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Location, Location, Location: Assessing the Role of Context in Moderating the Relationship Between Childhood Adversity and Mental Health Burden

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Location, Location, Location: Assessing the Role of Context in Moderating the Relationship Between Childhood Adversity and Mental Health Burden

By

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Dissertation

Presented to the Faculty of the School of Public and Population Health of

The University of Texas Medical Branch

In Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas Medical Branch,

November 2023

Dedication

To William, for supporting me through all of my dreams and aspirations.

Acknowledgements

Dr. Peek and Dr. Prochaska, you both have been tremendous mentors to me even before I entered graduate school, and I would not have been able to finish without both your support, guidance, and kindness. I feel very lucky and blessed that I had the honor of being under both of your tutelages, and I couldn't have asked for better mentors during my PhD.

Even before entering the PhD program, Dr. Peek has always provided guidance and support for my career, and I cannot put into words how much her help has meant to me throughout these years (and throughout all the changes in my life).

Dr. Prochaska has always been a ray of sunshine in graduate school (both in his insight and in his ability to be so caring and encouraging). It has been a joy having him as a mentor.

Thank you to my committee for always pushing me to improve and dig deeper. Through all our discussions, I am able to grow so much during my graduate school career. Your comments have always guided me, and I appreciate having you all be part of my committee.

I would also like to thank my friends (Yejin, An, Susan, Rachel, Joy) and my family (Austin/Austina, my mom, and dad) for supporting me.

Location, Location, Location: Assessing the Role of Context in Moderating the Relationship Between Childhood Adversity and Mental Health Burden

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Abstract:

Adverse childhood experiences (ACEs) have profound mental health implications throughout the life course. While literature has focused on individual risk factors for ACEs and their burden on health, there are social and physical environmental contextual factors outside the individual that have been overlooked in studies of childhood adversity. This dissertation sought to understand how environmental context (social and physical environment) moderates the relationship between prior ACE exposure and mental health by using the 2015 Behavioral Risk Factor Surveillance System (BRFSS) and County Health Rankings. By using the BRFSS and the County Health Rankings, this dissertation assessed ACE burden and mental health as well as examined participants' context at the county level. The goals of this dissertation are to: (1) explore how to define context using social and physical contextual variables, (2) evaluate if context can act as an effect modifier in the relationship between childhood adversity on mental health, and (3) assess if there are racial/ethnic differences on how context moderates ACE burden on mental health. The results of this proposal shed light on how certain aspects of context can buffer the burden of ACEs on mental health, and these results can be used as evidence for allocation of funds to help alleviate the ACE burden at the county level.

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List of Abbreviations

ACES	Adverse Childhood Experiences
BRFSS	Behavioral Risk Factor Surveillance System
CCH	Community, Crime, and Health
CDC	Centers for Disease Control and Prevention
CRP	C-Reactive Protein
HPA	Hypothalamic-Pituitary-Adrenal axis
OR	Odds Ratio
SAS	Statistical Analysis Software
SES	Socioeconomic Status
SF-36	36-Item Short Form Health Survey

Chapter 1: Summary

Associated with many top causes of mortality and over half of adults reporting at least one adverse childhood experience (ACE), experiences of childhood adversity are pressing and prevalent issues in the United States (Felitti et al. 1998, Anda et al. 2006). ACEs are experiences of adversity during the formative years of growth and development (from birth to 18 years of age), and accumulation of ACEs has negative physiologic implications and downstream physical and mental health complications (Felitti et al. 1998, Kim et al. 2021, Schilling et al. 2007, Scully et al. 2020). In particular, the mental health complications from ACE burden has been extensively assessed in cross-sectional and longitudinal studies, and these studies provide evidence that adversity in childhood is associated with many mental health issues, like depression and anxiety (Kalmakis & Chandler 2015, Petruccelli et al. 2019). While ACEs are experienced during childhood, they have enduring impacts on the mental well-being in adulthood.

An important social determinant of health is context, which is defined in sociology as environment, circumstances, and settings that determine, specify, or clarify the meaning of an event occurring. Even after controlling for individual attributes, like income and race/ethnicity, the variation and disparities in health cannot be fully explained, and studies have established the importance of context in influencing health outcomes. (Nurius et al. 2013, Diez Rous & Mair 2010). Poor physical context (poor distribution of resources, environmental exposures, and quality of the built environment) and social context (violent crime, low social associations) have been implicated in poor health, especially mental health (Diez Rous & Mair 2010, Kestens et al. 2017, Nurius et al. 2013). In a study using the Community, Crime, and Health (CCH) survey, adults living in neighborhoods with high percentage of households living below the federal poverty line and with a majority of households with female-headed households with children exhibited higher levels of depression than their counterparts in other neighborhoods, even after controlling for race/ethnicity, education, employment, household income, household crowding, and marital status (Ross 2000). Similarly, the same study of CCH data showed that high poverty neighborhoods had higher levels of psychological distress than low poverty neighborhoods even after controlling for a multitude of variables (eg. household income, employment, gender, education) (Ross 2000). Context is an important social determinant to account for and understand when studying health outcomes, and it is a determinant that has yet to be explored within the context of ACEs.

While ACE literature has focused on the association between individual characteristics and downstream health outcomes, little is known how context may influence this relationship. The role of the social and environmental context of where people live, work, and study has been associated with health, and poor contextual determinants are implicated in poor health outcomes (Diez Rous & Mair 2010, Nurius et al. 2013). Exposure to ACEs impairs health, and the environment may either exacerbate these health consequences or buffer them. Based on the Protective Factors Theory, there are resources and assets that serve to moderate the relationship between exposure to ACEs and the poor health outcome, explaining why not every person who experiences childhood adversity may develop health consequences in their adulthood (Zimmerman 2013). While there is evidence of this theory applying to individuals and their access to resources, like having social support moderating the relationship between ACE exposure and health burden (Davis et al. 2019), there is evidence that this theory applies to context, with studies examining sources outside of the individual, like violence and safety in their community, and how these sources moderated the relationship between adversity and health (Liu et al. 2019). The context in which individuals live and interact with others may be a protective factor that moderates their risk for health consequences after childhood adversity.

Using the 2015 Behavioral Risk Factor Surveillance System (BRFSS) in Texas and California and indicators of county contextual quality in the County Health Ranking from 2015, this cross-sectional study will assess the relationship between ACE exposure and adult mental health burden as well as the impact of context on this relationship. The overall objective of this project is to assess how context impacts the relationship between ACEs and mental health. The goals for this project are to:

Aim 1: To construct a context measure using both physical and social attributes.

1a. Using factor analysis, create a contextual factor that will incorporate social and environmental attributes of counties using data from the County Health Ranking data.

1b. Assess the associations between context and mental health as well as context and ACEs.

Aim 2: To examine how context may interact in the relationship between ACEs and mental health

2a. Assess the relationship between ACEs and mental health.

2b. Examine if context moderates the relationship between ACEs and mental health.

Aim 3: To investigate how race/ethnicity identification impacts the role of ACEs and mental health in areas of poor context and areas of good context

3a. Evaluate how the relationship between ACEs and mental health varies by race/ethnicity in areas of poor and good context.

The answers to all three of these specific aims will increase the understanding of the contextual determinants of ACEs and will direct future research into improving important contextual attributes that impact ACE burden on mental health.

This dissertation has 6 total chapters, including this introduction. Chapter 2 introduces the conceptual framework that underpins the specific aims of this dissertation, and it introduces the definitions and literature surrounding childhood adversity, context, race, and mental health. Chapter 3 is the article addressing specific aim 1, and this article evaluated multiple context measures, including physical, social, and environmental aspects of context. Chapter 4 is the article that answered specific aim 2, which verified the relationship between ACE burden and mental health burden in our sample while also evaluating if context moderates the relationship between ACEs and mental health. The last specific aim was addressed in Chapter 5, and this aim answered if there is moderation by racial/ethnic group and essentially if there are differences in how context moderates ACEs and mental health by racial/ethnic group. The last chapter sums up the findings from all three specific aims and addresses limitations and future directions.

Chapter 2: Adverse Childhood Experiences, Context, and Health Burden

This chapter will begin by discussing the conceptual frameworks and theories that underpin the hypotheses created in this dissertation. By discussing the conceptual framework first, this chapter provides a guide into the discussion of the literature surrounding each component of the model and how this dissertation fills a hole in the literature on childhood adversity.

Conceptual Framework

Based on Urie Bronfenbrenner's systems theory, the environment is a vital component in influencing health and behavior (Bronfenbrenner 1979). This theory describes 5 main levels that interplay to influence health: the microsystem (which refers to the interactions between the child, like between the child and the parent or the child and their teachers), the mesosystem (which refers to the interactions between microsystems in the child's life, such as an interaction between the parents and the teacher), the exosystem (which refers to social structures, which may indirectly influence the microsystem that the child is in, such as the neighborhood), the macrosystem (which refers to the larger cultural and political environment that individuals are in), and the chronosystem (which refers to changes in the environment throughout the life course) (Bronfenbrenner 1979). Bronfenbrenner's system theory underpins the theoretical framework of this study.

The application of Bronfenbrenner's systems theory can be conceptualized using the Protective Factors theory from the *Resiliency Theory*

(Zimmerman 2013). The Protective Factors Theory states that there are variables that can moderate the relationship between adversity and poor health (Zimmerman 2013). Studies have applied the protective factors theory to show that healthy environments and positive relationships moderated the impact of exposure risk and poor health outcomes, and these findings elucidate the impact of larger systems from Bronfenbrenner's theory as moderating the relationship between the individual and their health outcomes (Liu et al. 2019, Davis et al. 2019).

The focus of mitigating ACE burden on health has largely been on resilience (Poole, Dobson, & Pusch, 2017, Morgan et al. 2022). Resilience is the individual's ability to process and adapt in response to difficult experiences (Poole, Dobson, & Pusch 2017). The Protective Factors theory from *the Resiliency Theory* is a conceptual framework that helps conceptualize how not all those who are exposed to childhood adversity have negative consequences in adulthood (Zimmerman 2013). In this theory, there are promotive factors, which are contextual, social, and individual factors that act in opposition to risk to help children build resilience (Zimmerman 2013). The Protective Factors model theorizes that assets and resources moderate the relationship between adversity and health outcomes as seen in Figure 1 (Zimmerman 2013). An example of this model is in a study of adolescents that showed those with high protection (safety, community resources, family and school resources) and high adversity had much lower health conditions and higher adult-rated health than those with low protection and high adversity (Liu et al. 2019). Similarly, a study comparing middle schoolers with family conflict and community violence showed that there was an interaction with social support and parental monitoring separately on family conflict in its impact on teen dating violence (Davis et al. 2019). In a study of over 4000 patients in Calgary, resilience (as defined by the 10 item Connor-Davidson-Resilience Scale, CDRISC, which is a self-reported measure of negative affect, ability to focus under pressure, and approach to solving problems) significantly moderated the relationship between ACE exposure and depressive symptoms in adulthood (Poole, Dobson & Pusch 2017).

While much of the adverse childhood experience (ACE) literature has been focused on examining the child and the household, the contribution of the systems surrounding these units has been understudied. Bronfenbrenner's theory postulates that both proximal and distal systems shape child development and outcomes. From the Protective Factors model, promotive resources help to modify the relationship between the exposure and outcome, and studies have shown individual level and community level protective factors do interact with adversity to affect health outcomes in adolescents (Davis et al. 2019, Liu et al, 2019). The Pair of ACEs tree is a framework that was developed to illustrate the relationship between family adversity and community adversity, and it helps visualize how the community's health may impact the health of the individuals residing in it. The leaves of the tree represent the symptoms of ACEs, and the tree itself is planted in poor soil that are deficient in proper nutrients (eg. systemic discrimination, limited access to affordable housing) for the tree to properly flourish. This framework is used to conceptualize how a systems approach is needed to address childhood adversity. While ACEs impact health on an individual level, not every individual with ACE exposure will surely have health consequences; the Pair of ACEs framework conceptualizes that the quality of the context (the soil that the tree is planted in) may moderate the relationship between ACEs and health.

In addition to understanding the protective physical and social contextual factors in ACEs and mental health, there may be state differences in mental health burden. Given the differences in ACE exposure by state and by region in the United States (Sacks & Murphy 2018) as well as the socioeconomic, environmental, and political differences in state legislation, it is important to understand how to best intervene and reduce ACE burden. While combining the states helps to boost statistical power and generalizability to the United States, the application of findings of the sample ignores the state differences at play.

Using the Protective Factors theory as a model to generate testable hypotheses, this dissertation conceptualizes the models outlined in Figure 2. The first aim (1 in Figure 2) explored context and the many variables that can be used to define context, and data reduction techniques were used to assess these variables and to inform how to define context in the future aims. The role of context as a moderator (protective factor) between mental health and childhood adversity was tested in the second aim (2b in Figure 2), and the potential race and ethnic differences in how context moderates childhood adversity and health were evaluated using a three-way interaction (3 in Figure 2).

Figure 1.1. The Protective Factors model from the Resiliency Theory. *Figure reproduced with permission from Zimmerman.*

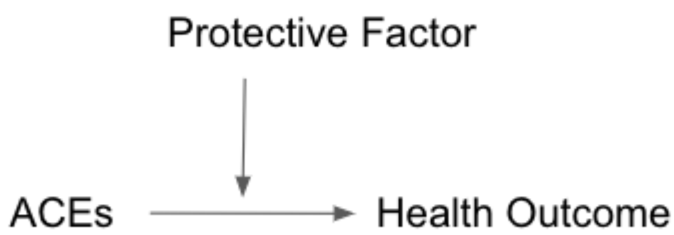
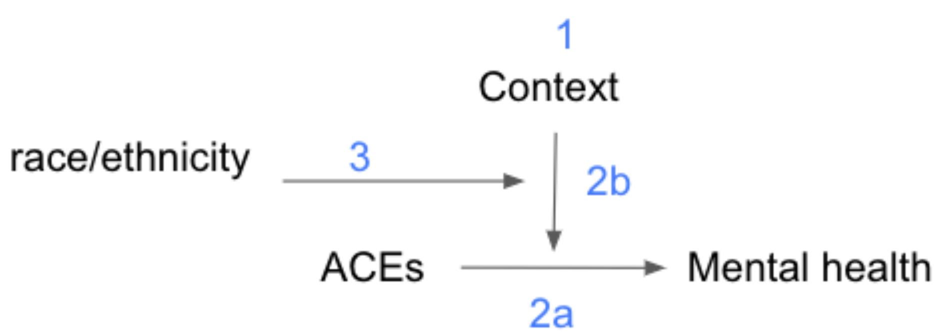


Figure 1.2. The models and hypotheses that were tested in this dissertation using the concepts and theories from Bronfenbrenner and the Protective Factors theory.



Based on the conceptual models and testable hypotheses outlined in this section, the rest of this chapter will go through each component of the model (Figure 2) and expand on the literature surrounding it.

Adverse Childhood Experiences

Adverse childhood experiences (ACEs), like neglect and maltreatment, have profound implications in health (Felitti et al. 1998, Anda et al. 2006). With over half of adults reporting at least one ACE and almost 1 out of 6 reporting 4 or more ACEs, adversity in childhood is a prevalent problem in the United States (Anda et al. 2006). ACEs have been linked to many of the top causes of mortality, including cardiovascular disease, respiratory issues, cancer, and psychological distress (Felitti et al. 1998). In particular, ACEs have been linked to mental health throughout the entire life course (Kim et al. 2021, Schilling et al. 2007, Scully et al. 2020). From childhood to later life, both cross-sectional and longitudinal studies have shown adversity in childhood is associated with mental health implications, like depression and anxiety (Kalmakis & Chandler 2015, Petruccelli et al. 2019).

While current physical (eg. air pollution) and social (eg. community relationships) contexts impact health, the role of context in childhood adversity remains understudied (Nurius et al. 2013). The purpose of this project is to understand how context may impact the relationship between ACEs and poor mental health. While the relationship between ACEs and poor mental health appears to be well-established within literature, the role of context in moderating this relationship has not been well explored. Moderation of ACEs and health have focused on resilience, but contextual factors have yet to be understood within this model.

Childhood Adversity/ACEs and Health

According to the Center for Disease Control and Prevention (CDC), ACEs are distressing experiences that occur during childhood (0-17 years old). Child maltreatment is a concept of abuse and neglect of a child; the most common four types of abuse are: physical abuse, sexual abuse, emotional abuse, and neglect. While childhood adversity and childhood maltreatment appear to be synonymous concepts, childhood adversity is not limited to maltreatment; the trauma encompassed by childhood adversity is much broader than childhood maltreatment (Felitti et al. 1998). These events included in the ACE list “are aspects of the child’s environment that can undermine their sense of safety, stability, and bonding” (CDC). The 10 ACEs are: physical abuse, sexual abuse, emotional abuse, substance abuse in the household, witnessing domestic violence, physical neglect, household member suffered mental health issues, loss of a parent, emotional neglect, and household incarceration (Felitti et al. 1998).

The formative study of childhood adversity and health was the CDC’s The Adverse Childhood Experiences (ACE) Study in 1998. This retrospective study asked over 17,000 insured adults in San Diego about their childhood experiences. These experiences could be categorized into seven categories: sexual abuse, physical abuse, psychological abuse, household substance abuse, household mental illness, witnessing domestic violence, and household criminal behavior (Felitti et al. 1998). While this study showed the prevalence of these experiences in the sample (52% reported having one of the categories), a key finding of this study was the dose-response relationship between the number of ACEs reported and poor health. (Felitti et al. 1998) Those with 4 or more ACEs had 4-to-12-fold increased risk for drug abuse, depression, and suicide attempts compared to those who experienced no ACEs (Felitti et al. 1998). A number of poor health outcomes were linked to ACE exposure, including liver disease, heart disease, and cancer (Felitti et al. 1998).

