and the low R-squared value (0.0002) suggests that additional work is needed to better understand the relationship between ACEs and high school graduation.

Table 7.

Linear Regression Results of ACE Composite on Education Outcomes

	Model 1: High School Graduation				
Variable	Coefficient	Standard Error	t-statistic	p-value	95% Confidence Interval
Intercept	0.83	0.04	19.91	<2e-16***	[0.75, 0.91]
ACE Composite	0.00	0.01	0.11	0.92	[-0.01, 0.01]
	Model 2: High School Suspension				
Intercept	0.05	0.01	4.86	1e-05***	[0.03, 0.06]
ACE Composite	0.00	0.00	1.95	0.06	[-0.00, 0.00]
	Model 3: High School Expulsion				
Intercept	0.00	0.00	1.19	0.24	[-0.00, 0.00]
ACE Composite	0.00	0.00	1.75	0.09	[-0.00, 0.00]

Note. The following table represents the OLS regression results for the three models of ACE composite on education outcomes of high school graduation, suspension and expulsion.

***$p < 0.001$.

Research Question 2B. The Relationship of the ACE Composite and High School Suspension

Research question 2b corresponds to the second model of the regression, analyzing the relationship between the ACE composite and high school suspension. The null hypothesis that was tested is that there is no relationship between the ACE composite and high school suspension. The alternate hypothesis is that there is a significant

relationship between the ACE composite and high school suspension. There was no significant relationship between ACE composite and high school suspension, $t(57) = 1.95$, $p = .06$, and the overall model was also not significant, $F(1, 55) = 3.80$, $p = 0.06$. The results suggest that there is no support for a linear model, failing to reject the null hypothesis that there was no relationship between the two variables. In addition, the low R-squared value of 0.06 is further indication that this model is not appropriate for this research question.

Research Question 2C. The Relationship of the ACE Composite and High School Expulsion

The last regression model analyzed the relationship of the ACE composite and high school expulsion to answer question 2c. The null hypothesis that was tested is that there is no relationship between the ACE composite and high school expulsion. The alternate hypothesis is that there is a significant relationship between the ACE composite and high school expulsion. This model also showed no significant relationship between ACE composite and high school expulsion, $t(57) = 1.80$, $p = .09$, and the overall model was also not significant, $F(1, 55) = 3.08$, $p = 0.09$. Similarly, the low R-squared value (0.05) is further indication that there is no support for this linear model.

Brief Summary of Results

The results of the geospatial analysis and linear regression point to a complicated picture of how ACEs across California counties relate to education outcomes. The geospatial analysis points to more rural and suburban counties of concern where exposure is high proportionally compared to their urban county counterparts.

Large urban counties, such as Los Angeles, were anticipated to be in the "darkest" regions given their historic marginalization of neighborhood de-investment and perpetuated economic inequality that research suggests is related to higher ACE exposure (Ong, Pech, Chhea, & Lee, 2016; Phelan & Link, 2015; Sampson, 2019; Soja, 2013). Yet, the results of the analysis point to rural and suburban counties, such as counties in the northwest (Humboldt, Shasta), which have some of the highest exposure to ACEs. These results are consistent with research that criticizes previous definitions and stereotypes attributed to "rural vs urban" divides (Tieken, 2017), and how the concerns of "rural" areas' higher exposure to ACEs versus "urban" areas have merit (Crouch, Radcliff, Probst, Bennett, & McKinney, 2020). However, there was no statistically significant relationship between ACEs and the three education outcomes. This lack of relationship fails to explain ACEs' impact within a county in terms of educational outcomes as measured–which falls short in confirming what prior research and theory suggest regarding the relationship between ACEs and education (CDC, 2019; Felitti et al., 1998; Ream, Cohen & Lloro-Bidart, 2014; Wilkinson & Marmot, 2003). These perplexing results lead to the implications, discussion and future research in Chapter 5.

