Alternative Narrative to Inadequate Parenting:

The Community Adversity Index

By

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ABSTRACT

This dissertation examines the role of adverse community environments in explaining individual-level adverse outcomes and social inequality. Specifically, it examines "How do adverse community environments contribute to the incidence of childhood adversity?" Through three related studies, this work contributes empirical evidence that can assist policymakers in designing more effective interventions to mitigate childhood adversity. Research, policy, and practice have emphasized changing parental behavior to minimize the effects of childhood adversity. However, critics of this parent behavior-focused approach claim these efforts contribute to a public narrative that centers family deficiencies as responsible for childhood adversity. This narrative oversimplifies toxic stress processes while obscuring broader social inequities that combine to overload families. This is especially important when understanding racial and economic disparities in rates of childhood adversity because poor, Black, Indigenous and Hispanic/Latino families are more likely to live in distressed communities.

An alternative narrative is established through introducing the Community Adversity Index. This tool defines and quantifies community-level adversity and is used to demonstrate that community adversity is a strong predictor of family separation via foster care placement. Chapter 1 describes the three studies and concluding policy implications that form this dissertation. Chapter 2 establishes the theoretical support for a composite measure of community-level adversity and proposes data sources and indicators to calculate the index. The resulting single metric is then used to rank communities and describe how adversity is geographically distributed. Subindices are

also used to determine how adversity is bundled or typically grouped in urban communities. Chapter 3 uses five criteria featuring statistical, validity, and sensitivity tests to establish the reliability of the index as a tool for directing policy efforts. Chapter 4 uses regression analysis to establish that measures of community adversity predict family separations. Findings suggest that reducing community-level adversity could reduce family separations in general, as well as for White, Black, and Hispanic/Latino populations specifically. The dissertation concludes with a final chapter summarizing how the index can be useful for influencing policy.

DEDICATION

To William Woodard, Kirk Brandt, and Alissa Feldman.

Tragic death now prevents your voices from raising consciousness about homelessness, the lack of mental health resources, the way systems conspire against Black people and the lack of inclusivity for queer and disabled people. May this work amplify your sentiments that our collective well-being depends on alleviating unjust adversity.

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CHAPTER 1

INTRODUCTION

The Context of Childhood Adversity

Adverse childhood experiences (ACEs) is a conceptual framework that links child maltreatment to poor health outcomes across the life course (Felitti et al., 1998). Maltreatment is a word used to aggregate *neglect*, or failure to materially provide for children, and *abuse*, a far less common type of maltreatment that is concerned with emotional, physical, or sexual harms. The terms neglect and abuse are terms typically employed to describe the willful acts of parents. However, neglect is difficult to distinguish from poverty and behaviors that are labeled as abusive are often responses to unmanageable stress (Condon & Sadler, 2019; Pressley, 2020).

Adverse childhood experiences are prevalent, problematic, and preventable[1]. Several measures show adverse childhood experiences to be widespread (Garcia et al., 2017; Sacks et al., 2014). Parents report that nearly half (45%) of the children in the United States have experienced adversity (Sacks & Murphey, 2018), and almost 40% are the subject of maltreatment investigations before reaching adulthood (Kim et al., 2017). Without the buffer of positive relationships with caring adults or of needed interventions, these adverse childhood experiences can disrupt a child's development (K. A. Moore & N. Ramirez, 2016). Such disruptions pose a potential for lifelong impact because

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[1] This dissertation adopts the Frameworks Institute's principles for framing childhood adversity, including stressing that this is a preventable problem, that we have collective responsibility for ensuring the well-being of children, and that community stressors can overload parents. See: Sweetland, J. (2021). Reframing Childhood Adversity: Promoting Upstream Approaches.

traumatic stress can lead to notable changes in children's developing bodies and brains (Anda et al., 2006; Brummelte, 2017).

Many social structures, institutions, and adults beyond just parents collectively contribute to a child's development. However, research, policy, and practice have primarily targeted parent behavior as the main site for preventing childhood adversity. Research has investigated modifying parent behavior to improve childhood outcomes (Smagner & Sullivan, 2005) and policymakers have promoted parenting behavior interventions by connecting these strategies to reimbursement funding (Garcia et al., 2020). Child welfare agencies, children's commissions, and nonprofit organizations respond to parent-focused policy by practicing behavioral change interventions that rely on research-based strategies such as Triple P (Positive Parenting Program) or the Strengthening Families Framework (Delawarde-Saïas et al., 2018; Kumpfer & Magalhães, 2018). However, critics of this family-focused approach claim these efforts contribute to a public narrative that centers the family as responsible for preventing childhood adversity and oversimplifies sources of toxic stress (White et al., 2019). Efforts focusing on intervening at the family-level can blame families while obscuring ecological influences that contribute to family distress.