Both physical and mental health implications can arise in adulthood from exposure to childhood adversity. Since the ACE Study, the literature surrounding childhood adversity and health has grown. Studies have ranged from retrospective cross-sectional studies in adulthood to longitudinal studies in childhood, demonstrating the influential role of ACEs on health**.** The majority of literature on ACEs are retrospective studies, and these studies ask respondents to reflect on past childhood adversity and correlate these previous experiences to their health at interview. In a systematic review of 42 retrospective studies, ACEs have been associated with many physical health conditions, including cardiovascular disease, lung disease, autoimmune disease, and obesity, and mental health, including anxiety, depression, posttraumatic stress disorder and substance abuse (Kalmakis & Chandler 2015). In a more recent literature review of 96 articles on ACE exposure and adult health outcomes, a number of psychosocial and behavioral problems were associated with ACE exposure (Petruccelli et al. 2019). Of the 96, four studies revealed that the odds of psychological distress (defined using the Mental Component Summary score from the SF-36) is nearly twice as likely with just one ACE reported than the odds of those without any ACEs (Petruccelli et al. 2019).

Studying children has shed light on how childhood adversity can result in early signs of poor health. Both behavioral issues and below average academic performance were associated with ACE exposure in a cohort of over 1000 kindergarten children from the Fragile Families and Child Wellbeing Study (Jimenez et al. 2016). Children with ACEs were up to 1.5 times more likely to develop behavioral issues and poor academic reports than children without any ACEs (Jimenez et al. 2016). Along with psychosocial and behavioral issues, a systematic review found that both cross-sectional studies and longitudinal studies of children have shown that ACE exposure increases the risk of developing childhood obesity (Schroeder et al. 2021). In a cohort of 4-year-old children from the Longitudinal Studies of Child Abuse and Neglect, children who reported at least one ACE at age 4 were nearly twice as likely to report poor overall health (OR=1.89) or to report an illness requiring professional care (OR=1.79) at age 6 than children who reported no ACE exposure at age 4 (Flaherty et al. 2006). In addition, the same study showed that children with 4 or more ACEs were 4 times more likely to develop a serious illness within 2 years than those without any exposure to ACEs (Flaherty et al. 2006).

ACEs have profound implications on health throughout the life course. Since the ACE study, studies have elucidated the downstream physical and mental health after exposure to ACEs. Studies of adult health and child health have shed light on how detrimental exposure to childhood adversity is, and further studies have linked the biologic and pathologic mechanisms of ACEs on health, especially mental health.

Physiological Mechanism of ACEs on Health

Adversity is a psychosocial stressor, and stress is a risk factor for many mental health conditions, like depression and anxiety, as well as poor health behaviors, like substance abuse (Jones et al. 2018). Impacting the machinery and interplay between biologic systems, stress has deleterious effects on development and health (McEwen 2000). Exposure to stress activates the hypothalamic-pituitary-adrenal (HPA) axis and sympathetic nervous system, and this concerted biologic cascade can be dysregulated by continuous exposure to stress (McEwen 2000). The recurrence of stressful conditions, like experiences of childhood adversity, disrupts the coordinated biologic systems and causes weathering of the body (McEwen 2000). This process of biological wear and tear catalyzed by stress is called allostatic load, and allostatic load is a key concept in the mechanism between adversity and health (McEwen 2000). The continual expending of energy to match the demands of the stressed neuroendocrine and autonomic nervous system leads to deterioration and dysregulation of these systems (McEwen 2000). Deterioration and dysregulation of the body's systems through stress are implicated in downstream physical and mental health outcomes.

A biologic system susceptible to wear and tear is the immunologic system. Retrospective analyses exploring the association between inflammatory biomarkers and childhood adversity show that there is elevation of IL-6 and C-reactive protein (CRP) for those exposed to adversity in childhood, and these analyses of inflammatory biomarkers indicate their involvement in mediating the relationship between adversity and health (Steptoe et al. 2007). In a cohort of adolescent girls, increases in early life adversity scores consistently were associated with greater odds of having hyperactive pro-inflammatory immune cells, which is indicative of chronic basal inflammation and risk for long-term health consequences (Ehrlich et al. 2017). In a longitudinal study of children, IL-6 and IL-1B were inflammatory markers associated with exposure to a specific ACE (Heard-Garris et al. 2020). The negative consequences of ACEs on the inflammatory system are also evident after childhood. In a retrospective study of adults over the age of 50, exposure to ACEs resulted in higher signs of depressive symptoms compared to those without ACE exposure, and this relationship between ACEs and depression was partially mediated by elevated C-reactive protein, an inflammatory marker (Iob et al. 2020).

Exposure to ACEs not only has immunological consequences but it also has neurodevelopmental implications. As a central component in the regulation of behavioral and physiologic stimuli, the brain is vital, and any morphological and circuitry changes can have dire consequences. Because of the brain's sensitivity to the environment during childhood, early adversity has deleterious consequences to the neurocircuitry of the brain. Neuroplasticity is a vital component of neurodevelopment as it is the process in which neural connections are strengthened or weakened. Signaling from the environment, like the response of a caregiver and the caregiver's cognitive, emotional, and social input, is necessary for normal brain development through altering gene expression patterns that allow for functional and structural development as well as the winnowing away of neural connections that are not used and strengthening the connections that are in use, and lack of vital stimuli results in stunting of higher-order cognitive and emotional function as well as changes the circuitry of the brain (Bick & Nelson, 2016).

While ACEs themselves act as stressors, ACEs also sensitize the body to react to stress (Bandoli et al., 2017). The amygdala is a part of the brain that is responsible for initial responses to stimuli, and it coordinates with the autonomic nervous system and the HPA axis to stimulate inflammation (Miller et al. 2011). Along with the rest of the nervous system, the amygdala is undergoing neuroplasticity during childhood, and it is vulnerable to changes in its long-term function and structure (Miller at al. 2011). When observing the amygdala using fMRI, college students with early adversity had greater reactivity when matching faces to emotions, especially faces of anger, than participants without adversity, even after controlling for current SES, distress, and neuroticism (Gianaros et al. 2008). Exposure to early adversity leads to heightened amygdala activity and reactivity to threatening stimuli (Sheffer et al. 2020). Sensitization to stress further triggers psychopathology (Wade et al. 2019). Evidence of stress sensitization in response to early childhood adversity is well observed in the literature (Bandoli et al. 2017, Hammen 1991, Wade et al. 2019).

ACEs have structural and biological implications on neurodevelopment. Structurally, children of maltreatment tend to have lower volumes of both gray and white matter of several areas of the brain compared to that of children without exposure, signifying morphological changes to the brain that may impair proper development (De Brito et al. 2013). Differences in neurochemistry and neurobiology extend past morphology; developmental issues negatively affect cognitive functioning and educational achievement for those exposed to ACEs compared to those without exposure (Bick & Nelson 2016). The structural and functional integrity of the brain is dependent on proper development during childhood, and exposure to ACEs impedes proper neurobiological development and increases risk for psychological disease (Bick & Nelson 2016).

During the formative years of development, ACEs pose a physiologic threat to normal childhood development. Through impairing the neuroendocrine system and disrupting proper neurological structure and function, exposure to ACEs increases the risk of developing psychosocial disease.

The Distribution of ACEs

While ACEs impact across all levels of socioeconomic and racial/ethnic classifications, childhood adversity is not equally distributed across these groups (Nurius et al. 2012). In the BRFSS from 2011-2014, those who identified as non-Hispanic Black, Hispanic, or multiracial had significantly higher ACE exposures than those identifying as non-Hispanic White (Merrick et al. 2018). In the same sample, exposure to ACEs decreased as income increased (Merrick et al. 2018). Other studies have observed how low household income as well as self-identified racial and ethnic minorities (non-Hispanic Black or Hispanic identification) are associated with higher rates of adversity compared to their respective counterparts (Hafton et al. 2017, Slopen et al. 2016).

Socioeconomic status and racial and ethnic identification are key individual/household attributes that are associated with ACE exposure, and these attributes influence mental health outcomes. A longitudinal study of 34,653 adults observed that incident mental disorders were associated with lower levels of income even after controlling for potential confounders (eg. marital status, past mental health history) (Sareen et al. 2011). While lifetime diagnoses of mental health disorders appear lower in racial and ethnic minority populations than white populations, measures of psychological distress and stress are higher in racial and ethnic minority populations; and when minority populations do experience psychiatric morbidity, these disorders are more likely to be persistent (Breslau et al. 2005, Williams 2018). In a study of the 2012 BRFSS, race/ethnic identification was associated with increased risk of psychological distress and a medical comorbidity (angina, heart attack, and coronary heart disease) (Ahmed & Conway 2020). Disparities in ACE exposure have downstream consequences on health disparities.

Race and Health

Psychosocial stress and disease are not equally distributed across the United States, and a major disparity in psychosocial burden is by race/ethnicity. While the concept of race itself is not a genetic categorization of people, racial categories reveal health disparities in mortality as well as prevalence of health issues (Williams 1997). Non-Hispanic Black people in the United States have higher rates of mortality and chronic conditions (like diabetes and hypertension) than their non-Hispanic white counterparts, but non-Hispanic black people are underutilizing health care systems (Dickman, Gaffney, and McGregor 2022, Williams 1997). In a study assessing trends of health care utilization from 1963-2019, racial inequities in health care have persisted for over 6 decades even after major policy changes, like the Affordable Care Act (Dickman, Gaffney, and McGregor 2022). When discussing race and its implications on health, it is imperative to understand racism.

Racism itself is a psychosocial stressor that has its own implications in physical and mental health, and it is a lifelong experience that is unique to the minorities (Williams et al. 1997). Through acting as a negative and chronic stressor, racism and its results in can accelerate the process of cellular aging, induce biological wear and tear, have adverse effects on allostatic load (which refers to the ability of the body to biologically respond appropriately), and subsequently increase vulnerability to disease and infection (Anderson 2013). Racism also may play a role in stimulating unhealthy coping mechanisms, like substance abuse and overeating to help alleviate the symptoms of stress (Anderson 2013).

In the context of childhood adversity, minorities report having ACEs more frequently than their non-Hispanic white counterparts (Merrick et al. 2018). The unequal distribution of ACEs across racial/ethnic groups reflects racial disparities in health.

Context and Health

Context is defined in sociology as the environment, circumstances, and settings that determine, specify, or clarify the meaning of an event occurring. The contextual factors may be divided by the physical contexts (eg. the built environment, the air quality) and the social contexts (eg. the community, the social connections). Both physical context and the social context have important implications on health, especially mental health. While understanding individual risks to disease is important, the context in which disease occurs (eg. in neighborhoods and communities) is vital to recognize how health and disease are unequally distributed (Diez Roux & Mair 2010). The traditional individual level factors used in public health studies, like individual SES, only accounts for a portion of the gradient of health outcomes, and the context in which people live and interact is another determinant of health that explains more of the variation in health (Kestens et al. 2017). Essentially, the place in which one lives, builds social ties in, and works in has implications on their health.

Inequalities in the physical (distribution of resources, environmental exposures, and service) and social (safety, violence, institutions) contexts impact the role of stress on health. Generally, those living in poor socioeconomically disadvantaged neighborhoods are associated with adverse health outcomes, including poor self-rated health, higher prevalence of chronic disease risk factors, and greater incidence of chronic disease, even after accounting for household income (Diez Roux & Mair 2010). In a longitudinal study spanning 38 years, residence in low-income neighborhoods was significantly associated with self-rated adult health compared to non-low-income neighborhoods (Johnson et al. 2012). Independent of individual self-reported poverty, neighborhood disadvantage is significantly associated with greater allostatic load, and the long-term implications of this relationship result in downstream rates of cardiovascular disease, metabolic syndrome, depression, and risk behaviors (smoking, alcohol use, risky or early sex) (Jutte et al. 2015).

Context, even after controlling for individual factors, has profound implications on mental health outcomes (depression, anxiety, psychological distress) (Hill & Maimon 2013). Residents of neighborhoods with low social organization and disadvantage (low SES) tend to report more depressive symptoms than those who live in advantaged neighborhoods (Hill & Maimon 2013). In a study using the Community, Crime, and Health (CCH) survey, adults living in neighborhoods with high percentage of households living below the federal poverty line and with a majority of households with female-headed households with children exhibited higher levels of depression than their counterparts in other neighborhoods, even after controlling for race/ethnicity, education, employment, household income, household crowding, and marital status (Ross 2000). Similarly, the same study of CCH data showed that high poverty neighborhoods had higher levels of psychological distress than low poverty neighborhoods even after controlling for a multitude of variables (eg. household income, employment, gender, education) (Ross 2000).

Most of the literature about place and health has been focused on the neighborhood unit as the place. Neighborhoods can be defined by particular boundaries, either established informally by landmarks or its residents, or formally by classifications like census tracts (Hill & Maimon 2013). While the majority of literature is looking at the neighborhood-level of place, there are clear distinctions when comparing and contrasting counties (eg. Lieu & Peng 2018, O'Brien et al. 2020). Similar to aggregating attributes of individual data to understand the demographic attributes of the neighborhood, counties may be defined based on the residents' demographic composition (eg. median income of the county, race and ethnic composition of the county) (Hill & Maimon 2013). Social organization of the county may be defined by the social organizations and social ties residents have, which is similar to measures of neighborhood social organization (Hill & Maimon 2013). These two units of location have similar ways to measure their contextual attributes; however, they vary greatly on the level of location and the application of policy. Counties are areas within the states of the United States, and while the areas of the counties vary between states (eg. Texas has 243 counties while California, only 1.7 times smaller than Texas, has 58 counties), they all represent administrative bodies within the federal, state, and local governments in the United States. From a public health standpoint, policies may be enacted to intervene at the county-level, and providing evidence of county-level differences influences the interventions and policy to improve communities and health.

In addition, on the state level, there are disparities in ACE exposure. Using data from the National Survey of Children's Health (NSCH) from 2016, exposure to ACEs was accessed at the state level, and there were significant differences in

ACE count as well as types of ACEs that children were exposed to by state (Sacks & Murphy 2018). When assessing the racial/ethnic distributions of children exposed to ACEs, there were clear distinctions between regions in the United States in which racial and ethnic minority groups were most burdened with ACEs than their white counterparts (Sacks & Murphy 2018). Besides the Pacific region (California, Hawaii, Alaska, Oregon, and Washington), non-Hispanic Black children were more likely than non-Hispanic White to have been exposed to at least one ACE (Sacks & Murphy 2018). Given the disparities of mortality and life expectancy across the states, it is not surprising that there are differences in ACE distribution, and subsequently health disparities (Farina et al. 2021).

Literature surrounding ACEs have largely centered on individual and household risk factors for ACE exposure, but from what we know about the role of context in impacting health, expanding our perspective is needed. Bronfenbrenner coined the bioecological theory of development, and this theoretical perspective posits “that human development is a transactional process in which an individual's development is influenced by his or her interactions with various aspects and spheres of their environment” (Patel 2011). Interplay between the individual, the microsystem (family, school, peers), the mesosystem (kinship and informal networks), the exosystem (neighborhood community, social services, legal services), the macrosystem (cultural attitudes, ideologies, policies), and the chronosystem (changes over time) are all vital components in impacting a child’s development. From this framework, we can understand that development is not just centered on the individual or even the household but beyond these microenvironments. In a longitudinal study of over 3800 Australian adolescents, ecological factors (neighborhood advantage, neighborhood livability, neighborhood safety, and school connection) were associated with developing emotional, social, and academic difficulties (Rowe et al. 2016). While the authors mention that the associations were weaker compared to their observed associations between more proximal factors (eg. family environment) and adolescent emotional, social, and academic difficulties, they note that disparities in neighborhoods are not as evident in Australia as they are in the United States (Rowe et al. 2016).

In addition, the focus on the individual and its household unit places the onus of burden away from the social conditions and structural factors the families are in, and instead the onus is on the families and children (Kelly-Irving & Delpierre 2019). Instead, the focus of research can be shifted to understand the environments that ACEs occur in and the contexts in which coping of exposed children and families are in. As Bruner (2017) eloquently states, “Place matters most for very young children—first in the safety and security of their home environment and then their immediate environment.” The contextual features of the environment in which exposure and development occurs is paramount.

The Physical Context - The Addition of the Environmental Burden

One contextual aspect that is important and understudied is environmental burden. Environmental burden is the negative impact of activities on environmental pollution or toxicity, and this burden is entrenched in environmental justice communities. An environmental justice community is an area that is overburdened by environmental exposure risk and is vulnerable to the impacts of environmental risk (US Environmental Protection Agency). The communities that are overburdened by these environmental pollutants and toxicities are typically composed of low SES and ethnic minority residents, and these residents are exposed to a number of toxicants and subsequently a number of health complications, including cardiovascular disease, respiratory disease, and mental health issues (Massey 2004). Environmental burden leads to poor health outcomes, and it disproportionately impacts racial and ethnic minority populations.

While environmental burden is linked to many physical and mental health complications, the use of environmental factors in modeling context is underutilized. In a study of over 4,000 residents in Philadelphia, the presence of hazardous waste facilities enhanced the association between stress and health (Matthews & Yang 2010). This study observed the moderating role of the built environment based on the presence of facilities with hazardous waste, but this study does not explore the role of the pollutants themselves on health. Outside the definition of the built environment, pollutants and other environmental factors serve to impact health. For example, food insecurity was significantly associated with increased odds of depressive symptoms in a study of participants from the 2005-2014 National Health and Nutrition Examination Survey (Brooks et al. 2019). In addition, several studies on air pollution, using particulate matter data, observe a positive association with particulate matter and depressive symptoms in participants from the UK and China (Bakolis et al. 2021, Chen et al. 2018). Similarly in a systematic review of seventeen studies around the globe, pollution was associated with mental health conditions, like depression, generalized anxiety, and psychosis, in adolescents (Theron et al. 2022). Evidence of environmental factors impacting mental health have been published, and incorporating environmental variables describes another aspect of context that may not be captured just by assessing the traditional definitions of the built and social environments. In addition to incorporating physical and social aspects of context in this study, it will also incorporate the environmental aspects of context that are not traditionally included in studies on context.