Chapter 5: Discussion

The results of the current study offered a unique opportunity to review the relationship of adverse childhood experiences, geographic space and education outcomes in the state of California. The combined analytical approach of geospatial analysis and linear regression attempted to offer a nuanced look into how researchers and policymakers can move forward on a macro level framework with the understanding of ACEs as a public health concern, and one that the field of education should be paying much more attention to. Here, in Chapter 5, discussion of particular implications for research and policy are emphasized and informed by the understanding of the incidence of ACEs over California's counties, and their anticipated relationship to each county's education outcomes, respectively.

Space Is An Important Variable for Consideration: ACEs and Rural Geographies Are Not To Be Overlooked

The results of the study revealed how the variable of space cannot be overlooked when considering the impact of ACEs in the state of California. Space is particularly important, as Soja's theory (2013) of spatial equity suggests, given that it plays a crucial role in the generated geographies where endogenous geographies are shaped by the policies local jurisdictions enforce and implement. In the current study, regional trends of California counties rose to the forefront of concern with varying degrees of ACEs exposure proportionally higher in some counties in the rural and suburban northwest compared to more urban southern regions. This particular finding corroborates recent research that has both attempted to understand the nationwide spread of ACEs across

geographic types (Crouch et al., 2020) and criticized the stereotype between rural and urban areas that anticipate environmental exposures to violence and poverty to be higher in urban areas (Tieken, 2017).

The results of the current study's geospatial analyses pairs well with the recent research signaling that more rural areas across the nation have a higher exposure to ACEs compared to their urban counterparts (Crouch et al., 2020). Crouch et al. (2020) conducted their analysis across 34 states and the District of Columbia, with a sample size of roughly 26,000 respondents. The results and discussion mention that rural youth can have higher proportional exposure to ACEs compared to urban youth, and that contextual factors are particularly important–highlighting a constellation of effects from poverty and the scarcity of resource availability in health care. Additional studies corroborate the common issues of service availability in more rural areas for youth to acquire proper care that can exacerbate the effects of ACEs in their life (Probst et al., 2018). It is clear from the research and from the results of this study that common stereotypes of environmental stressors thought to be primarily an urban concern, are potentially distracting stakeholders from the importance of rural spaces as they influence ACE exposure.

The work by Mara Casey Tieken (2017) highlights the important critical race perspective of understanding how the stereotypes of the rural and urban divide can perpetuate narratives that continue to push racialized narratives of a nonwhite turbulent, violent urban center, compared to a white, calm and backwards rural region. The article dives deep into the historical connections of how communities of color, across the rural and urban spectrum, have a shared history of marginalization in social structures such as

education. Here, communities of color witness a scarcity of resources and poverty in their districts that have similar impacts on teacher retention, service availability and subsequently college degree attainment across rural and urban school systems. The issues of investment and service availability also impacts access to health care (Probst et al., 2018), which combined with the concerns of education services for communities witnessing high ACE composite scores, can be a severe burden on the people in that jurisdiction. It is therefore that the current study's results can be informative when considering public funding to combat ACEs within a county, especially in more rural and less densely populated spaces that can receive less public resources compared to their urban counterparts (Douthit et al., 2015; Swindell & Kercher, 2009).

When reviewing the chloropleth maps, it becomes apparent that understanding the relevance of space from a geospatial analysis vantage point can be a novel approach especially in education research. For example, Yuba county's high exposure of ACEs with their composite score of 14 witnessed lower graduation rates and higher rates of suspension and expulsion, when compared to Los Angeles county (ACE composite of 12, respectively). When investigating deeper into the education context between the two counties, most recent data on the ratio of available pupil support services reveal Yuba county's ratio of students to counselors in 2019 was 990:1 and Los Angeles county's ratio in 2019 was 489:1 (Population Reference Bureau, 2023). This type of case building could lend itself useful for investigating further the ties between ACEs, education outcomes and subsequent education variables that could paint a picture of the web of influence between the public health and education phenomena.

The conclusions from the current study also pair with those described in the geography of opportunity (Tate, 2008). The work by Tate calls for the integration of research from the fields of not just education and public health, but industry and business as well, in understanding the crucial interplay between the aforementioned fields and geography. How opportunity can be segregated, segmented and even stalled by the various financial, social and cultural capital over space is paramount considering how ACEs inequitable distribution across communities and its intergenerational effects, when left unchecked, can lead to the continued growth of an "uneven geography of opportunity."