Overview

While the ACEs literature surrounding the exosystem or the macrosystem has been limited, evidence of these contexts exacerbating ACE burden has emerged in the past few years. In a cross-sectional study of over 500 adults in Chicago, exposure to childhood adversity only resulted in elevated cumulative biological risk (a measure incorporating biomarkers of health, like systolic blood pressure and CRP) in neighborhoods with low affluence, even after controlling for individual income (Slopen et al. 2014). Disproportionately, those of low SES and with limited access to social and health resources are exposed to ACEs during childhood, but those exposed to adversity are the most burdened and most isolated from necessary resources (Nurius et al. 2016). Individually and collectively, race and ethnicity, poverty, resource access, and community factors serve to impact health outcomes (Nurius et al. 2016). Context itself may be both the environment in which exposure to ACEs occurs and the environment where ACEs' poor influences on health can thrive.

While the focus on ACEs and their burden on mental health has been on individual characteristics, the literature surrounding how social and physical context is associated with health sheds light on the need to expand our perspective to the larger systems that impact health burden.

General Methods

For this study, the Texas BRFSS and California BRFSS in 2015 are the data sources, and the County Health Rankings data in 2015 for each of these states were also obtained to merge county context measures with the BRFSS datasets by county-level residence of the participants. There were 14,697 participants and 12,601 participants from the Texas and California BRFSS datasets respectively, and after excluding participants without complete demographic data as well as those who refused to answer questions about depression, mental health days, or ACE exposure, 7,477 and 3,105 participants from the Texas and California were eligible for the study sample. The ACE module is an optional module in the BRFSS that was used to assess exposure to childhood adversity, and the module is offered to participants and uses the phrasing "Please keep in mind that you can ask me to skip any question you do not want to answer" (BRFSS 2015). After exclusion of incomplete ACE data in the BRFSS, over 75% of the Texas sample and 30% of the California sample were retained, and while the number excluded may be a limitation of the study sample, there are a number of studies that have published the impact of ACEs on health (Campbell, Walker, & Egede 2016, Crouch et al. 2018, Crouch et al. 2020, Waehrer et al. 2020).

Context will be defined by multiple contextual variables (social and physical context measures) at the county-level based on previous literature from data in the 2015 County Health Rankings in California and Texas, and data reduction techniques (principal component analysis and factor analysis) will be used to simplify and understand the data structure of these context variables at the county-level.

The BRFSS data includes measures on adverse childhood experiences through their optional ACE module as well as demographic factors (age, sex, race, income). There are two measures of mental health that will be utilized for this study: mental distress and depression diagnosis. By merging the BRFSS data and the County Health Rankings data by county, each participant eligible for the study can be assessed by the county that they reside in as well as their individual-level measures. Multivariable analyses will be conducted to understand effects of each variable, and interaction terms will be assessed as well to assess significant moderation. In all, this study can study the influence of individual-level factors on mental health burden as well as the influence of county-level measures.

Software

Statistical Analysis Software (SAS) 9.4 (SAS Inc, Cary, NC) was utilized for all data management and statistical analysis for this study. Descriptive statistics were generated using proc means and proc freq. Principal component analysis and factor analysis were conducted using proc factor. Proc logistic was used to conduct multivariable analyses for aims 2 and 3.

SAS code for all three aims may be made available upon request.

Chapter 2: Reduction of Social and Physical Context at the County Level

Aim 1: What is Context? Reduction of Social and Physical Context at the County-Level in California and Texas using County Health Rankings Data

ABSTRACT

Background: Context is an important social determinant of health, but it is understudied within adverse childhood experience literature. The goal of this study was to use multiple measures that approximate context (social, physical, and environmental) and use data reduction to evaluate a statistical index to evaluate context in future studies.

Methods: Data reduction using principal component analysis and factor analysis were utilized using data from the County Health Rankings in 2015 for counties in California and Texas (n=311). County-level measures of social and physical context were extracted and used to understand the innate structure of the data for both states' counties, Texas counties, and California counties. High data loadings were defined by values greater than 0.7 to extract significant variables, and Cronbach's alpha were used to understand the internal consistency of the constructed indices from the data reduction techniques.

Results: There were no significant indices that emerged from the data reduction techniques, as many factors that resulted had either low internal consistency (Cronbach's alpha <0.6) or had only two variables loading on the factors. There were state-level differences in factors emerging from the analyses, but the results

from all samples from the analyses show that there are no significant factors to condense the social and physical context measures.

Conclusion: Reduction of context into simple factors did not yield statistically significant results, and these results suggest the complexity of context on health. While it may be statistically advantageous to reduce these variables, each context variable may be influencing mental health burden in different ways, and therefore, each variable should be assessed as independent variables when assessing the role of context on health.

Background

The context in which people live, work, and make social connections has an impact on health (eg. Diez Roux & Mair 2010, Kestens et al. 2017). Context is important and can be broken down into the physical context, like the resources and opportunities available in the community, and the social context, like the social ties and interactions in the community (Diez Roux & Mair 2010). Disadvantaged contexts, which are typically defined using measures of poverty, deprivation, crime, and racial/ethnic minority composition, are associated with negative effects on mental health, specifically depression, anxiety, and mental distress, even after accounting for individual attributes (Hill & Maimon 2013, Ncube et al. 2016).

Within literature on burdened contexts, many studies have focused on assessing the built/physical context and social context. For example, Ncube et al.

conducted a meta analysis on neighborhood disadvantage, which included 21 studies with varying definitions of disadvantage using poverty, racial/ethnic differences, and crime (2016). While the neighborhood disadvantage index (NDI) is well-established measure of contextual disadvantage, it only uses the percentage of households below the poverty line, percentage of female-headed households, prevalence of homeownership, and percentage of adults (24 years or older) with college degrees to calculate disadvantage (with an alpha reliability of 0.78) (Li et al. 2019, Ross & Mirowsky 2001). Another measure of place-level disadvantage is area-level deprivation, which is based off of a British index of deprivation and uses factors like unemployment rate, percent non-white, and household crowding to calculate a deprivation index (Eibner & Sturm 2006). While these measures serve to evaluate components of context, the emerging consequences of environmental pollutants and toxicity and the implicit tie of these exposures to residential location have not been included in traditional definitions of context (Eibner & Sturm 2006, Ross & Mirowsky 2001). As studies show the negative associations between air pollution and water violations on physical and mental health (Bakolis et al. 2021, Chen et al. 2018), it is imperative to understand how these variables are correlated with the standard variables of contextual disadvantage. Residents of areas with poor environmental regulation as well as toxic exposures tend to also be disadvantaged at the socioeconomic level (Evans & Kantrowitz 2002, Hajat et al. 2013). This study seeks to assess multiple variables of traditional physical and social contexts as well as the environmental aspect of context.

Childhood Adversity and Health

Context also has not been an area of focus within literature on childhood adversity. Adverse childhood experiences (ACEs) are traumatic experiences that occur during childhood (0-17 years of age) but have enduring impacts on mental health throughout the life course (Felitti et al. 1998). With 1 out of every 6 people in the United States reporting four or more ACEs and the many publications citing the negative implications of ACEs on health (Anda et al. 2006), understanding how to mitigate the burden of ACEs is vital. The resiliency theory is a conceptual framework to frame how risk exposure does not manifest in consequences in every exposed individual (Zimmerman 2013). Promotive factors are positive contextual and social variables that oppose the negative impacts of child adversity, and the protective factors theory, which is within the resiliency theory, postulates the moderating relationship of the protective factor in the impact of adversity on health outcomes (Zimmerman 2013).

While the protective factors theory is studied, research has focused mainly on the individual and the individual's household to understand what moderates the relationship between ACE exposure and health outcomes. In a study using Behavioral Risk Factor Surveillance System (BRFSS) data in South Carolina, there was a 30% reduction in frequent mental distress if a participant reported having a safe, stable, and nurturing relationship (SSNR) during their childhood compared to those without a SSNR (Crouch et al. 2019). In addition, studies have observed the contribution of individual and community level protective factors (eg. community resources, neighborhood safety, neighborhood livability) in moderating the relationship between childhood adversity and adolescent health outcomes, like teen violence in dating and adult-reported health (Davis et al. 2019, Liu et al. 2019). However, these studies focus solely on social contexts, and none explore the physical attributes of context, like the food environment or housing burden, which have their own associations with poor health (eg. Bakolis et al. 2021, Chen et al. 2018). In addition, these studies used adolescents as their study sample, and none have looked into how these protective contextual factors may moderate adult mental health specifically.

Despite the research supporting how context impacts mental health, the implications on context have not been explored within the framework of childhood adversity on mental health burden. This study uses the County Health Rankings in 2015 as well as BRFSS data in 2015 in California and Texas to assess multiple physical and social contextual factors and how they are correlated with mental health. By using exploratory factor analysis, the assessment of a latent variable within all the contextual variables in the County Health Rankings can be done. In addition, principal component analysis will be utilized to understand and maximize the variability of the county context data. The use of these data reduction techniques in this study is to assess the data structure of the contextual variables in counties in California and Texas and help simplify these measures for future studies.

Methods

Sample

The 2015 Behavioral Risk Factor Surveillance System (BRFSS) and the County Health Rankings are the data sources for this study. The BRFSS is a national cross-sectional study survey of health risk behaviors for adults 18 years or older that began in 1984, and it is a yearly survey conducted in the United States with over 400,000 participants every year (CDC 2011). Each state health department recruits participants using random digit dialing (CDC 2011). Given the way that it employs iterative proportional fitting, or raking, for specific sociodemographic characteristics for each state, BRFSS data can be more representative of the population in each state (CDC 2011). Age, sex, ethnicity, marital status, education, home ownership, and type of phone were the variables used to weight the BRFSS data, and this statistical process limits the potential for nonresponse bias (CDC 2011).

The County Health Rankings was developed by the University of Wisconsin’s Population Health Institute and the Robert Wood Johnson Foundation to understand the health of the nation’s over 2000 counties. Each county is ranked within each state by health outcomes (morbidity and mortality) and health factors (eg. social and economic attributes and physical environment factors). Using datasets, like the American Community Survey and the Environmental Public Health Tracking network, health outcomes and health factors can be assessed at the county level and be compared within the state.

Given the nature of the County Health Rankings in comparing counties within states, this study takes into account state-level variation of context. The analyses will assess Texas and California, two culturally and environmentally diverse states, contextually and compare the distributions of variables using two sample t-tests.

There are 254 counties and 58 counties in Texas and California, respectively. One county in Texas (Loving County) did not have complete context data in County Health Rankings in 2015 and was therefore excluded from the analyses. For the analyses, 253 counties and 58 counties were utilized separately to understand context in Texas and California, respectively. The two states' counties were merged (n=311) and the same analyses were run as an aggregated sample.

For the second part of the analysis, Texas BRFSS and California BRFSS participants in 2015 will be merged with County Health Ranking data. Based on the county of residence of the participants, participant county-level context factors will merge with BRFSS data. There were 14,697 participants and 12,601 participants from the Texas and California BRFSS datasets respectively, and after excluding participants without complete demographic data as well as those who refused to answer questions about depression, mental health days, or ACE exposure, 7,477 and 3,105 participants from the Texas and California were eligible for the study sample. While there were many participants that were excluded from the study sample because incomplete or refusal of the ACE module (24% and 70% for Texas and California BRFSS samples), studies assessing the impact of ACEs on health have used BRFSS samples (Campbell, Walker, & Egede 2016, Crouch et al. 2018, Crouch et al. 2020, Waehrer et al. 2020).

Variables

The following variables were used for the factor analysis and principal component analyses: food environment index, social association rate, violent crime rate, air pollution (average PM 2.5), percent water violations, percent severe housing, percent food insecure, and income ratio (Table 1). These variables were selected based on prior literature of context and environmental burden (Chen et al. 2018, Diez Rous & Mair 2010, Hajat et al. 2013). Each contextual variable from the County Health Rankings in 2015 was assessed continuously within the factor analysis and principal component analysis. As a requirement for factor analysis and principal component analysis, all the variables are to be going in the same direction, so the food environment index and social association rate were transformed by -x.

Mental distress was defined using the question "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" For this analysis, the mental distress variable was coded as a continuous variable, representing the respondent's number of mental health days.

Depression was assessed by the question "Has a doctor, nurse, or other health professional ever told you that you have a depressive disorder, including depression, major depression, dysthymia, or minor depression?” The variable for depression was divided into: depressive disorder present and absent.

ACE exposure was assessed using the ACE module in the BRFSS in 2015. This module is an optional module, and it has 11 questions to assess the participant’s exposure to 8 different ACEs: household mental illness, household substance use, household incarceration, parental separation/divorce, witnessing household violence, physical abuse, emotional abuse, and sexual abuse). The answers to these questions range from simple “yes” or “no” to frequency (“never,” “once, “more than once”). Questions that pertain to frequency of the ACE exposure were collapsed to a binary exposure (“yes” if any frequency of exposure or “no” if participants answered “never”). The total ACE exposure variable ranges from 0-8, and it reflects how many of the ACE domains a participant has been exposed to.

Table 3.1. County Health Ranking variables that will be assessed in the factor analysis and the definitions of the variables. These variables were selected based on previous literature, and these are all variables available in the 2015 County Health Rankings in Texas and California.

Variable	**Definition in the County Health Ranking**
Severe housing burden	Percentage of households with at least 1 of 4 housing problems: overcrowding,

	high housing costs, or lack of kitchen or plumbing facilities
Air pollution	Average daily density of fine particulate matter in micrograms per cubic meter (PM2.5)
Drinking water violations	Indicator of the presence of health-related drinking water violations
Income inequality	Ratio of household income at the 80th percentile to income at the 20th percentile
Social associations	Number of membership associations per 10,000 in the population
Violent Crime	Number of reported violent crime offenses per 100,0000 population
Food environment index	Index of factors that contribute to a healthy food environment, with a range of 0 (worst) to 10 (best) - Takes into account limited access to healthy foods as well as food insecurity of residents using the

	American Community Survey, Community Population Survey, and Bureau of Labor Statistics
Percent food insecure	Percentage of residents who do not have access to adequate food

Analytic Plan

Factor Analysis and Principal Component Analysis

Factor Analysis and Principal Component Analysis are standard techniques within neighborhood-level research to reduce data and create indices in statistical models (Messer et al. 2006). For both factor analysis and principal component analysis, the standard rule of thumb is to have at least three variables for each factor for it to be meaningful (Suhr 2005). If this rule was not fulfilled, then the factor would not be used (Suhr 2005). Only the county data from the County Health Rankings in 2015 will be used for this part of the analytic plan (n=311).

To explore the variability of all of the contextual factors, factor analysis was utilized to understand if there are latent variables that explain the variation in the data. Factor analysis, as opposed to principal component analysis, is a technique to understand the shared variance of variables. Factor analysis was utilized with and without promax orthogonal rotation in SAS. Factors were selected if its eigenvalues were greater than 1 (Suhr 2005). Kaiser's MSA was used to assess the partial correlations and the original correlations, and a

Kaiser's MSA equal to or less than 0.5 is poor (Ayuni & Sari 2018). The overall MSA of the models were used to assess if additional variables should be included to determine a common factor.

Principal component analysis is an exploratory data analysis technique that is used to reduce the dimensionality of the data while maintaining the most data variation to create models of prediction. While similar to factor analysis statistically, principal component analysis does not seek a latent variable for explanation of the variation; it maximizes the variation of the data and summarizes it in the least number of variables. Essentially, principal component analysis analyzes the total variance of the variables, and in turn, this method will provide an empirical information of the county-level variation explained by the contextual variables, rather than confirming a factor structure. This method has been used to create the Standardized Neighborhood Deprivation Index (Messer et al. 2006). Relevant factors were selected based on Scree plots of the eigenvalues of the factor. If a factor's eigenvalue was greater than 1, then the factor was kept (Suhr 2005). If a variable had 0.6 or greater value for the factor pattern, then that variable was selected for the factor based on thresholds typically used in principal component analyses (Guadagnoli & Velicer 1988). Cronbach's alpha correlations were calculated for each of the factors to analyze the internal consistency of each factor, and a threshold of 0.7 for Cronbach's alpha was used to evaluate test reliability (Tavakol & Dennick 2011). Formation of the equations for the factors was based on the standardized scoring coefficients of the variables for each factor after omission of variables that were irrelevant in the original principal component analyses.

Assessment of the internal consistency and the linear strength between context variables was determined by the Cronbach's alpha and Pearson correlation coefficients, respectively.

Mental Health Variables and Context

Using the 2015 BRFSS data from Texas and California, the county level measures from the County Health Rankings from the earlier analytic plan will be merged. Exploration of the factor(s), as well as contextual variables individually, will be done using Pearson correlation coefficients, and significance will be statistically defined as the results of a two-tailed significance test at a p value <0.05.

Results

From the 253 counties from Texas and 58 counties from California, the two sample t-test analysis showed significant differences between the average value of contextual variables of food environment index, violent crime rate, average PM2.5, percent water violations, and percent severe housing (Table 2).

Table 3.2. Average values for all contextual variables from the counties in Texas (n=253) and California (n=58) in the County Health Rankings data in 2015. Significant differences between the averages from each state were assessed

using two sample t-tests, and p-values are denoted to express significant differences by state.