Implications for Educational Research, Practice and Policy

Systematically Gathering and Using Data on ACEs

The results from the analysis of incidence of ACEs across California counties provides crucial context into how county level jurisdictions can use existing data to understand the prevalence of ACEs in their communities. The exogenous geography (Soja, 2013) of the county level jurisdiction has particular opportunity to utilize its political power to advocate for solutions in addressing ACE exposure, especially in counties that research reveals receiving disproportionally less funding (Douthit, Kiv, Dwolatzky & Biswas, 2015; Swindell & Kercher, 2009). In the last decade, one of the greatest pushes in the US to address the impact of ACEs on students and their communities has come from statewide coordinated efforts. Examples from movements such as the one in Philadelphia (Cronholm et al., 2015) show that progress can be made in the efforts to educate, coordinate and implement significant change in the communities

being affected by ACEs. This momentum for a statewide coordinated effort has not been implemented in California but there are steps that California can take to take advantage of the existing data on ACEs.

First, California should create a statewide consortium of current ACE-focused organizations to best determine data practices, including those already established with a particular review of those in San Diego and Sonoma. The consortium would act as a "initiation" of California moving towards an annual convening of experts that can create statewide goals and timelines to address the concerns of ACEs in the state's tracking of population level data and interventions. One tool that has shown to be fruitful for other states attempting this feat is the PACE's Connection (PACEs Connection, 2023). This online networking and communication tool can be a great start for California organizations such as San Diego Trauma Informed Guide Team (SD-TIGT) and Sonoma County ACEs Connection, among others, to continue to organize themselves, provide updates and even produce content that can then be translated to policy makers for action. The platform has shown to be a great way for California to participate in learning best strategic practices from coordinated efforts such as PACE's Creating Resilient Communities Accelerator Program (PACEs Connection, 2023), while also contributing their results to the larger nationwide network.

Second, California needs to make a case for policy change that will impact statewide legislation to fund and support integrated efforts of addressing ACEs as a public health concern in its communities and schools. San Diego and Sonoma counties would have some data to begin understanding the impacts of their efforts in addressing

ACEs, but other localities should also be conducting and analyzing impacts of local initiatives addressing ACEs to build the legislative cases. Counties with high ACE composite scores as shown in the current analysis are a great place to start campaigning for coordinated ACE initiatives and pilot programs, integrating them into current programing or requesting funding to address their high exposure concerns.

Third, a legislative push should be made through coordinating meetings with California's current Assemblymembers on the Committee for Education. Al Muratsuchi from District 66 has supported equity leaning legislation in the past two years (California State Assembly Democratic Caucus, 2023) on raising pay for educators and expanding mental health services for involuntarily held patients after intake, which could mean that trauma-informed integrated practice legislation might gain traction with this legislator. Similarly for Assemblymember Megan Dahle, they have authored AB 2640 and co-authored SB 234 which both focus on increasing health professionals and services to address student health needs on school campuses (Assembly District 01, 2024). In regards to California's Senate and subcommittee on Education, senators Dave Cortese (Senate District 15, 2024) and Lola Smallwood-Cuervas (Senate District 28, 2024) would also be potential allies for issues surrounding youth services and safety, as well as intersectionality. A coordinated, data-focused approach on campaigning for state legislation will make the possibility of engaging current committee members and policy makers more likely to champion legislation addressing ACEs in the state, their communities and their schools.

Finally, California should join the likes of Philadelphia and others in the PACEs connection network to provide longitudinal data that can inform the national discourse on combating ACEs in the US. This effort would not only assist the state of California, and other states in the country, but would also assist researchers and studies such as the current one in providing the best science possible to be of service to local communities impacted by ACEs. It is a coordinated effort, such as the one outlined, that can utilize the results from the current study to advocate for ACE research and interventions that permeate the exogenous geographies (Soja, 2013) at the county level and beyond.