	Texas (n=253)	California (n=58)
Food environment index*	6.45	7.027
Social association rate	13.31	13.70
Violent crime rate*	261.77	403.46
Average PM2.5**	9.47	8.80
Percent water violations*	16.34	7.45
Income ratio	4.69	4.75
Percent severe housing*	14.14	24.71
Percent food insecure	16.3	16.02

Footnote: *p value <0.05, ** p value <0.0001

Factor Analysis

The initial, unrotated factor analysis in Texas resulted in a Kaiser's overall MSA of 0.64. Each of the variables had Kaiser's MSA greater than the threshold of 0.5, and there was only one factor that emerged based on eigenvalues in the Scree plot (eigenvalues >1). However, when assessing the factor patterns, only 2 variables loaded highly onto the factor (factor loading values >0.5 indicated that the variables percent severe housing and percent food insecure loaded on the factor). Orthogonal rotation of the data showed that two factors emerged, but similar to the unrotated results, showed that only percent severe housing and food insecurity (percent food insecure and food environment index) loaded onto factor 1 and factor 2 respectively. The standard for factor analysis is that there should be at least three variables per factor, so none of the factors provided meaningful interpretation (Suhr 2005).

For California, the initial, unrotated factor analysis model had an overall MSA = 0.49. Each of the variables in the model also had low Kaiser's MSA values, with only the variable of social association rate having the highest MSA value of 0.57. Based on Scree plots and eigenvalues >1, only one factor was retained in the factor analysis; however, the factor pattern had only the two variables of food environment index and percent food insecure loading on the factor (factor loading pattern >0.8). Orthogonal rotation was not warranted since there was only one factor.

Using both Texas and California counties, the unrotated factor analysis resulted in an overall MSA value of 0.61. All of the factors had values of MSA greater than 0.5. Based on eigenvalues of the factors, only one factor was retained, and the variables that loaded onto that factor were percent severe housing and violent crime rate (factor loading pattern >0.5). Orthogonal rotation was not necessary since there was only one factor.

Principal Component Analysis

For Texas, two factors emerged based on Scree plots and eigenvalues >1 (factor 1 eigenvalue = 2.318 and factor 2 eigenvalue = 1.355). The two factors from the principal component analysis account for 45.9% of the variation. Two variables (social association rate= 0.70 and percent severe housing burden= 0.72) had factor loadings greater than 0.6, so these two variables were kept and the other 6 context variables were omitted from factor 1. Factor 2 had two variables that had factor loadings greater than 0.7 (food environment index = 0.80 and percent food insecure =0.83), so the other 6 context variables were omitted from factor 2. The standardized Cronbach's alphas of factor 1 and factor 2 were 0.52 and 0.67, respectively.

Three factors emerged from the principal component analysis in California based on Scree plots and eigenvalues > 1 (factor 1 eigenvalue = 2.370, factor 2 eigenvalue = 1.610, and factor 3 eigenvalue = 1.175). From the three factors, over 64% of the variation of the data is explained. Based on the loading factors for each of the variables, factor 1 is the food environment index (factor loading = 0.97) and percent food insecure (factor loading = 0.92), factor 2 is the variables percent severe housing (factor loading = 0.75) and violent crime rate (factor loading = 0.63), and factor 3 is the water violation variable (factor loading = 0.80). The standardized Cronbach's alphas for factor 1 and factor 2 were 0.92 and 0.48, respectively.

When the Texas and California counties were merged, there were three factors that emerged based on the Scree plots and eigenvalues (factor 1 eigenvalue = 2.150, factor 2 eigenvalue = 1.562, and eigenvalue = 1.029). The three factors account for 59.2% of the variation in the data. Factor 1 for this sample was percent severe housing (factor loading = 0.76) and violent crime rate (factor loading = 0.65), and factor 2 was food environment index (0.86) and percent food insecure (0.84). Factor 3 was composed of percent water violations (factor loading = 0.86). Cronbach's alpha for factor 1 was 0.59, which suggested poor internal validity and consistency.

Table 3.3. Principal component analysis factor variable retention based on eigenvalues >1 and factor loading >0.6 in Texas, California, and combined counties from the County Health Rankings data in 2015. The factor loading is denoted in parentheses.

Sample	Factor 1	Factor 2	Factor 3
Texas	Social association rate (0.70) Percent severe housing (0.72)	Food environment index (0.80) Percent food insecure (0.83)	----
California	Food environment index (0.97) Percent food insecure (0.92)	Percent severe housing (0.75) Violent crime rate (0.63)	Drinking water violations (0.84)
Texas and	Percent severe	Food environment	Drinking water

California	housing (0.76) Violent crime rate (0.65)	index (0.86) Percent food insecure (0.84)	violations (0.86)

Due to the few variables that loaded together in each factor, assessment of the correlations of all of the context variables and the mental health variables was warranted. The correlation matrices are summarized in Table 4. Consistently from each sample, there were no strong interactions between contextual variables and mental distress or depression diagnosis. While there was a correlation between depression and mental distress consistently (p value < 0.05), the other non-zero correlations of note were the correlation between social association rate and depression in Texas, average PM2.5 and mental distress in California, and food environment index and both mental distress and depression in the combined sample.

Table 3.4. Pearson correlation matrix for the mental health variables (depression and mental health days) as well as ACE score and context variables for Texas (n=7477) (a), California (n=3105) (b), and combined (n=10582) (c) from participants in the 2015 BRFSS and 2015 County Health Rankings data.

a. Texas (n=7477)

	Mental distress	Depression	ACE score
Mental Distress	1	0.38*	0.21*

Depression	0.38*	1	0.24*
Ace score	0.21*	0.24*	1
Food environment index	-0.02	-0.02	0.04*
Social association rate	0.004	0.03*	0.005
Violent crime rate	0.01	0.008	0.028*
Average PM2.5	0.02	0.01	-0.02
Percent water violations	0.007	-0.01	-0.008
Percent severe housing	0.0003	-0.02**	-0.02*
Percent food insecure	-0.002	0.01	-0.02*
Income ratio	0.002	-0.01	-0.03*

b. California (n=3105)

	Mental distress	Depression	ACE score
Mental Distress	1	0.28*	0.092*
Depression	0.28*	1	0.14*
ACE score	0.092*	0.14*	1
Food environment index	-0.02	-0.006	-0.02
Social association rate	-0.03	0.009	-0.006
Violent crime rate	-0.006	0.006	0.016
Average PM2.5	0.04*	0.004	0.03
Percent water violations	0.01	-0.007	-0.02
Percent severe housing	-0.03	-0.003	-0.058*
Percent food	0.007	0.003	0.01

insecure			
Income ratio	-0.03	-0.008	0.01

c. Combined (n=10582)

	Mental distress	Depression	ACE score
Mental Distress	1	0.35*	0.14*
Depression	0.35*	1	0.12*
ACE score	0.14*	0.12*	1
Food environment index	-0.02*	0.08*	-0.07
Social association rate	-0.01	0.03*	-0.03*
Violent crime rate	0.01	-0.09*	0.002
Average PM2.5	0.03*	-0.05*	0.05*
Percent water violations	0.009	-0.02*	0.01

Percent severe housing	-0.007	0.005	-0.10*
Percent food insecure	0.006	-0.06*	-0.098*
Income ratio	-0.004	0.01	-0.011

* signifies that the correlation p value <0.05, ** signifies the p value <0.1

Discussion

Context has an important role in impacting health, especially mental health outcomes (Hill & Maimon 2013, Jutte at al. 2015, Ross 2000). While published literature show that various aspects of the social and built environment are implicated in the gradient of health outcomes, the context is defined usually by only a few variables (eg. violence, median income of the geographic location) (Hill & Maimon 2013, Jutte at al. 2015, Ross 2000). The context in which people live is a broad concept made up of many different variables, and while it would be advantageous to sum up all of these measurements of context into one variable analytically, each variable itself may have an independent impact on health.

The results from the factor analysis and the principal component analysis from Texas, California, and combined sample show that context cannot be simply condensed. While some of the analyses showed initial promise with high eigenvalues on the Scree plots, the loading of the variables showed that there were only a few variables that explained the variation of the data. With both of these two analytical techniques, the rule of thumb is to have at least three variables in one factor, and consistently, only one or two variables were loaded onto one factor, indicating that there was not a simple condensing of these contextual variables. In addition, the use of high thresholds for loading factors (0.6) was based on prior literature (Guadagnoli & Velicer 1988), but there are published studies that have much lower thresholds (loading factors greater than or equal to 0.3 were accepted) used to create the Standardized Neighborhood Deprivation Index (Li et al. 2019, Ross & Mirowsky 2001) and the area-level deprivation index (Eibner & Sturm 2006). Taking into consideration the lower loading factor thresholds, similar results were observed. While more variables could be loaded onto a factor using 0.3 as the factor loading threshold, the internal consistency of the factors were all consistently lower than 0.7 (and only increased marginally because of the increase in the number of factors included). Even with these lower thresholds for factor loading, the addition of variables in the factors did not improve the internal consistency of the factor. Cronbach's alpha for the factors were consistently less than 0.7, signifying that the factors are not closely related. In a more recent study to introduce neighborhood-ACEs (ACEs that may be entwined in the neighborhood environment), principal component analysis and Bayesian Index Regression were used as techniques to create an index of many neighborhood-level measures similar to our study (eg. air quality and access to supermarkets) (Schroeder et al. 2022). This study created a few indices and regressed them onto ACE exposure to choose the index of contextual measures that best fit in the model with ACE exposure

(Schroeder et al. 2022). While this study found multiple indices with multiple factors loading onto the same component through their analytic plan, their thresholds for the factor loading were lower than this study's use of thresholds of 0.6, and while the utility of lower thresholds for factor loading was assessed for this study's analytic plan, ultimately, the same results would have been seen in that the factors created from the principal component analyses were not internally consistent and conceptually meaningful. The Schroeder study had a goal to create a contextual index that best fit ACE exposure in a sample of adults in Philadelphia (Schroeder et al. 2022). In contrast, this study sought to condense context into a simple and meaningful measure to use in modeling the interaction between context and ACE exposure using counties in Texas and California, and the data reduction techniques did not create a meaningful factor of context. Instead, there were multiple factors without much internal consistency, and it showed that context cannot be condensed simply. Context is multifaceted and statistically cannot be simplified into one or two factors.

For this analysis, the inclusion of multiple environmental context measures (water violations, food environment index, average PM2.5) in indices of contextual burden (for example, neighborhood disadvantage uses socioeconomic information) was justified by the number of studies observing the multiple sources of environmental concerns on mental health (Bakolis et al. 2021, Chen et al. 2018) that are not included in the traditional definitions of built environment or the social environment. Because of the nature of the variables and the distinct aspects of context that each variable was representing, it was natural to expect that the physical, social, and environmental variables would group together in the data reduction results; however, there were no statistically significant or meaningful ways the variables could be simplified, meaning that they all represent different aspects of context. While all these contextual variables are associated with poor mental health, the results of these analyses again serve to show evidence that context is multifaceted.

While the context factors themselves did not hold up statistically, the results of the principal component analysis show there is state variation in context. In Texas, the variables that held up in the first factor were social association and percent severe housing burden. In contrast, the variables of food environment index and percent food insecure were loaded onto the first factor in California. While both California and Texas represent two of the most diverse states culturally and ethnically, they are distinct states with different politics, distinct differences in socioeconomic diversity (diversity in household income and education attainment), and different industries and environmental exposures (Almaraz et al. 2018, Jarrell & Ozymy 2010, McCann 2021). The political differences between California (as a Blue state) and Texas (as a Red state) is an area of interest within environmental literature since the dominant political ideologies inform the policies enacted within the state (Khalidi & Ramsey 2021). In addition to the contrasting political ideologies, California is a large source of NO2 emissions due to its dominant agricultural industry (Almaraz 2018) while much of the pollution in Texas is contributed by the petroleum industry (Jarrell &

Ozymy 2010). Synthesizing the contrasting results from the analyses with the state distinctions, the context and environment between the two states differ.

The use of cross-sectional data is a major limitation of this study. Future studies to assess context over time could provide valuable information to assess how improvements to context impacts other health outcomes. In addition, the limitation of the study is the use of county as the geographical unit of context. The BRFSS in California and Texas only provided county residence, so the study is limited to this geographical unit to assess context. While county has been used to study context before (Hill & Maimon 2013, Niazi et al. 2021)

While condensing and simplifying context is analytically favorable, the justification for it statistically is not sound, based on the results of this study. Each variable appears to be independent aspects of context, so future analyses with multiple contextual variables should assess the independent associations of each on health outcomes.

Chapter 3: The Moderation of Context on ACEs and Mental Health Burden

Aim 2: Location, Location, Location: Assessing the Moderating Roles of Social and Physical Contexts on Adverse Childhood Experiences on Mental Health Burden in Adulthood

ABSTRACT

Background: The impact of adverse childhood experiences (ACEs) on mental health burden is a pressing concern for public health. While efforts have been made to understand the individual-level factors that buffer the impact of childhood adversity, there is a need to understand the contexts that may buffer or exacerbate the impact of adverse childhood experiences on mental health.

Methods: Using the Behavioral Risk Factor Surveillance Survey (BRFSS) from 2015 in Texas and California and the County Health Rankings in 2015, a cross-sectional study was conducted to understand the moderating role of county-level context in the relationship between adverse childhood experience exposure and mental health burden (mental distress and depression) in adulthood. Adverse childhood experience exposure was assessed via the BRFSS ACE module, and county-level measures of context were extracted from the County Health Rankings data and merged by county residence of participants in the BRFSS. Each context measure was evaluated independently as a moderator with ACE exposure, and multivariable analysis was conducted using logistic regression, and moderation was assessed using significant interaction terms (p value <0.05).

Results: The food environment index of the county as well as the income ratio of the county were significant moderators of ACE exposure on mental health burden (p value <0.05), and there were state-level differences in what county-level context measures were significant moderators (p value <0.05).

Discussion: There are contexts that exacerbate or buffer the impact of childhood adversity on adult mental health burden. The food environment index was a significant effect modifier when looking at mental distress and depression as the outcome variables, and the state-level differences in significant moderators suggest the need for nuanced interventions to effectively reduce burden.

Background

With over 50% people in the United States reporting at least one adverse childhood experience (ACE) as well as one out of six people reporting four or more ACEs, childhood adversity is a prevalent issue with long-term health complications (Felitti et al. 1998). Adverse childhood experiences are traumatic events or experiences that occur during formative years of development and have enduring implications on physical and mental health throughout the life course (Felitti et al. 1998). While a number of studies have published the negative implications of ACE exposure on mental health (Felitti et al. 1998, Petruccelli et al. 2019), there is a need to expand our understanding of child adversity beyond its negative impacts towards how to mitigate ACE burden on health.

According to the Protective Factors Theory, there are factors that moderate the relationship between exposure and outcome (Zimmerman 2013), and this theory has been tested within ACE literature to understand the moderating impact of social relationships and how positive social environments buffer the negative impact of ACEs on health (Davis et al. 2019, Liu et al. 2019). These findings help to understand how to mitigate ACE burden, but the protective factors largely focus on the individual (eg. whether or not the individual has a positive relationship with an adult) or the ambiguously defined community that the individual perceives (eg. the perception of violence of the community) (Crouch et al. 2018, Davis et al. 2019, Lieu et al. 2019). However, from Bronfenbrenner's socioecological theory, there are aspects *outside* of the individual that are implicated with health, including the context in which the individual resides (Bronfenbrenner).

The context, which is defined as the environment or setting in which people live, has been tied to many health implications, including mental health complications like depression and mental distress (Mair, Diez Rous, Moore et al. 2018, Stockdale et al. 2007). Disparities in health cannot be fully explained just by the individual and their characteristics alone; the attributes of the context, the physical and social environment, in which people live and interact contribute to health disparities (Diez Rous & Mair 2010). The socioeconomic attributes of location, like the median income of the neighborhood and the number of households living under the poverty line, are associated with poor mental health outcomes, and poor socioeconomic context is associated with a number of mental health implications, including anxiety and depression (Mair and Diez Rous 2010). Other studies observe how the poor built environment (eg. the physical infrastructure, urban planning) and the social context (eg. social connections and violence) have negative impacts on mental health outcomes (Moore et al. 2018, Stockdale et al. 2007). Burdened contexts have detrimental consequences on health, even after accounting for individual risk factors.

While there is a large understanding of how burdened contexts impact health, studies have defined burdened contexts by poor built environments and social environments, and environmental burden is largely ignored when studying burdened contexts (Eibner & Sturm 2006, Ross & Mirowsky 2001). Environmental burden, which is the risk of health consequences due to proximity to environmental hazards and pollutants, is a consequence of poor built environments, and studies have shown how environmental burden, like poor air quality and water violations, have negative physical and mental health consequences (eg. Bakolis et al. 2021, Chen et al. 2018). Expanding the definition of context to include the environmental impact of the built environment is necessary to understand the multiple facets of context (aim 1).

While it is understood in public health that context is an important determinant in health, the role of the multiple facets of context have not been explored in studies on childhood adversity. Expanding both the definitions of context and of protective factors, this study seeks to understand the role of physical and social context in moderating the relationship between ACEs and mental health burden in adulthood. Using the 2015 Behavioral Risk Factor

Surveillance System from Texas and California and the 2015 County Health Rankings, this study will explore socioeconomic, environmental, and social attributes of the county that participants reside in and how these factors interact with ACEs to impact mental health burden. This study will also compare the two states, distinct in terms of policy, culture, and sociodemographics, by their contextual attributes and evaluate state-level differences or similarities.

Methods

Sample

Using the 2015 Behavioral Risk Factor Surveillance System (BRFSS) in Texas and California as the dataset, the sample for this analysis included participants who completed the ACE module as well as had complete demographic data and mental health data (Figure 1). For California, over 8,000 participants had incomplete or refused the ACE module, and comparisons between the final sample and the missing ACE are shown in Table 1A and Figure 1B. The final sample after omission of incomplete data had 7,477 participants from Texas and 3,105 participants from California. For the main models of this analysis, the combined sample was 10,582 participants from both Texas and California.