Limitations

Data Compromises and Availability

There are several important limitations regarding data that occurred in the pursuit of this study. First, some ACEs such as “substance abuse” and “mental health/illness” are crucial to the holistic understanding of how students' life experiences can impact their academic outcomes. Unfortunately, on a population and geographic level, this type of data in California was quite difficult to come by. Research suggests that these two categories are important in understanding ACEs effects intergenerationally and on psychosocial behavior (Anda et al., 2002; Muniz et al., 2019), so excluding this information in the ACE composite raises concern that all aspects of ACEs were not included in this study. In the future, it is recommended that consistent and comprehensive ACE data is collected across county jurisdictions, as outlined above.

Another key component that was missing in the ACE composite is more nuanced data on incarceration in respect to data year. The collection of this data involves the

carceral systems which are historically very difficult to access, navigate and utilize, given the diverse organizing and governing bodies and their reporting requirements to the state. This, along with the sensitivity of such data, makes it difficult to understand which communities have been affected the most by having their residents incarcerated. In these situations, the study had to rely on the efforts of advocacy groups and nonprofits for the data they could produce when their funding and reporting are available. However, this is not the most ideal data source compared to a standardized assessment on a population estimate level across counties for each ACE category, where estimated error, data year and processing would be more commensurate. It is not clear whether the data included in this study fully captures all potential direct (and indirect) effects of ACEs as it relates to education outcomes, but it is an example of how to envision ACEs research in California for the future.

As for unit of analysis, county level in respect to geospatial analysis was fruitful in answering research question 1. In respect to the results of research question 2, unit of analysis could potentially have been a limitation given that issues of linearity may have impacted the results of significance which were hypothesized otherwise. Here, diving deeper into jurisdictions such as school district level could provide a larger sample and diversity in distribution which could account for the lack of measurable associations between ACEs and high school completion as experienced in the current study.

Additional covariates such as the demographics or urbanicity of the county were also not considered in this study. These additional variables could help better understand the relationship between ACEs and school completion/suspension/expulsion in a way that

is consistent with the current literature on ACEs and would build greater confidence in the conceptualization and operationalization of ACEs. Another possibility is considering a different type of relationship between ACEs and educational outcomes that is not linear. Testing out non-linear models–such as density dependence matrices–could contribute to the existing literature while representing the complex relationship between ACEs and educational outcomes, incorporating additional mitigating variables as outlined below (Bates & Watts, 1988; Caswell, 2008).

Implications for Future Research

The results of the study point to a complex picture of the relationship between ACEs, space and education. In regards to ACEs and space across California, the findings lead to the implications that regions deemed more "rural" and "suburban" (albeit not isolated in their connection to similar issues in urban areas for communities of color) are areas of interest to investigate further as to the potential effects that high cumulative ACE composite scores have on local student populations. Although direct effects on educational outcomes, including high school completion, were found statistically insignificant, the field of research and theory points to diving deeper into understanding what mitigating effects could be influencing the results of the current analysis. This conclusion is what leads to two primary research objectives outlined below.

Qualitative Analyses to Pursue "Highly Exposed" Counties

One of the next steps that could be undertaken to further the current research is to investigate counties that were in the "highest exposed" class break. The two specific samples to be investigated are those that are in the highest exposed class breaks who

either experienced negative high school academic outcomes or experienced positive high school academic outcomes, despite their exposure status. The importance for analyzing these two groups, especially qualitatively, is to assess what types of programming and policies are active in those public school districts to see whether there exists a difference between these two high exposure sub samples–high exposure/negative outcomes and high exposure/positive outcomes–in regards to their service allocation, availability and quality for students.

Once these qualitative analyses are completed, they can serve as contextualizing studies to illuminate the how and why of ACEs exposure and further support or alter the types of interventions for ACEs as it relates to education that California counties should consider.