Regarding the 24% of participants in Texas and 70% of participants in California who refused or did not complete the ACE module survey in the 2015 BRFSS, two sample t-tests as well as ANOVA tests were used to determine sociodemographic differences between the two sample, and for both the Texas and California samples, the missing participants were statistically different from the final sample in age, race, income, and mental health distribution (Table 1). The missing samples represented more younger age group categories as well as lower socioeconomic status and racial and ethnic minorities than the final samples for both Texas and California. Although the missing samples are distinct from the study sample, studies have published BRFSS data despite the percentage of incomplete ACE data (Campbell, Walker, & Egede 2016).

Variables

ACEs information was extracted based on participants' answers to the ACE module in the 2015 BRFSS. This module is an optional module for each state every year in the BRFSS, and it is a 11 question survey that assesses 8 different adverse childhood experiences. Based on previous published factor analysis literature, the ACEs can be divided into categories of household dysfunction, emotional and physical abuse, and sexual abuse (Brown et al. 2013, Crouch et al. 2018). Questions referring to mental illness, substance use, and incarceration in the household as well as parental separation/divorce are within the category of household dysfunction ACEs. Emotional and physical abuse were assessed using the questions involving witnessing household violence and experiencing physical abuse. Three questions surveyed the category of sexual abuse. ACE score was calculated by summing up the presence of the 8 different adverse childhood experiences, so the range of scores was from 0 to 8. From the ACE score, the variable of ACE exposure was dichotomized to categorize those with 0-3 ACEs and those with 4 or more ACEs. Categorization of the ACE exposure in this manner has been published extensively in the literature (eg. Crouch et al. 2018, Felitti et al. 1998).

Dependent variables for this analysis were mental distress and depression. Mental distress can be defined using the question, “Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?” For this analysis, the mental distress variable was coded as a dichotomous variable, with a cut-off point of 14 days or more signifying frequent mental distress. The use of this cut-off has been published using BRFSS, specifically, (Crouch et al. 2018) and 14 days is a frequent marker for depression and anxiety (Bonnie & Monahan 1997). Depression will be assessed by the question “Has a doctor, nurse, or other health professional ever told you that you have a depressive disorder, including depression, major depression, dysthymia, or minor depression?” The variable for depression will be divided into: depressive disorder present and absent.

The contextual variables that were included in the analysis were from the County Health Rankings from 2015. Context variables were all included in the models based on previous factor analysis and principal component analysis (aim 1). These variables will be individually assessed as moderators of the main effects model, and each variable was assessed as a continuous variable. Moderation was assessed using an interaction term, and if the p value is <0.05, then significant moderation is occurring. Initial modeling had each of the variables as continuous variables.

Covariates to account for socioeconomic status and demographic factors in the model were age, sex, income level, and race/ethnicity. Selection of these covariates was based on prior literature using BRFSS data (Crouch et al. 2018). Age is a categorical variable divided into the groups: 18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, and 65+ years of age. Income categories were as follows: less than $25,000, $25,000 to less than $50,000, and $50,000 or more. The race/ethnicity variable was categorized into: non-Hispanic White, non-Hispanic African American, Hispanic, and other non-Hispanic races. Non-Hispanic White was the referent group.

Figure 4.1. A. Flow chart of the eligible sample from the 2015 BRFSS in Texas and California with 14,697 participants and 12,601 participants, respectively. The final sample of the combination of the states is 10,582 participants.

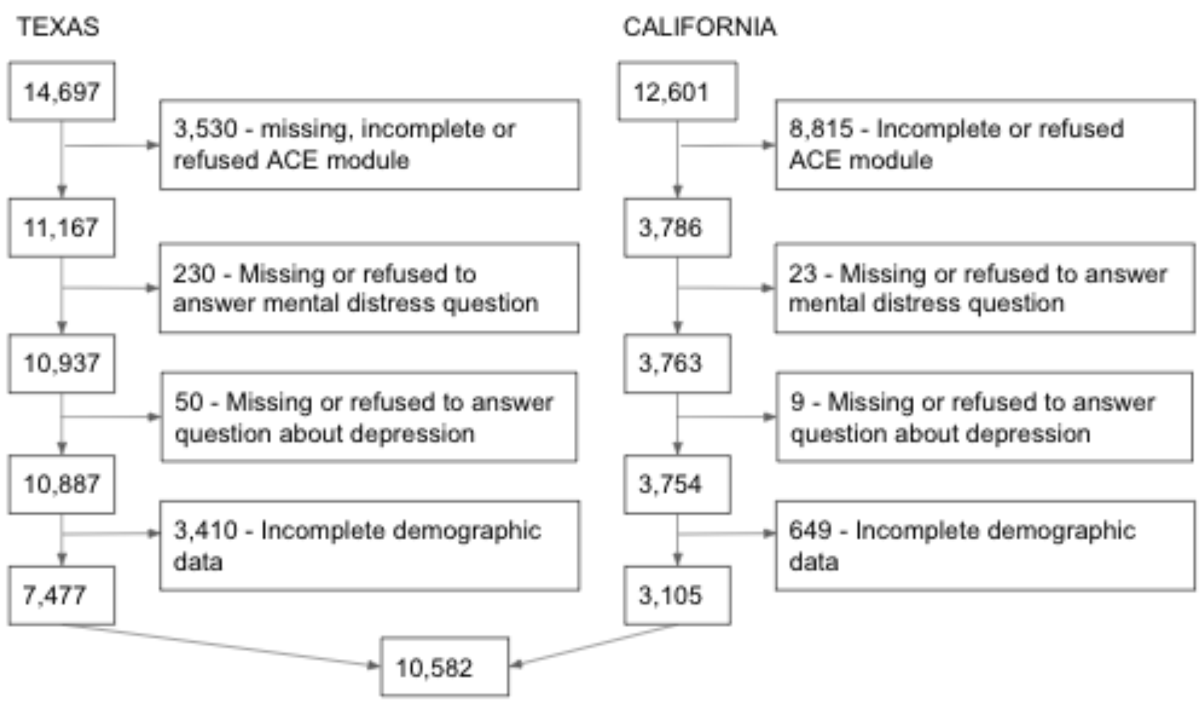


Table 4.1. A. Final samples from the 2015 BRFSS in Texas (n=7,477) compared to the 2015 BRFSS samples in Texas without ACE module data (n=3530). B. Final samples from the 2015 BRFSS in California (n=3,105) compared to the 2015 BRFSS samples in California without ACE module data (n=8815)

A.		**Texas**		**Missing ACEs Texas (n=3530)**	
	Characteristics	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**
Age groups, in years**	18-24 years	274	3.66	289	8.35
	25-34 years	625	8.36	631	18.22
	35-44 years	888	11.86	539	15.56
	45-54 years	1139	15.24	500	14.44
	55-64 years	1628	21.76	556	16.06
	65+ years	2923	39.1	948	27.38
Race**	White, non-Hispanic	4710	62.99	1835	53.61
	Black, non-Hispanic	558	7.46	385	10.46
	Hispanic	1944	26	1031	30.12
	Other, non-Hispanic	199	2.66	150	4.38
	Multiracial	66	0.88	49	1.43
Income Categories**	less than $15,000	850	11.36	418	15.85
	$15,000 to less than $25,000	1313	17.54	497	18.85

	$25,000 to less than $35,000	813	10.86	305	11.57
	$35,000 to less than $50,000	1016	13.57	327	12.4
	$50,000 or more	3493	46.67	1090	41.33
Depression ***	Diagnosed depressive disorder	1344	17.89	557	15.78
	None to less than 5 days of poor mental health	6238	83.43	2823	82.4
Mental Distress**	5 Days or more of poor mental health	1239	16.57	603	17.6
	Female	4492	60.08	2027	57.45
Sex	Male	2985	39.92	1502	42.55

B..		**California**		**Missing ACEs California (n=8815)**	
	Characteristics	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**
	18-24 years	274	3.66	932	10.67
	25-34 years	625	8.36	1595	18.26
	35-44 years	888	11.86	1414	16.18
	45-54 years	1139	15.24	1516	17.35
	55-64 years	1628	21.76	1519	17.39
Age groups, in years**	65+ years	2923	39.1	1761	20.16
Race*	White, non-Hispanic	4710	62.99	4316	49.6

	Black, non-Hispanic	558	7.46	441	5.07
	Hispanic	1944	26	2734	31.42
	Other, non-Hispanic	199	2.66	980	11.26
	Multiracial	66	0.88	1761	20.16
	less than $15,000	850	11.36	1167	13.24
	$15,000 to less than $25,000	1313	17.54	1042	11.82
	$25,000 to less than $35,000	813	10.86	685	7.77
	$35,000 to less than $50,000	1016	13.57	851	9.65
Income Categories**	$50,000 or more	3493	46.67	3605	40.9
Depression**	Diagnosed depressive disorder	1344	17.89	1480	16.79
	None to less than 5 days of poor mental health	6238	83.43	7062	80.1
Mental Distress**	5 Days or more of poor mental health	1239	16.57	1754	19.9
	Female	4492	60.08	4557	51.68
Sex	Male	2985	39.92	4259	48.32

*Footnote: ** denotes p value <0.001 for a two sample t-test or ANOVA test, * denotes p value <0.05 for either a two sample t-test or ANOVA test between the two samples

Footnote: sociodemographic information for the samples missing the ACE module may be missing as well

Analytic Plan

The distribution of the participants was assessed, and 2 sample t-tests were used to evaluate the differences of the samples between states as well as differences between participants with low ACEs (0-3 ACEs) or high ACEs (4+ ACEs). Significance was reported at a p value >0.05.

To assess nesting in the sample by state, the intraclass correlation (ICC) was calculated for each of the mental health variables. If the ICC was greater than 0.1, then significant nesting by state is present and hierarchical modeling is warranted (Janjua et al. 2006). However, since the ICC was less than 0.1, no nesting was present by state in any of the two mental health variables, and hierarchical modeling was not necessary (Table 2).

In addition to assessing nesting within states, it was necessary to evaluate the potential nesting of counties within each state. The ICC was calculated for each of the mental health variables by counties in each state, and for both Texas and California, there was no significant nesting for either of the mental health variables (Table 2).

Table 4.2. Results of ICC for each of the states (Texas (n=7477) and California (n=3105)) by county and by each of the mental health variables as well as the combined dataset of Texas and California residents (n=10582) by state for each of the mental health variables.

Sample	Variable	ICC
Texas (n=7477)	Mental health days	0.001
	Depression	0.0005
California (n=3105)	Mental health days	0.0007
	Depression	0
All (n=10582)	Mental Health days	0.0007
	Depression	0.02

The dichotomous nature of the outcome variables warrants the use of logistic regression for the main modeling (summary of models are displayed in Figure 2). The main effects models assess the relationship between ACE exposure (0-3 ACEs and 4+ ACEs) and the two mental health variables: mental distress and depression, independently (Figure 2, a and b). Fully adjusted models (Figure 2, e and f) have all the contextual variables in the model as well as covariates; these models were constructed based on prior principal component analyses and factor analyses (aim 1) that showed that the contextual variables do not cluster together and potentially can impact health outcomes independently. Consequently, the models assessing moderation of each of the contextual variables (Figure 2, g and h) still account for the other contextual variables to account for the impact of multiple independent contexts in the model.

Figure 4.2. Logistic regression models tested to assess the unadjusted (a and b) and adjusted (c and d) main effects of ACE exposure and mental health burden

in adulthood. Models e and f have contextual effects added into the model. Moderation by each context variable can be evaluated using models g and h.

a. ACE exposure --> mental distress

b. ACE exposure --> depression

c. ACE exposure + covariates --> mental distress

d. ACE exposure + covariates ---> depression

e. ACE exposure + covariates + context variables --> mental distress

f. ACE exposure + covariates + context variables --> depression

g. ACE exposure + ACE exposure * context variable + covariates + context variables --> mental distress

h. ACE exposure + ACE exposure * context variable + covariates + context variables --> depression

Moderation will be assessed for each of the variables with ACE exposure, and statistical significance will be evaluated at a p value <0.05. If the interaction term is statistically significant, then moderation is occurring.

Results

Of the 10,582 participants from Texas and California in the 2015 BRFSS, there were a total of 1,668 participants who reported having 4 or more ACEs (15.8% of the sample). There were statistically significant differences between the two states by sociodemographic factors (age, race, sex and income) as well as depression prevalence (Table 3). While there are significant differences between the two states in terms of the distribution of the values of the contextual variables (see aim 1, table 2), the distribution across these contextual variables by ACE exposure show that there were no significant differences (Table 4).

Table 4.3. Distribution of sociodemographic variables as well as the main dependent and independent variables by state in the 2015 BRFSS sample. Statistical significance was assessed using two-sample t-tests, evaluated at the threshold of p value <0.05.

		Texas		**California**		**Combined**	
	Characteristics	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**
Age groups, in years*	18-24 years	274	3.66	249	7.99	523	4.93
	25-34 years	625	8.36	451	14.48	1073	10.14
	35-44 years	888	11.86	474	15.22	1362	12.87
	45-54 years	1139	15.24	548	17.59	1684	15.91
	55-64 years	1628	21.76	560	17.89	2187	20.67
	65+ years	2923	39.1	833	26.74	3754	35.48
Race*	White, non-Hispanic	4710	62.99	1594	51.34	6304	59.57
	Black, non-Hispanic	558	7.46	135	4.35	693	6.55
	Hispanic	1944	26	991	31.92	2935	27.74
	Other, non-Hispanic	199	2.66	332	10.69	531	5.02
	Multiracial	66	0.88	53	1.71	119	1.12
	less than $15,000	850	11.36	428	13.74	1272	12.02

Income Categories*	$15,000 to less than $25,000	1313	17.54	397	12.74	1707	16.13
	$25,000 to less than $35,000	813	10.86	315	10.11	1125	10.63
	$35,000 to less than $50,000	1016	13.57	346	11.11	1362	12.87
	$50,000 or more	3493	46.67	1629	52.3	5116	48.35
ACEs*	No ACEs	3421	45.75	8	0.26	3429	32.40
	1-3 ACEs	3390	45.34	2102	67.48	5485	51.83
	4 or more ACEs	666	8.91	1005	32.26	1668	15.76
Depression*	Diagnosed depressive disorder	1344	17.89	306	9.86	1659	15.59
Mental Distress	None to less than 5 days of poor mental health	6238	83.43	2618	84.32	8856	83.69
	5 Days or more of poor mental health	1239	16.57	487	15.68	1726	16.31
Sex*	Female	4492	60.08	1596	51.4	6088	57.53
	Male	2985	39.92	1509	48.6	4494	42.47

Footnote: * denotes 2 sample t-test p value <0.05 between Texas and California

Table 4.4. Distribution of contextual variables and mental health variables by ACE exposure using the Texas BRFSS in 2015 and the California BRFSS in 2015.

A. Combined

ALL	0-3 ACEs (n=8914)	4+ ACEs (n=1668)
food environment index**	6.48	7
social association rate**	9.42	11.09
violent crime rate**	387.87	403.23
average PM2.5**	9	8.81
percent water violations**	7.712	5.59
percent severe housing**	21.24	23.98
income ratio	4.88	4.85
depression**	13.75%	25.42%
mental health days	1.14	1.27
female*	57.35%	58.51%

B. Texas

TEXAS	0-3 ACEs (n=6811)	4+ ACEs (n=666)
food environment index	6.132	6.1911
social association rate	8.23	8.1997
violent crime rate	384.7	399.88
average PM2.5	9.19	9.19
percent water violations	9.19	9.58
percent severe housing	1.17	1.1
income ratio	4.88	4.826
depression**	15.80%	40.24%
mental health days**	1.15	1.345

Footnote: ** p value <0.001 for the two-sample t-test

C. California

CALIFORNIA	0-3 ACEs (n=2103)	4+ ACES (n=1002)
food environment index	7.59	7.53
social association rate	13.18	12.98
violent crime rate	400.7	406.29
average PM2.5	8.46	8.57
percent water violations	3.18	3.01
percent severe housing	27.79	27.31
income ratio	4.88	4.87
depression**	7.13%	15.57%
mental health days**	1.13	1.22

Footnote: ** p value <0.001 for the two-sample t-test

Since there was no significant nesting in the data by state, all 10,582 participants were used as the sample for logistic regression using ACE exposure as the main independent variable and mental distress and depression as separate dependent variables (Table 5 a and b, respectively). Consistently in the modeling, having 4 or more ACEs increased odds of mental distress and depression at least 2 times that of having 0-3 ACEs, even after adjusting for sociodemographic factors as well as contextual factors. Interestingly for both mental distress and depression as outcome variables, severe housing burden decreased the odds of the mental health outcome, and while the magnitude was weak (OR =0.979 for mental distress and OR = 0.962 for depression), the values were statistically significant ($p<0.05$).

Each context variable was tested as an interaction with ACEs, and food environment index and income ratio emerged as statistically significant moderators in the relationship between ACEs and mental distress (Table 5a). For every one point increase in the food environment index of the county, there is a 0.2327 decrease in the log likelihood of reporting mental distress for those with high ACEs (p value 0.0041). In contrast, the food environment index of the county does not have a significant influence on the likelihood of reporting mental distress ($p > 0.05$) for those with 0-3 ACEs. Similarly, the income ratio of the county has no statistically significant influence on the likelihood of reporting mental distress for those with low ACEs (p value >0.05); but for those with high ACEs, the log likelihood of reporting mental distress increases by 0.3136 for every one point increase in the income ratio of the county (p value =0.0178).

The food environment index was the only context variable with a significant interaction in the models with depression as the dependent variable (Table 5b). The higher the food environment index score of the county, the less likely depression was reported for those with low ACEs (p value <0.0001). However, the magnitude of influence that the county's food environment index has on depression is greater for those with 4 or more ACEs; the log likelihood of reporting depression decreases by 0.1756 for every one unit increase in the county's food environment index score for those with high ACEs ($p = 0.0154$).

Table 4.5. Results from logistic regression modeling for the combined sample from the 2015 BRFSS in Texas and California (N=10,582) using mental distress (5a) and depression (5b) as outcome variables, respectively.

a. Mental Distress

	unadjusted OR	adjusted OR	Full model OR	ACEs*variable estimate
ACEs	2.396**	2.215**	2.488**	
income		0.718**	0.726**	
age		0.913**	0.906**	
black		1.139	1.124	
hispanic		0.727**	0.795**	
Other, non-Hispanic		1.003	1.175	
Multiracial		1.639	1.726**	
sex		1.362**	1.329**	
food environment index			0.879	-0.2373**
social association rate			1.002	-0.0286
violent crime rate			1	0.00043
average PM2.5			0.967	0.0482
percent water violations			1.006**	-0.00057
percent severe housing			0.979**	-0.00879
income ratio			0.950	0.3136**

Footnote: **denotes p value <0.05

b. depression

	unadjusted OR	adjusted OR	Full model OR	ACEs*variable estimate
ACEs	2.137**	2.149**	2.703**	
income		0.780**	0.794**	

age	1.031**	1.019	
black	0.818	0.719	
hispanic	0.512**	0.558**	
Other, non-Hispanic	0.461**	0.579**	
Multiracial	1.235	1.316	
sex	1.769**	1.703**	
food environment index		0.785**	-0.1752 (p value=0.0136) **
social association rate		0.985**	0.00560
violent crime rate		1	-0.00015
average PM2.5		0.908**	-0.0421
percent water violations		0.999	-0.00637
percent severe housing		0.962**	-0.0114
income ratio		0.937	0.1872

Footnote: ** denotes p value <0.05

The same set of analyses were carried out in Texas and California, separately, to understand the differences in context between the two states (Tables 6 and 7, respectively). For both states, there were no significant interactions between any of the contextual variables and ACEs when the dependent variable was depression (Table 6b and Table 7b). However, there were differences in the variables that were moderators when the dependent variable was mental distress by state (Table 6a and Table 7a).

For Texas, the food environment index and percent severe housing variables were significant moderators in the relationship between ACEs and mental distress (Table 6a). For every one unit increase in the food environment index in the county, there was a 0.34 log likelihood decrease in reporting mental distress for those with 4 or more ACEs (p value =0.0126). While the food environment index has no significant impact for those with low ACEs on mental distress, there is a significant reduction in reporting mental distress when the food environment improves in the county for those with high ACEs. In addition, severe housing had no significant influence over the log likelihood of reporting mental distress for those with low ACEs, but every one unit increase in severe housing, the log likelihood of reporting mental distress increases by 0.23 for those with high ACEs (p value = 0.0228).

Table 4.6. Logistic regression results using the 2015 BRFSS in Texas as the sample (n=7477) and using mental distress (a) and depression (b) as the outcome variables.

a. Mental Distress

	Unadjusted OR	**Adjusted OR**	**Full model OR**	**ACEs*context variable estimate**
ACEs	3.383**	2.757**	2.760**	
income		0.714**	0.717**	
age		0.867**	0.869**	
black		1.032	1.029	
hispanic		0.760*	0.803	
non-Hispanic, other		0.835	0.862	
multiracial		1.391	1.386	

sex		1.311**	1.312*	
food environment index			0.921	-0.3381 (p value =0.0138)*
social association rate			1.006	-0.0141
violent crime rate			1	0.000249
average PM2.5			0.976	0.00270
percent water violations			1.004	-0.0024
percent severe housing			0.932	0.2297 (p value = 0.0241)*
income ratio			0.971	0.23

Footnote: * denotes p value <0.05, ** denotes p value <0.0001

b. Depression

	Unadjusted OR	**Adjusted OR**	**Full model OR**	**ACEs*context variable estimate**
ACEs	3.589**	3.343**	3.350**	
income		0.773**	0.775**	
age		1.008	1.010	
black		0.816	0.813	
hispanic		0.561**	0.560**	
Other, non-Hispanic		0.596*	0.597*	
Multiracial		1.254	1.241	
sex		1.707**	1.701**	
food environment index			0.931	-0.0776

social association rate	1.016	-0.0196
violent crime rate	1	-0.00037
average PM2.5	0.995	-0.1167
percent water violations	0.998	-0.00982
percent severe housing	1.084	0.0746
income ratio	0.827	0.1178

Footnote: * denotes p value <0.05, ** denotes p value <0.0001

In California (n=3105), there was only one context variable that emerged as a significant moderator in the full models (Table 7a). While income ratio had no impact on the likelihood of reporting mental distress for those with zero to three ACEs, the log likelihood of reporting mental distress increased by 0.975 for every one unit of increase in the income ratio of the county for those with four or more ACEs (p value <0.0001). As the county's income inequality worsens, the likelihood of reporting mental distress increases for those with high ACE burden. In contrast to Texas, there were no contextual variables that emerged as statistically significant moderators for the models with depression as the outcome variable (Table 7b).

Table 4.7. Logistic regression results from the 2015 BRFSS California sample (n=3105) using mental distress (a) and depression (b) as outcome variables.

a. Mental distress

	Unadjusted OR	**Adjusted OR**	**Full model OR**	**ACEs*context variable estimate**

ACEs	2.135**	2.189**	2.192**	
income		0.738**	0.742**	
age		1.006	1.007	
Non-Hispanic Black		1.547	1.588	
Hispanic		0.791	0.797	
Other, non-Hispanic		1.547	1.591*	
Multiracial		2.492*	2.489*	
sex		1.358*	1.361*	
food environment index			0.984	-0.2650
social association rate			1.008	-0.0251
violent crime rate			1	0.00138
average PM2.5			1.017	0.0199
percent water violations			1.011	-0.00963
percent severe housing			1	0.0263
income ratio			0.891	0.9750**

Footnote: * denotes p value <0.05, ** denotes p value <0.0001

b. Depression

	Unadjusted OR	**Adjusted OR**	**Full model OR**	**ACEs*context variable estimate**
ACEs	2.401**	2.273**	2.256**	
income		0.847**	0.845**	
age		1.034	1.034	

Non-Hispanic Black	0.601	0.612	
Hispanic	0.470**	0.475**	
Other, non-Hispanic	0.585*	0.584*	
Multiracial	1.592	1.657	
sex	1.648**	1.635**	
food environment index		0.976	0.0294
social association rate		1.010	0.0267
violent crime rate		1.001	0.000558
average PM2.5		0.966	-0.1561
percent water violations		0.99	-0.0170
percent severe housing		0.986	0.0570
income ratio		0.916	0.4825

Footnote: * denotes p value <0.05, ** denotes p value <0.0001

Discussion

The burden of experiences of childhood adversity are evident in mental health outcomes (Felitti et al. 1998, Petruccelli et al. 2019). Results from this study show that even after accounting for individual-level sociodemographic factors and context, the odds of reporting depression and mental distress were significantly two to three times higher for those with four or more ACEs than those with zero to three ACEs, and this result was consistent for all three study samples (Texas, California, and combined).

The aim of this study was to take a multi-faceted approach to context and analyze the interactions of many context variables with ACEs in impacting mental health. Given the results of prior factor analyses and principal component analyses with the same context variables, this approach of assessing each variable individually as an interaction with ACEs shed light on how different facets of context are more important than others when evaluating ACEs and mental health. When looking at the sample with both Texas and California, the food environment index was a moderator of the relationship between ACEs and depression as well as a moderator of the relationship between ACEs and mental distress (Table 5a and 5b). For those with high ACEs, the log likelihood of reporting either mental distress or depression decreased with every unit improvement in the food environment index score of the county. A study of over 11,000 respondents in North Carolina showed that high ACEs are a predictor for food insecurity in adulthood, but this study assessed food insecurity at the individual level (using questions about the respondent's food insecurity) and not at the macro-level of the county that the respondent lives in (Roy et al. 2019). At the county-level, food insecurity does not have a statistically significant influence on mental distress. However, when the county food insecurity index is assessed through its interaction with childhood adversity, there is a significant difference in the burden of ACEs on mental health for those with high ACEs. County-level improvements in the index (higher score on the food environment index) significantly reduces the burden of ACEs on both mental health measures, even after controlling for individual-level socioeconomic factors.

When assessing perceived food insecurity at an individual level, food insecurity is associated with depression and mental distress (Jones 2017). The stress associated with food insecurity at the individual level encompasses feelings of anxiety of acquiring enough food and negative feelings of shame and guilt, and all these feelings manifest in higher mental distress and depression (Jones 2017). However, when assessing food environments, the literature is focused on obesity and how poorer food environments are associated with higher rates of this chronic condition (Campbell 2016, Larsen et al. 2014, Remigio-Baker et al. 2014). Obesity and depression both have mechanisms in dysregulating the hypothalamic-pituitary-adrenal (HPA) systems and are associated with poor health behaviors (increased food intake and reduced physical activity) (Campbell 2016, Larsen et al. 2014, Remigio-Baker et al. 2014). The food environment index represents the proximity to healthy food, the availability of healthy food, and the cost barriers to healthy food based (County Health Rankings 2015). While there were many context variables used in this study, the food environment index emerged as a significant protective factor against the burden of ACEs on adult mental health. When looking at ACEs, perhaps the food environment is a protective factor because it is a measure reflecting the psychosocial stress of the county as well as the income of the county, and improvement of the food environment index may buffer the relationship between ACEs and mental health by reducing the stress from the context that one lives in.

Differences in statistically significant moderators by state shed light on how Texas and California are different contextually. While the food environment index and severe housing burden were both significant effect modifiers in the relationship between ACE exposure and mental distress in Texas, these two variables were not statistically important in the same models in California. Instead, the income ratio at the county-level was significant as a moderator in the same models in California. From the data reduction study prior to this one (see chapter 3, aim 1), there were statistical differences in the food environment between Texas and California, with California having on average a better food environment index score than Texas, and this difference is highlighted in the role of the food environment as a significant moderator in Texas and not in California.

Generalizability is a concern when assessing sample size as well as sample demographics, which is why many studies combine states from the BRFSS to create a sample more generalizable to the United States population. However, combining states, as seen with this study, may not be the most effective in targeting interventions since it ignores context issues that vary location to location. For example, implementing a country-wide program to improve food insecurity to alleviate the burden of ACEs may improve those with ACEs in Texas, but in California, there will be little to no improvement based on the results of this study.

A clear limitation of the study is the cross-sectional nature of the data as well as the lack of information on the length of time that participants lived in their counties of residence. While these are major limitations, the results from this study yield evidence of significant moderation and valuable information that context does matter within childhood adversity, and future studies should elucidate the components of time that were not available in this particular study.

Another clear limitation of this study is the issue of non-response bias based on the ACE module in the 2015 BRFSS for Texas and California. With 70% and 24% of respondents not completing the module in California and Texas (respectively), the missing sample represented younger, lower SES, and more racially and ethnically diverse categories compared to the final samples from both states (Table 1). While there is bias in the final sample, the results of these analyses still show statistically significant moderation by county context (specifically, the food environment index) on ACEs and mental health. While the bias in the data introduces a concern for the validity of the study, there are several studies using BRFSS as the sample source to assess ACEs and their impact on health (Campbell, Walker, & Egede 2016, Crouch et al. 2018, Crouch et al. 2020, Waehrer et al. 2020). Future studies using a survey with higher response rate on ACE questions are needed to further validate the findings of this study.

While this study has its limitations, the results generated show that approaching the prevalent issue of the burden of ACEs on adulthood at macro levels (rather than individual levels) can be beneficial for the communities and individuals susceptible to childhood adversity.

Chapter 5: Assessment of Racial and Ethnic Differences in Burden of ACEs and Context

Aim 3: Racial/Ethnic Disparities in Buffering Adverse Childhood Experiences (ACEs) Burden on Adult Mental Health: Using Three Way Interactions to Assess Differential Impacts of Context as an Effect Modifier

ABSTRACT:

Background: Childhood adversity is a growing public health concern, and although exposure to adverse childhood experiences (ACEs) exists across racial/ethnic groups, non-Hispanic Blacks and Hispanics frequently report more ACE exposures and subsequently are at higher risk of mental health burden in adulthood than their non-Hispanic white counterparts. This study seeks to understand if there is a racial/ethnic disparity in how context buffers the relationship between ACE exposure and mental health.

Methods: This cross-sectional study used participants from 2015 Behavioral Risk Factor Surveillance Survey (BRFSS) from 2015 in Texas and California as well as data from the 2015 County Health Rankings Data to create a sample of 9,932 participants. Using this sample, three-way interactions were assessed between ACEs, race/ethnicity, and context at a significance of $p < 0.05$ with the outcome of mental health (mental distress and diagnosis of depression).

Results: Of the 7 contextual variables used, the food environment index and average PM2.5 were statistically significant and meaningful ($p < 0.05$), indicating that there was a meaningful racial/ethnic difference in how the food environment and average PM2.5 moderated the impact of ACEs on mental distress.

Discussion: This study provides evidence on the differential moderating effect of context on the impact of ACEs on mental health based on race and ethnicity. These findings provide evidence to help guide potential interventions targeting racial and ethnic minority groups in hopes to reduce ACE burden at the community level.

Background

The original adverse childhood experiences (ACEs) study was seminal in understanding the pervasive impact of childhood adversity during formative years of growth on adult health and well-being (Felitti et al. 1998). Even in this original study, there were differences in exposure to ACEs by race/ethnicity, with 50% of non-Hispanic White adults reporting zero ACEs and only 39% and 43% of non-Hispanic Black adults and Hispanic adults reporting zero ACEs (Felitti et al. 1998). While non-Hispanic White adults were more likely to report having no experiences of childhood adversity, they were less likely to report having three or four ACEs compared to non-Hispanic Blacks and Hispanics (Felitti et al. 1998). Since the original ACE study, the differential rates of ACEs among non-Hispanic Whites, non-Hispanic Blacks, and Hispanic children have persisted (Slopen et al. 2016).

These patterns in disparities in ACEs by race/ethnicity are similar to the patterns of health burdens that are differentially distributed across race and ethnic groups. While racial and ethnic minority populations may report lower levels of mental health disorder diagnoses than their non-Hispanic White counterparts, measures of psychological distress and stress are higher in racial and ethnic minority populations, and mental health disorders in racial and ethnic minority populations are more likely to be persistent (Breslau et al. 2005, Williams 2018). Similarly, in a study of the 2012 BRFSS, race/ethnic identification was associated with increased risk of psychological distress and a medical comorbidity (angina, heart attack, and coronary heart disease) (Ahmed & Conway 2020).

Another racial/ethnic disparity to consider is context, which can be defined by the places and spaces that people work, live, and interact with others, and context can be further delineated as the physical context (the built environment, the physical infrastructure of the area, the pollutants in the area, the accessibility to healthy food) and the social context (the social connections, the accessible community). Disadvantaged contexts, which are typically defined using measures of poverty, deprivation, crime, and racial/ethnic composition, have negative effects on mental health, specifically depression, anxiety, and mental distress, even after accounting for individual attributes like family history of mental health (Hill & Maimon 2013, Ncube et al. 2016). Even within many definitions of disadvantaged contexts involves the racial/ethnic composition of the area unit, which alludes to how statistically often racial and ethnic minority populations are residing in disadvantaged contexts (Hill & Maimon 2013, Ncube et al. 2016). Not accounted for in many definitions of disadvantaged contexts, environmental burden, which is the risk of health consequences due to proximity to environmental hazards and pollutants, is a consequence of poor built environments, and studies have shown how environmental burden, like poor air quality and water violations, have negative physical and mental health consequences (Bakolis et al. 2021, Chen et al. 2018).

Based on the Protective Factors Theory in ACE literature, there are factors that help to bolster individuals after exposure to ACEs to reduce the burden of ACEs on their lifetime health (Zimmerman 2013). This theory was used in Aim 2 (Chapter 4) to outline how context can buffer the relationship between ACE exposure and mental health burden in adulthood, and food environment index was a key effect modifier in the relationship between ACE exposure and adult mental distress and ACE exposure and diagnosis of depression. While racial/ethnic differences in ACE burden, mental health burden, and context burden exist, the synthesis of these concepts has not been studied to understand how to reduce the burden on racial and ethnic minority groups and how to take steps towards health equity. The goal of this study is to assess if there are racial/ethnic differences in how context modifies the relationship between ACE exposure and mental health burden using the 2015 BRFSS data in Texas and California.

Methods

Sample

The sample for this study are participants from the 2015 Behavioral Risk Factor Surveillance Survey (BRFSS) from Texas and California, who participated in the optional ACE module in the BRFSS that year. To answer the main hypothesis of this study, the racial/ethnic groups of non-Hispanic White, non-Hispanic Black, and Hispanic were used, so those who answered “multiracial” or “non-Hispanic other” were excluded from the analytic samples. For this study, there will be three samples for our analytic plan: the combined sample (n=9,932), Texas sample (n=7,212), and California sample (n=2,720).

Variables

In the 2015 BRFSS, the ACE module is an optional module that both California and Texas participated in, and this module is a survey of 11 questions to assess 9 different adverse childhood experiences. Based on previous published factor analysis literature, the ACEs can be divided into categories of household dysfunction, emotional and physical abuse, and sexual abuse (Brown et al. 2013, Crouch et al. 2018). The category of household dysfunction ACEs is evaluated using questions referring to mental illness, substance use, incarceration in the household as well as parental separation/divorce. Emotional and physical abuse were assessed using the questions involving witnessing household violence and experiencing physical abuse. Three questions surveyed the category of sexual abuse. ACE score was calculated by summing up the presence of the 8 different adverse childhood experiences, so the range of scores was from 0 to 8. From the ACE score, the variable of ACE exposure was dichotomized to categorize those with 0-3 ACEs and those with 4 or more ACEs. Dichotomization of ACE exposure in this manner has been published extensively in the literature (Crouch et al. 2018, Felitti et al. 1998).