Investigate Possible Mitigating Variables in Relationship Between ACEs and Education Outcomes

To be done in conjunction with deeper qualitative investigations is understanding what variables could be potentially mediating the relationship between ACEs and education outcomes. Figure 3 in chapter 1 outlines how ACEs can contribute to concerns in psychosocial behaviors and academic performance, which can lead to disciplinary action in the classroom (Muniz et al., 2019; Nowicki, 2018). As the research from Muniz et al. (2019) concluded, multiple ACE categories significantly impacted both specifically internalizing youth and externalizing youth's behaviors in their sample of 30,909. Although profound, what was also interesting is that nearly 33,500 youth who reported a mixture of both internalizing and externalizing behaviors were omitted from the study in

order to focus their analysis on two distinct categories of behaviors. The reality of youth in their total population is therefore even more complex than the significant findings of their distinct categorizations–leading to even more questions of just how the educational effects of ACEs can permeate through how a student internalizes and/or externalizes adverse experiences in life and ultimately in the classroom.

That is why one of the conclusions for future research is to investigate that complexity even further into the potential mediating effects that externalizing and internalizing behaviors may have on a youth experiencing ACEs in California's high ACE exposed counties. By investigating this qualitatively, the research could collect two vital elements of data: first, data on the types of externalizing and internalizing behaviors that students could be exhibiting in the classroom environment; second, data on how these types of behaviors and conditions are treated, and typically disciplined (Nowicki, 2018), in a classroom environment. Investigating these two elements of data can build upon the results of the current study to amplify what is happening on the ground for youth in high ACE composite counties, and possibly add clarity to the results found in the OLS analyses and research question 2.

Adverse childhood experiences are not something that researchers, practitioners and those with lived experience necessarily want to have as a reality to investigate. It is a difficult and emotional topic to pursue and just like any other public health concern, one that demands attention to attempt to disrupt its impact on the communities in question. ACEs are impacting not just individuals, but their families, communities, schools, workplaces and beyond (CDC, 2023). They seem to follow trends that see some

communities, especially those historically overlooked, have multiple occurrences across generations that can impact their academic outcomes and future well being. Addressing how to localize this public health concern by engaging local jurisdictions and their constituents to rally around solutions that are benefiting their students starts with understanding what the problem is, how it's connected to their communities' wellbeing and where it is happening.

Advocating for ACEs is not new, nor is California the first in the country to bring this concern to the table. If anything, California is *late* to the current movement and needs to take note of those states who are creating legislation, producing data in collaboration with local jurisdictions, and contributing to the nation's effort to combat adverse childhood experiences. It is with this momentum, and with the results, implications and conclusions from this study, that the researcher hopes a coordinated California effort to combat ACEs will be ignited.

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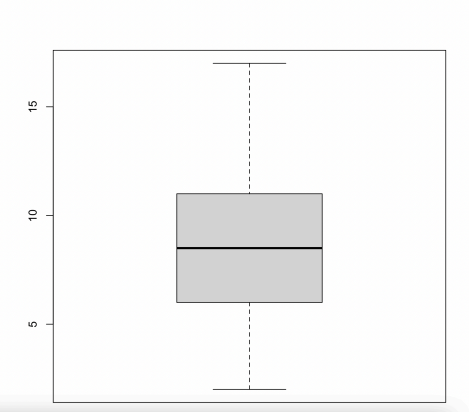
Appendix A

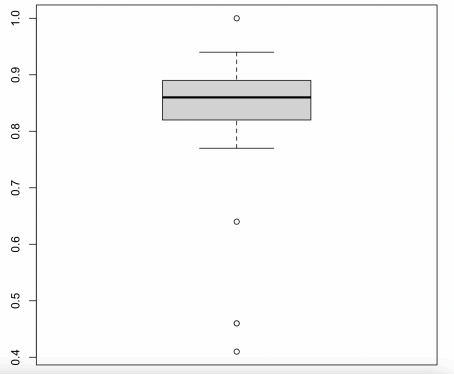
Appendix A1.

Boxplot Results for ACE Composite



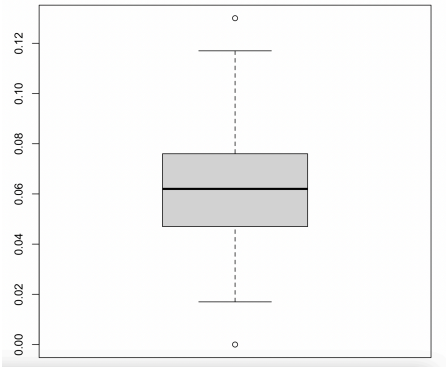
Appendix A2.

Boxplot Results for High School Graduation



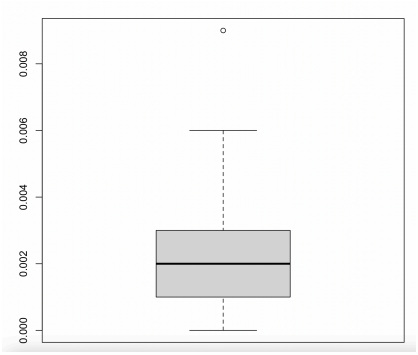
Appendix A3.

Boxplot Results for High School Suspension



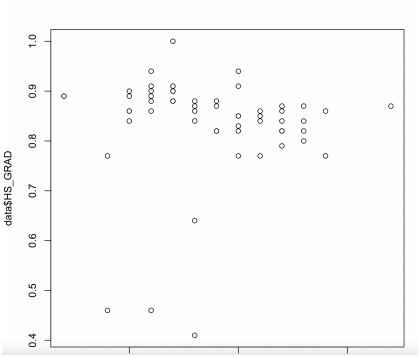
Appendix A4.

Boxplot Results for High School Expulsion



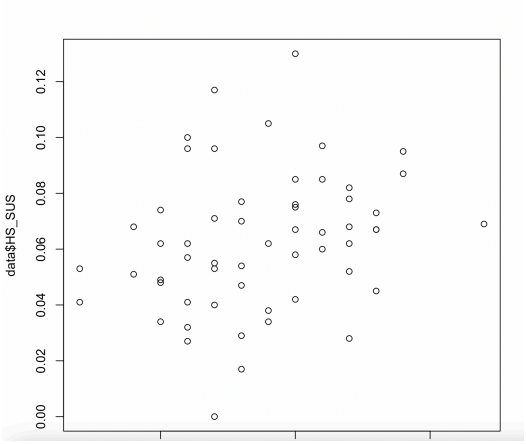
Appendix A5.

Scatterplot Results of ACE Composite and High School Graduation



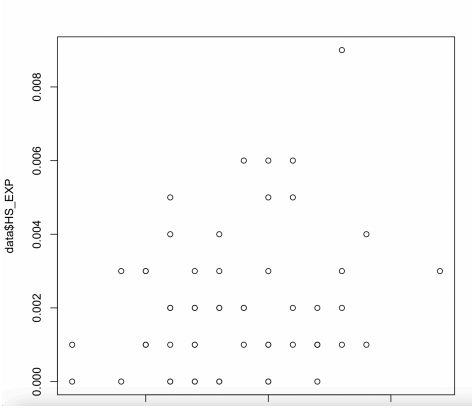
Appendix A6.

Scatterplot Results of ACE Composite and High School Suspension



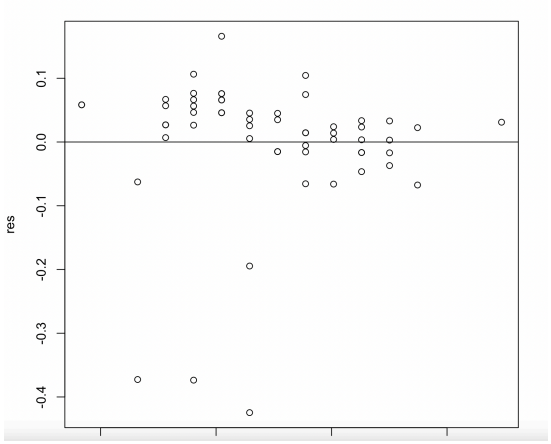
Appendix A7.