The main dependent variables assessed in this study were mental distress and depression. In the BRFSS, mental distress was evaluated using the question: “Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?” Data from this question was dichotomized for this analysis: 14 or more days of bad mental health and less than 14 days. The cut-off of 14 days is a frequently used threshold, specifically in the BRFSS to assess frequent mental distress, and it is a threshold associated with mental health conditions like depression and anxiety (Bonnie & Monahan 1997, Crouch et al. 2018). Depression in the BRFSS is evaluated by asking participants if a doctor has ever diagnosed them with depression, and in this study, the variable of depression was dichotomized as present or absent.

Covariates to account for socioeconomic status and demographic factors in the model were age, sex, and income level. Selection of these covariates was based on prior literature using BRFSS data (Crouch et al. 2018). Age is a categorical variable divided into the groups: 18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, and 65+ years of age. Income categories were as follows: less than $25,000, $25,000 to less than $50,000, and $50,000 or more. Race/ethnicity were defined using dummy variables with non-Hispanic White as the referent group.

Context was assessed previously using the County Health Rankings data from 2015, and from previous data reduction analyses (see aim 1), each context variable was assessed independently as continuous variables. While there was significant moderation by specific contextual variables from aim 2 (specifically food environment index), the possibility of masking necessitated the thorough investigation of all contextual variables as potential moderators in the three way interaction between ACE exposure, context, and race/ethnicity.

Analytic Plan

Distributions of the samples were generated, and Analysis of Variance (ANOVA) tests were used to assess contextual differences between non-Hispanic White, non-Hispanic Black, and Hispanic populations within each of the samples.

The preliminary logistic regressions to assess significant three-way interactions between race/ethnicity, ACE exposure, and context are summarized in Figure 1. Figure 1A summarizes a simple scheme of assessing three-way interactions and the terms that are needed to be included for the analysis, including the A*B*C interaction term that needs to be specifically evaluated. Race/ethnicity was categorized as non-Hispanic white, non-Hispanic black, and Hispanic for the preliminary analyses. If the interaction term of ACE exposure * context variable * race/ethnicity has a p-value <0.05, then the effect size of the interaction will be evaluated and further stratification by race/ethnicity may be warranted to understand the differential moderation of context by race/ethnicity. These preliminary analyses were conducted on the combined sample (n=9,932), Texas (n=7,212), and California (n=2,720) samples independently to consider state differences.

Figure 5.1. Logistic regression models used to assess three way interaction between ACE exposure, context, and race/ethnicity. Each context variable was assessed for the three samples of Texas (n=7,212), California (n=2,720), and the combined sample (n=9,932). A.The simple scheme of a three-way interaction between A, B, and C, and outcome variable (D). B. The model used to assess mental distress in this study. C. The logistic regression this study used to assess the three way interaction with depression as the outcome variable.

A. A + B + C +A*B*C + A*B + A*C + B*C --> D
B. ACE exposure + ACE exposure * context variable * Hispanic + ACE exposure *context + ACE exposure *context variable * non-Hispanic Black + context variable * non-Hispanic Black + ACE exposure * non-Hispanic Black context variable *Hispanic + ACE exposure *HIspanic + covariates + context variables --> mental distress
C. ACE exposure + ACE exposure * context variable * Hispanic + ACE exposure *context + ACE exposure *context variable * non-Hispanic Black + context variable * non-Hispanic Black + ACE exposure * non-Hispanic Black context variable *Hispanic + ACE exposure *HIspanic + covariates + context variables --> depression

Results

Of the 9,932 participants in the combined sample of Texas and California, there were 6,304 non-Hispanic White participants (63.4%), 693 non-Hispanic Black participants (6.98%), and 2,935 Hispanic participants (29.6%). The distribution of sociodemographic factors by race/ethnicity for the combined sample, the Texas sample, and the California sample are outlined in Tables 1, 2, and 3, respectively. Consistently for each of the samples, non-Hispanic blacks reported having 4 or more ACEs more frequently than non-Hispanic white and Hispanic participants. In terms of context, there were statistically significant differences between non-Hispanic White, non-Hispanic Black, and Hispanic in physical and social contexts, with racial and ethnic minority populations residing in counties with poorer contextual conditions than the white population (lower food environment indexes, higher rates of violent crime, and higher rates of severe housing problems) in all three sample populations (Table 4).

Table 5.1. Distribution of demographic characteristics in the combined 2015 Texas and California BRFSS sample (n=9,932) as well as main dependent and outcome variables by race/ethnicity.

		non-Hispanic White	Frequency (%)	non-Hispanic Black	Frequency (%)	Hispanic	Frequency (%)
	0-3 ACEs	5308	84.2	573	82.68	2483	84.6
ACEs*	4 or more ACEs	996	15.8	120	17.32	452	15.2
Depression*	diagnosed depression	1087	17.24	128	18.47	364	12.4
Mental Distress*	frequent mental distress	505	8.01	88	12.7	278	9.47
	less than $15,000	408	6.47	142	20.49	653	22.25
	$15,000 to less than $25,000	728	11.55	150	21.65	768	26.17
	$25,000 to less than $35,000	568	9.01	91	13.13	414	14.11
	$35,000 to less than $50,000	859	13.63	91	13.13	339	11.55
Income*	$50,000 or more	3741	59.34	219	31.6	761	25.93

	18-24 years	173	2.74	31	4.47	257	8.76
	25-34 years	405	6.42	70	10.1	491	16.73
	35-44 years	541	8.58	79	11.4	611	20.82
	45-54 years	870	13.8	117	16.88	575	19.59
	55-64 years	1443	22.89	153	22.08	483	16.46
Age*	65+ years	2872	45.56	243	35.06	518	17.65
	Male	2730	43.31	240	34.63	1203	40.99
Sex*	Female	3574	56.59	453	65.37	1732	59.01

Footnote: * denotes that ANOVA test showed p value <0.05

Table 5.2. Distribution of sociodemographic factors in the 2015 Texas BRFSS sample (n=7,212) as well as main dependent and outcome variables by race/ethnicity.

		non-Hispanic White	**Frequency (%)**	**non-Hispanic Black**	**Frequency (%)**	**Hispanic**	**Frequency (%)**
	0-3 ACEs	4297	91.23	503	90.14	1768	90.95
ACEs*	4 or more ACEs	413	8.77	55	9.86	176	9.05
Depression*	diagnosed depression	893	18.96	115	20.61	296	15.23
Mental Distress*	frequent mental distress	394	8.37	69	12.37	202	10.39
	less than $15,000	306	6.5	113	20.25	404	20.78
	$15,000 to less than $25,000	606	12.87	136	24.37	537	27.62
	$25,000 to less than $35,000	459	9.75	67	12.01	265	13.63
Income*	$35,000 to less than $50,000	670	14.23	80	14.34	234	12.04

	$50,000 or more	2669	56.67	162	29.03	504	25.93
	18-24 years	105	2.23	16	2.87	140	7.2
	25-34 years	266	5.65	51	9.14	277	14.25
	35-44 years	371	7.88	60	10.75	407	20.94
	45-54 years	624	13.25	98	17.56	364	18.72
	55-64 years	1101	23.38	127	22.76	345	17.75
Age*	65+ years	2243	47.62	206	36.92	411	21.14
Sex*	Male	1958	41.57	178	31.9	727	37.4
	Female	2752	58.43	380	68.1	1217	62.6

Footnote: * denotes that ANOVA test showed p value <0.05

Table 5.3. Demographic distribution of the 2015 BRFSS California sample (n=2,720) as well as main dependent and outcome variables by race/ethnicity.

		non-Hispanic White	**Frequency (%)**	**non-Hispanic Black**	**Frequency (%)**	**Hispanic**	**Frequency (%)**
	0-3 ACEs	1011	63.43	70	51.85	715	72.15
ACEs*	4 or more ACEs	583	36.57	65	48.15	276	10.15
Depression*	diagnosed depression	194	12.17	13	9.63	68	6.86
Mental Distress*	frequent mental distress	111	6.96	19	14.07	76	7.67
	less than $15,000	102	6.4	29	21.48	249	25.13
	$15,000 to less than $25,000	122	7.65	14	10.37	231	23.31
	$25,000 to less than $35,000	109	6.84	24	17.78	149	15.04
	$35,000 to less than $50,000	189	11.86	11	8.15	105	10.6
income*	$50,000 or more	1072	67.25	57	42.22	257	25.93
Age*	18-24 years	68	4.27	15	11.11	117	11.81

	25-34 years	139	8.72	19	14.07	214	21.59
	35-44 years	170	10.66	19	14.07	204	20.59
	45-54 years	246	15.43	19	14.07	211	21.29
	55-64 years	342	21.46	26	19.26	138	13.93
	65+ years	629	39.46	37	27.41	107	10.8
	Male	772	48.43	62	45.93	476	48.03
Sex	Female	822	51.57	73	54.07	515	51.97

Footnote: * denotes that ANOVA test showed p value <0.05

Table 5.4. Distribution of contextual variables for the 2015 BRFSS combined sample (A) (n=9,932), TX sample (B) (n=7,212), and CA sample (C) (n=2,720).

A. Combined (n=9,932)

	Non-Hispanic White		**Non-Hispanic Black**		**Hispanic**	
	Average	**Std Deviation**	**Average**	**Std Deviation**	**Average**	**Std Deviation**
Food environment Index*	6.57	0.97258	6.39	0.87997	6.47	1.02747
Social association rate*	9.96	4.28806	9.63	3.71374	8.85	5.14194
violent crime rate*	379.97	151.30036	407.9	149.48786	405.48	136.02614
Average PM2.5*	8.99	0.72943	9.11	0.64938	8.97	0.84856
Percent Water Violations*	7.38	12.37384	7.9	11.73522	7.95	17.06342
Percent Severe housing*	20.62	5.72809	20.28	5.64201	23.79	5.49338
Income Ratio*	4.83	0.69649	4.86	0.6146	5.96	0.53039

B. Texas (n=7,212)

	Non-Hispanic White		Non-Hispanic Black		Hispanic	
	Average	Std Deviation	Average	Std Deviation	Average	Std Deviation
Food environment Index*	6.2	0.7787	6.1	0.69924	5.98	0.81679
Social association rate*	8.82	2.59569	9.03	2.75284	6.56	2.48398
violent crime rate*	377.57	148.2855	402.03	145.64925	402.22	134.01886
Average PM2.5*	9.19	0.55618	9.23	0.54605	9.17	0.73004
Percent Water Violations*	8.97	13.44663	9.14	12.34749	10.29	20.02526
Percent Severe housing*	0.97	1.01891	0.96	0.88102	1.68	1.07605
Income Ratio*	4.82	0.76241	4.85	0.63863	5	0.57714

C. California (n=2,720)

	Non-Hispanic White		Non-Hispanic Black		Hispanic	
	Average	Std Deviation	Average	Std Deviation	Average	Std Deviation
Food environment Index*	7.63	0.60	7.54	0.46	7.43	0.66
Social association rate*	13.25	6.11	11.97	5.64	13.33	5.98
violent crime rate*	390.33	157.99	435.89	159.74	411.91	139.48
Average PM2.5*	8.44	0.86	8.65	0.79	8.6	0.93
Percent Water Violations	2.99	6.68	3.11	6.90	3.4	6.66
Percent Severe housing*	27.13	3.84	28.2	4.93	28.51	3.70
Income Ratio*	4.85	0.45	4.94	0.5	4.88	0.41

Footnote: * denotes p value <0.05 for ANOVA test

The three-way interaction models for each of the samples are summarized in Tables 5, 6, and 7. For the combined model (n=9,932) with mental distress as the outcome variable, there was a significant interaction between the Hispanic variable, average PM2.5, and ACEs (estimate = -0.957, p value < 0.05) (Table 5A). The estimate of the significant three-way interaction (estimate = -0.957, p value < 0.05) suggests that among the Hispanic population in the sample, the moderation of the average PM2.5 on ACEs and mental distress is lower in magnitude than that of non-Hispanic Whites in the sample.

With the same sample (n=9,932) but with depression as the outcome variable, both the food environment index (estimate = -0.379, p value=0.03) and severe housing rate (estimate = -0.061, p value=0.044) were independently interacting with ACEs and the non-Hispanic Black variable (Table 5B). The three-way interaction between the food environment index, the non-Hispanic Black variable, and ACEs (estimate = -0.379, p value=0.03) indicates that the moderation of the food environment index on ACEs and depression is lower in the non-Hispanic Black population compared to the non-Hispanic White population in the sample (Table 5B). The same logic is utilized when looking at the three-way interaction between severe housing rate, non-Hispanic Black, and ACEs, so among the non-Hispanic Black population, the moderation of the severe housing burden and ACEs on depression is lower than that of the non-Hispanic White population.

In the California sample (n=2,720), the only significant three-way interaction was between the non-Hispanic Black variable, average PM2.5, and ACEs (estimate = -2.199, p value <0.05) when looking at mental distress as the outcome variable (Table 7A).The three-way interactions in the Texas and

California samples yielded no other statistically significant three-way interactions for both outcome variables, mental distress and depression (Table 6 and 7).

Table 5.5. Results from the three-way interaction models for the combined sample (n=9,932) with mental distress (A) and depression (B) as the outcome variables.

A. Mental Distress

Interaction	**estimate**	**p value**
aces*food_environment*Black	-0.183	0.340
aces*food_environment*Hispanic	0.370	0.216
aces*social_association*Black	-0.051	0.184
aces*social_association*Hispanic	0.055	0.393
aces*violent_crime*Black	-0.0015	0.316
aces*violent_crime*Hispanic	0.002	0.300
aces*avg_pm*Black	-0.156	0.494
aces*avg_pm*Hispanic	**-0.957**	**0.02**
aces*pct_water_violations*Black	0.025	0.052
aces*pct_water_violations*Hispanic	-0.017	0.574
aces*pct_severe_housing*Black	-0.044	0.187
aces*pct_severe_housing*Hispanic	0.008	0.083
aces*income_ratio*Black	-0.036	0.917
aces*income_ratio*Hispanic	0.4702	0.3113

*Footnote: Each three way interaction was modeled controlling for age, sex, and income.

B. Depression

Interaction	**Estimate**	**P Value**
aces*food_environment*Black	**-0.379**	**0.031**
aces*food_environment*Hispanic	-0.028	0.921

aces*social_association*Black	-0.023	0.512
aces*social_association*Hispanic	0.067	0.264
aces*violent_crime*Black	-0.002	0.036
aces*violent_crime*Hispanic	0.0003	0.883
aces*avg_pm*Black	-0.177	0.374
aces*avg_pm*Hispanic	-0.621	0.103
aces*pct_water_violations*Black	0.0.004	0.739
aces*pct_water_violations*Hispanic	-0.02	0.4944
aces*pct_severe_housing*Black	**-0.061**	**0.044**
aces*pct_severe_housing*Hispanic	0.010	0.828
aces*income_ratio*Black	-0.005	0.989
aces*income_ratio*Hispanic	0.168	0.68

*Footnote: Each three way interaction was modeled controlling for age, sex, and income.

Table 5.6. Results from the three-way interaction models for the Texas sample (n=7,212) with mental distress (A) and depression (B) as the outcome variables.

A. Mental Distress

Interaction	**estimate**	**p value**
aces*food_environment*Black	-0.006	0.984
aces*food_environment*Hispanic	0.899	0.079
aces*social_association*Black	0.003	0.974
aces*social_association*Hispanic	-0.090	0.532
aces*violent_crime*Black	-0.0004	0.790
aces*violent_crime*Hispanic	0.001	0.640
aces*avg_pm*Black	-0.60	0.11
aces*avg_pm*Hispanic	-0.412	0.536
aces*pct_water_violations*Black	0.028	0.0496
aces*pct_water_violations*Hispanic	-0.0142	0.709

aces*pct_severe_housing*Black	0.1181	0.611
aces*pct_severe_housing*Hispanic	0.109	0.795
aces*income_ratio*Black	0.304	0.454
aces*income_ratio*Hispanic	0.074	0.893

*Footnote: Each three way interaction was modeled controlling for age, sex, and income.

B. Depression

Interaction	**Estimate**	**P Value**
aces*food_environment*Black	-0.430	0.124
aces*food_environment*Hispanic	0.201	0.656
aces*social_association*Black	0.122	0.156
aces*social_association*Hispanic	0.148	0.273
aces*violent_crime*Black	-0.003	0.0778
aces*violent_crime*Hispanic	-0.003	0.281
aces*avg_pm*Black	-0.269	0.395
aces*avg_pm*Hispanic	-0.623	0.276
aces*pct_water_violations*Black	0.005	0.717
aces*pct_water_violations*Hispanic	-0.006	0.1981
aces*pct_severe_housing*Black	-0.202	0.318
aces*pct_severe_housing*Hispanic	-0.413	0.2888
aces*income_ratio*Black	-0.0003	0.9993
aces*income_ratio*Hispanic	-0.509	0.330

*Footnote: Each three way interaction was modeled controlling for age, sex, and income.

Table 5.7. Results from the three-way interaction models for the California sample (n=2,720) using mental distress (A) and depression (B) as the outcome variables.

C. Mental Distress

Interaction	**estimate**	**p value**
aces*food_environment*Black	-0.022	0.966
aces*food_environment*Hispanic	0.544	0.649
aces*social_association*Black	-0.048	0.358
aces*social_association*Hispanic	0.182	0.089
aces*violent_crime*Black	-0.002	0.350
aces*violent_crime*Hispanic	0.004	0.257
aces*avg_pm*Black	.159	0.656
aces*avg_pm*Hispanic	**-2.199**	**0.008**
aces*pct_water_violations*Black	-0.023	0.622
aces*pct_water_violations*Hispanic	-0.031	0.683
aces*pct_severe_housing*Black	-0.133	0.144
aces*pct_severe_housing*Hispanic	0.251	0.06
aces*income_ratio*Black	-1.29	0.147
aces*income_ratio*Hispanic	3.197	0.088

*Footnote: Each three way interaction was modeled controlling for age, sex, and income.