Scatterplot Results of ACE Composite and High School Expulsion



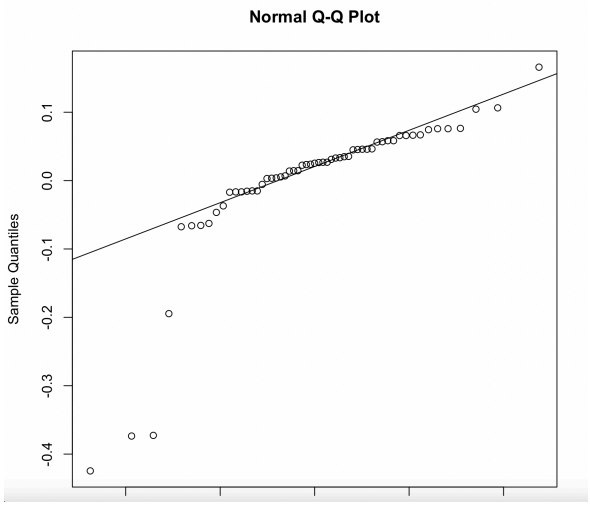
Appendix A8.

Fitted Regression Plot for ACE Composite and High School Graduation



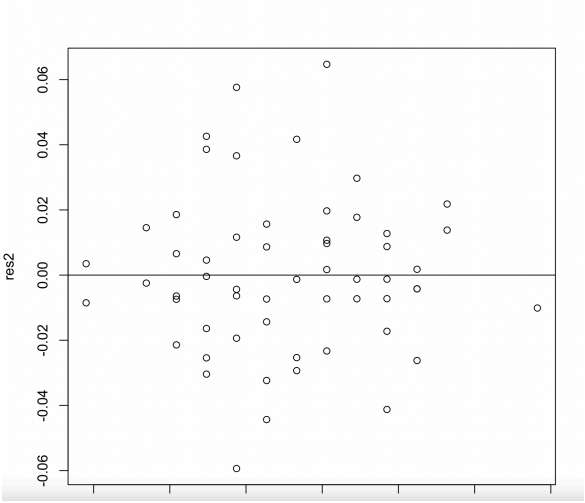
Appendix A9.

QQPlot of Residuals for ACE Composite and High School Graduation



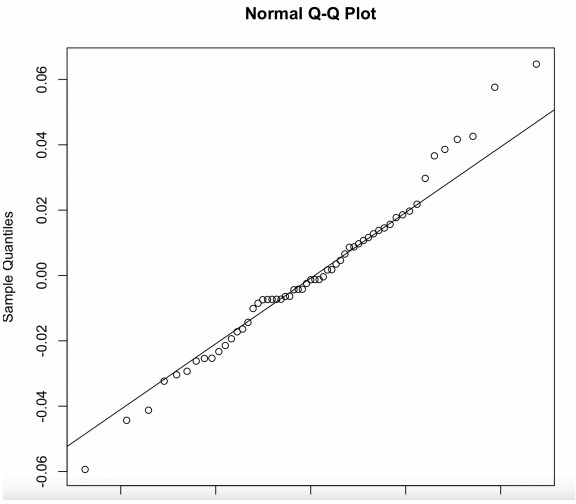
Appendix A10.

Fitted Regression Plot for ACE Composite and High School Suspension



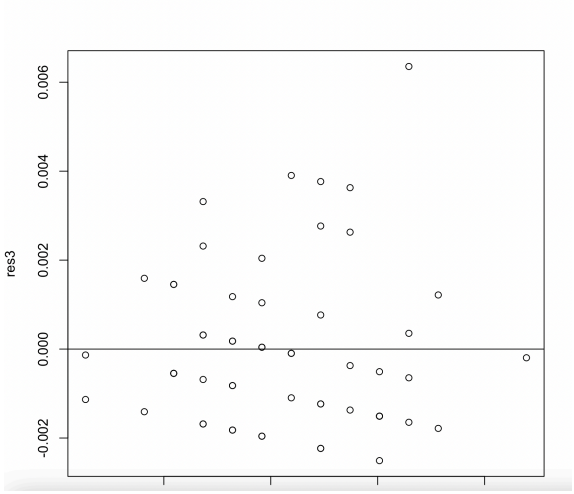
Appendix A11.

QQPlot of Residuals for ACE Composite and High School Suspension



Appendix A12.

Fitted Regression Plot for ACE Composite and High School Expulsion



Appendix A13.

QQPlot of Residuals for ACE Composite and High School Expulsion