D. Depression

Interaction	**Estimate**	**P Value**
aces*food_environment*Black	-0.021	0.965
aces*food_environment*Hispanic	-0.139	0.927
aces*social_association*Black	0.027	0.587
aces*social_association*Hispanic	0.113	0.328

aces*violent_crime*Black	-0.002	0.402
aces*violent_crime*Hispanic	0.0013	0.667
aces*avg_pm*Black	-0.296	0.402
aces*avg_pm*Hispanic	-0.544	0.621
aces*pct_water_violations*Black	-0.116	0.141
aces*pct_water_violations*Hispanic	-0.349	0.514
aces*pct_severe_housing*Black	-0.035	0.685
aces*pct_severe_housing*Hispanic	-0.068	0.638
aces*income_ratio*Black	-0.019	0.980
aces*income_ratio*Hispanic	1.5	0.261

*Footnote: Each three way interaction was modeled controlling for age, sex, and income.

Discussion

Adverse childhood experiences are a pressing and prevalent public health issue, and while the burden of ACEs is evident across race and ethnic groups, disparities in exposure to ACEs reflects the disparities in health (Slopen et al. 2016). The goal of this study was to assess racial/ethnic differences in moderation by context in the relationship between ACEs and mental health.

Non-Hispanic Black and Hispanic populations bear a greater ACE burden than their non-Hispanic White counterparts, with these racial and ethnic minority populations more likely to report more ACEs and less likely to report having no ACEs compared to non-Hispanic white populations (Slopen et al. 2016). In the 2015 BRFSS Texas and California sample, the non-Hispanic Black population reported a higher incidence of exposure to 4 or more ACEs than both non-Hispanic Whites and Hispanics (Table 1). While the disparity between non-

Hispanic white and non-Hispanic Black ACE burden was consistent with previous literature (Felitti et al. 1998, Slopen et al. 2016), only 15.2% of Hispanic population in this sample reported having 4 or more ACEs while 15.8% of the non-Hispanic Whites population reported exposure to 4 or more ACEs (Table 1). Though inconsistent with published findings, the distribution of ACEs within this sample is for two of the most culturally diverse states in the United States, and other studies have used samples that are more representative of the United States as a whole (McCann 2021, Slopen et al. 2016). In Slopen et al. (2016), the study sample had 7% Hispanic representation while the main sample of this study has 2935 Hispanic participants (29.6% of the study population). Another aspect to consider about the racial/ethnic distribution in the sample is the missing data because of the nonresponse to the ACE module in the 2015 BRFSS (Chapter 4). While the study sample was racially and ethnically diverse, the missing sample represented more racial and ethnic minorities as well as lower SES populations than the study sample. The missing data as well as the differences in ACE prevalence in combination suggest that the study sample has some bias and that future studies should include a more demographically and racial/ethnically diverse population.

The role of context in childhood adversity has been understudied despite the breadth of knowledge that physical and social context are important in understanding disparities in health (Diez Roux & Mair 2010). Based on the context variables used in this study, there are statistically significant differences between the contexts of our sample of non-Hispanic White, non-Hispanic Black, and Hispanic populations (Table 4). In our previous study (see aim 2, chapter 4), the food environment index was a statistically significant modifier in the relationship between ACE exposure and mental distress as well as the relationship between ACE exposure and depression. The food environment index is an index that assesses the accessibility to healthy foods in a county as well as the percentage of residents who report food insecurity, and the index ranges from 0 (poor food environment) to 10 (best food environment) (County Health Rankings 2015). For those who reported high ACE exposure, the likelihood of reporting depression or mental distress decreased for every unit improvement of the county's food environment index (Chapter 4). The food environment index of the county was a statistically significant moderator in the three way interactions when depression was the outcome variable (Table 5B) among non-Hispanic Blacks compared to non-Hispanic Whites. The moderation of the food environment index for non-Hispanic Blacks was lower in magnitude than that for non-Hispanic Whites, indicating that the impact of improving the food environment index is greater for non-Hispanic Whites than non-Hispanic Blacks.

Most of the literature on food environments and depression are in relation to obesity since the mechanisms of obesity and depression involve the dysregulation of the hypothalamic-pituitary-adrenal (HPA) systems as well as the associations of these two conditions with increased food intake and reduced physical activity (Campbell 2016, Larsen et al. 2014, Remigio-Baker et al. 2014). Most susceptible to poor food environments and subsequent risk of obesity and depression, the non-Hispanic black population reside in neighborhoods that are farther from the nearest supermarket and that have fewer supermarkets (Morland et al. 2002, Zenk et al. 2005, Li & Ashuri 2018). While there are less studies examining the Hispanic population within literature on food environment, Hispanic predominant (75% or more Hispanic) neighborhoods are more likely to have more convenience stores and less likely to have supermarkets than predominantly white neighborhoods in the Bronx (Moore & Diez Roux 2006). Similarly, the effect of having more convenience stores and less supermarkets in close proximity on body mass index was higher for non-Hispanic Black and Hispanic populations than white populations (Lovasi et al. 2009). Racial and ethnic minorities living in racial and ethnic minority-predominant areas are disproportionately contextually burdened compared to non-Hispanic white populations, and the results of this study highlight the differential impact of race/ethnicity on how ACE burden on mental health can be buffered by the food environment.

The statistically significant three-way interaction between Hispanic, average PM2.5, and ACEs was consistent in the combined and the California samples. While the average PM2.5 was not a statistically significant moderator in the previous study (see aim 2, Chapter 4), the results from the three-way interaction show that there are differences between Hispanic and non-Hispanic populations in the sample. When assessing the air quality of non-Hispanic Whites and Hispanics, Hispanics resided in counties with higher PM2.5 than non-Hispanic Whites, indicating that there is more harmful particulate pollution in the air and that Hispanics are residing in areas with higher exposure to air pollution.

A meta-analysis of studies assessing particulate pollution and depression showed that there is a long-term risk of 6 months of more exposure to particulate pollution on odds of depression (Braithwaite et al. 2019). Further investigation to stratify the study sample and further compare the differences in moderation of air pollution on ACEs on mental health burden are necessary for future studies.

While the Hispanic population may be overrepresented in this study sample and cannot be generalizable to the United States population, the results of this study highlight the importance of understanding state differences. Texas and California are two of the most racially and culturally diverse states in the United States (McCann 2021), and while these two states cannot represent the country as a whole, the differences between non-Hispanic white, non-Hispanic black, and Hispanic populations that exist in these two states may be masked when studying a more "generalizable" study population. The results of this study can be used to better allocate resources to properly target racial and ethnic minority populations in these two diverse states and effectively help mitigate the impact of ACE burden on adult mental health burden. Based on these results, special attention should be given to improve the food environment index of the counties of these two states. Further investigation into what aspects of the food environment index are the most impactful in buffering the impact of ACEs on mental health may help elucidate the most effective method of reducing mental health burden and help better allocate resources and funds efficiently.

This study looked specifically at racial/ethnic differences, but there is evidence to support differences even within the Hispanic experience based on nativity that is not explored in this study (Powers, Moule, & Severson 2022). There has been much research showing that Hispanic immigrants have better psychological and physical health outcomes compared to native-born Hispanics (Markides & Coreil 1986). In terms of ACE prevalence among Hispanics, first-generation (those who immigrated away from their country and are the first to live in the United States) Hispanics report less ACE exposure than their second-generation counterparts (Powers, Moule, & Severson 2022). Future studies should address nativity of the Hispanic sample and seek to understand if the moderation of context variables differ by nativity.

A major limitation of this study is the use of cross-sectional BRFSS data, which limits our conclusions about causality. In addition, the analyses in this study are assuming that the county of the participant at the point of interview is the only context they ever lived in, but even with this assumption, the context in which people reside has moderating effects on ACE burden and adulthood mental health. While the non-response rate for the ACE module was rather high (24% for Texas and 70% for California), the use of BRFSS data to study ACEs and their impact on health has been published (Campbell, Walker, & Egede 2016, Crouch et al. 2018, Crouch et al. 2020, Waehrer et al. 2020). Most studies do not report the response rate of the ACE module, but there is one study that reported using 2011 BRFSS data to study ACEs from 5 different states and still had less than 10% of the original sample for their study after removing participants who refused or did not complete the ACE module (Campbell, Walker, & Egede 2016). In comparison, this study retained more of the original sample (at least 30% in California) to address the study question. A future study to assess the response rates of the ACE module and compare the missing populations when assessing ACEs in BRFSS may be needed.

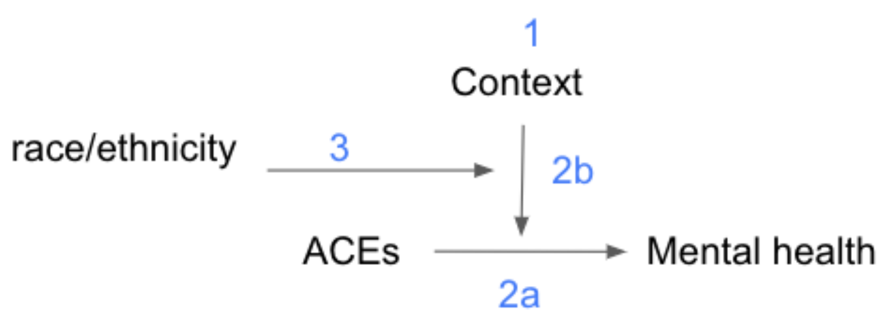
In conclusion, the results of this study highlight racial/ethnic differences in ACE burden and how the food environment index and air pollution differentially impacts ACE exposure on depression and mental distress in adulthood. This is one of the first studies to examine the relationship between context, ACEs, and mental health and how this relationship varies between race/ethnic groups.

Chapter 6. Summary & Discussion

Adversity during childhood is a prevalent problem that has many downstream physical and mental health implications in adulthood, and it has become a growing public health concern (Felitti et al. 1998, Petruccelli et al. 2019). While exposure to ACEs leads to serious mental health consequences (Petrucceli et al. 2019), there is little research seeking to understand how to aid those exposed to childhood adversity at a macro level. Context, the physical and social environment that one lives, works, and interacts in, is a major social determinant of health that has been understudied in childhood adversity literature (Felitti et al. 1998, Sareen et al. 2011). Using the Resiliency Theory, which postulates that there are factors that may buffer or even exacerbate the relationship between exposure of ACEs and poor health outcomes, this study sought to understand how the physical and social context of participants in the 2015 BRFSS Texas and California study may moderate the relationship between ACE exposure in childhood and their mental health. This study used both the 2015 BRFSS in Texas and California and the County Health Rankings in 2015 to 1. Determine the social and physical contexts of the counties and determine their relationship with ACEs and mental health, 2. Assess if context moderates the relationship between ACEs and mental health, and 3. Evaluate if there are racial/ethnic differences in how context moderates ACEs and mental health.

To re-address the conceptual framework that was introduced earlier in the first chapters of this dissertation, this project sought to understand context as defined by different variables in the County Health Rankings (Figure 1, 1), to understand if context was a protective factor in the relationship between ACEs and mental health (Figure 1, 2b), and to assess if there were racial/ethnic differences in how context moderates ACEs and mental health (Figure 1, 3). This project addresses the prevalence of ACEs (and subsequent downstream health implications) at a macro-level of intervention.

Figure 6.1. Conceptual framework highlighting the aims of this dissertation.



The first aim of this dissertation was to assess the social and physical contexts of participants in the 2015 BRFSS in Texas and California. Using data reduction techniques of factor analysis and principal component analysis, 8 variables of physical and social contexts were studied to reduce these factors into one or more “context” variables for other analyses. The results from these analyses revealed that context cannot be merely condensed into one factor and that context is analytically multifaceted since the variables did not statistically create any meaningful factors. While there are studies that have used these techniques to condense the concept of context statistically using lower thresholds on internal consistency, this study found that the physical and social context variables were independent and could have independent effects.

For the second aim of this dissertation, the potential moderating role of context in ACE exposure and mental health was assessed. Since the first aim found that there were statistically different measures of context, seven different components of context were independently evaluated for moderation, and there were a few context variables that were statistically significant moderators in the relationship between ACE exposure and mental health. The food environment index and the income ratio of the county were significant moderators, and improvement of either of these variables showed reduced likelihood of reporting mental health problems. The results of this study demonstrated that context is important in understanding ACEs and mitigating their impact on mental health, and importantly, it unveiled specific components of context that can be improved at the county level.

Because there are racial/ethnic differences in exposure to ACEs as well as mental health outcomes, the third aim sought to understand if racial/ethnic differences existed even in how context moderates ACEs and mental health. Using only participants that were non-Hispanic white, non-Hispanic black, and Hispanic in a three-way interaction between race/ethnicity, context, and ACEs, logistic regressions were used with all of the context variables from the second study,. This study revealed that there were meaningful racial/ethnic differences in how the food environment index buffers the relationship between ACEs and mental health.

Given that most of the literature on ACEs and health outcomes focused on individual factors (Felitti et al. 1998, Petruccelli et al. 2019), this dissertation uses a macro level approach to understand how the physical and social environment can be used to intervene and buffer the burden of ACEs on adult mental health. Improvement to the community has been a target for intervention to address ACEs (Hall et al. 2012, Pachter et al. 2017), and this study provides a conceptual framework to address ACE burden at the county-level. The results from these studies give insight on what aspects of context should be addressed to buffer ACE burden on adult health. For example, in Texas, since the food environment index was a significant moderator, a policy that could help mitigate ACE burden in Texas would be to implement nutrition assistance programs that are trauma-based rather than based only on financial need or hardship (Hecht et al. 2018, Jackson et al. 2019, Testa and Jackson 2020).

While this sample only includes participants from Texas and California, the results still provide evidence of clear moderation of context variables in reducing the burden of ACEs on mental health despite the limitation of generalizability. Throughout these studies, Texas and California separately were analyzed as distinct samples, and the results showed some statistically significant differences between the two states. For example, the food environment index and severe housing burden were statistically significant moderators in the relationship between ACE burden and mental distress in Texas, but these variables were not statistically significant moderators in California. While these results could be a limitation of the small sample sizes in both Texas and California samples, they do shed light on differences between the two states and allude to further differences in the other 48 states. Texas and California are two of the most diverse states in the United States (McCann 2021), which make these two states the most logical to approach aim 3 of this dissertation, but ultimately, the two states are distinct and cannot be used to generalize to the entire United States population. However, when approaching interventions to apply the results of these studies, the strategy to assess and improve contexts may be the most effective way to mitigate ACE burden. A “one size fits all” approach when assessing representative samples ignores regional or state differences in needs, and it may not be the most effective in improving the burden of ACEs on future generations. Further evaluation of state differences should be assessed with a larger sample from both states, and the addition of another state, possibly from a different region of the United States, would be used as another distinct comparison between Texas and California.

In addition, the number of non-respondents to the ACE module in the 2015 BRFSS in Texas (24%) and California (70%) is a major limitation to this study. It creates a bias in the results that were generated in these studies since there were statistically significant differences between the study samples and the missing samples (see aim 2, table 1). In another study that used 2011 BRFSS data from 5 different states, less than 10% of the data was used in the analytic sample due to incomplete data from the ACE module (Campbell, Walker, &

Egede 2016). While the missing population represented a younger, poorer (SES), and more racially and ethnically diverse population, the analyses conducted in these studies still yielded statistically significant results in the study sample (representing older, richer, and non-Hispanic White populations). The results of these studies may be underestimating the protective impact of the food environment index since the study sample is mostly representing those who have higher SES and reside in more contextually advantageous contexts (non-Hispanic Whites consistently lived in better physical, social, and environmental contexts than non-Hispanic Blacks and Hispanics). Future studies to minimize the number of non-respondent bias in the ACE module would help validate the findings from these studies.

Another major limitation with these studies was the cross-sectional nature of the sample and information. The analyses were carried out with the assumption that the participants only resided in the county that they reported (and never moved). In addition, the BRFSS in 2015 did not disclose any information on the duration that the participants resided in their county, so these studies essentially assumed each participant was exposed to the same duration of their county at the time of interview. Even with these limitations, there are statistically significant results showcasing the role of some contextual variables moderating the relationship between ACE burden and mental health. Further longitudinal studies to assess the time component of where participants live (and are exposed to their contexts) will elucidate the effect of context as a moderator.

In addition, the use of the county level information to understand context is another limitation of these studies. While County Health Rankings data provided rich social and physical context data for these studies, the BRFSS in Texas and California only provided participant residence at the county level. County level context is difficult to conceptualize since counties are not defined uniformly (in contrast to geographical units like Census block groups, which are defined by population size), but the benefit of studying context at the county level is that policies can be made at this level of government. These studies provide evidence in how county-level context can moderate ACEs and mental health burden, but using different geographical units may provide evidence of what precise geographical unit to better intervene at to buffer mental health burden.

A concern about the County Health Rankings and the contextual variables at the county level is that the measures in the data are essentially all measuring the county's wealth, and therefore, the wealthiest counties will have more favorable measures of context and health outcomes than other counties (McCullough & Leider 2017). However, this concern was debunked when county wealth did not always predict better health outcomes in a study using the County Health Rankings in 2013 (McCullough & Leider 2017). In this study, countries that invested more in community health care and public health had better health outcomes, and counties that were wealthy did not predict better health outcomes (McCullough & Leider 2017). While it is true that wealth is correlated with health (and perhaps context), the results of these studies shed light on aspects of the county that should be improved and where spending would be better allocated to improve ACE burden at the community level.

Childhood adversity has enduring impacts on health (Felitti et al. 1998, Slopen et al. 2016). The analyses used in these studies shed light on how interventions can be directed at a macro-level to reduce the burden of ACEs on adult mental health.

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