Persistent, high, and racially disproportionate rates of neglect point to these obscured social structures. Neglect is the most common form of confirmed child maltreatment (74.9% of 674,000 child maltreatment victims experienced neglect in 2017, Stedt 2018) and is commonly associated with child removal (neglect is a factor is 62% of removals to foster care, U.S. Department of Health and Human Services 2018). Scholars suggest it is nearly impossible to disentangle neglect (as an assumed parental behavior) from the consequences of poverty (Pressley, 2020). Poverty leaves parents vulnerable to neglect allegations, because visible signs of poverty—especially poverty concentrated at the community level—flag the attention of mandated reporters like police officers and teachers (Courtney et al., 2005; Edwards, 2019; Fong, 2020; Roberts, 2002). For example, crowded or poor housing, can be interpreted as neglecting to provide adequate shelter (Hall & Greenman, 2013; Roberts, 2002). Therefore, neglect statistics can equally be interpreted as indicating the larger problem of society's disinvestment in children and families, rather than simply poor parenting.

Structural racism and discrimination are related factors obscured by narratives that label parents as inadequate. Long-standing disproportional representation in the child welfare system specifically points to both distributive injustice and system bias (Curtis & Denby, 2011; Dettlaff & Boyd, 2020). Distributive injustice is evident in the way community disinvestment and housing segregation increases the likelihood of Black and Hispanic/Latino families living in low opportunity neighborhoods (Acevedo-Garcia et al., 2014). Forced relocation to reservations also contributes to distressed community conditions for Indigenous Peoples (Mauer, 2014). This uneven distribution of community resources places a higher burden of risk on Black, Indigenous and Hispanic/Latino families, contributing to more engagement with government agencies (Dettlaff, 2014; Edwards, Wakefield, et al., 2021; Kim et al., 2017; National Indian Child Welfare Association, 2019; Yi et al., 2020). Black, Indigenous and Hispanic/Latino children are typically reported and investigated more relative to White children, despite equal rates of confirmed child maltreatment (Edwards, Wakefield, et al., 2021; National Indian Child Welfare Association, 2019). This suggests reports, investigations, and neglect determinations arise partly from racial profiling by mandated reporters. Further, “family policing” activities administered by child welfare workers, make it difficult for families to escape the punishing gaze of authorities (Edwards, 2019; Lane et al., 2002; Roberts, 2022). Despite decades of reform targeting parent behavior, child welfare agencies consistently struggle to reduce poor outcomes for children—especially children of color. This suggests responsibility for overrepresentation and disparate outcomes should not be placed solely on the shoulders of parents, but rather on the systems they engage with.

Poverty and discrimination are two domains of influence in the community ecosystem surrounding a family. Evidence is quickly mounting that a host of community-level stressors, such as lack of childcare and poor housing, can compound for families and overload their resources—and indeed interventions on these stressors show promise in reducing child maltreatment (Fowler & Schoeny, 2017; Klevens et al., 2015). Universal policies, or policies that benefit all families regardless of eligibility criteria or program participation, appear to be particularly effective. For example, raising the minimum wage by $1 reduced neglect rates in one state by nearly 10% (Raissian & Bullinger, 2017). As such, those who seek to prevent adverse childhood experiences must consider reconceptualizing the issue and solutions in ways that render the problem in a broader ecological context.

A new narrative is needed to “influence what is politically possible (Hofrichter, 2018, p. 4)” and to garner a collective commitment to build the structural support families need so that children meet their full potential. Ellis and Dietz (2017) offer a solution for reframing the problem of childhood adversity by pairing the well-recognized concept of adverse childhood experiences with a new term, *adverse community environments*. Adverse community environments are defined as:

> "communities that have a high concentration of poverty and violence and/or low access to resources, such as food retail, public transportation, and services like education, health care, behavioral health, employment opportunities, economic development and limited social supports for health and wellbeing" (Sumner M. Redstone Global Center for Prevention and Wellness, 2017, p. 9).

Their communication tool, called the Pair of ACEs, uses imagery and mnemonics ("ACE" is used for both "adverse childhood experiences" and "adverse community environments") to communicate that families are influenced by their communities. The Pair of ACEs concept supports an essential change in discourse as it contextualizes family-level outcomes within the surrounding environmental stressors, including domains such as structural factors and discrimination. These domains—as evidenced in the social determinants of health, ecology, and neighborhood effects literature—negatively impact family functioning.

The "adverse community environments" concept has proved immensely popular with community coalitions (Wolff, 2020). It is routinely used by stakeholder groups seeking to reduce the incidence of childhood adversity (C. Young & Ellis, 2019). However, despite its popularity and potential, the alternative narrative put forth by Ellis and Dietz lacks empirical evidence to strengthen its credibility with policymakers. To develop a more substantial evidence base for the Ellis and Dietz framework, I create a Community Adversity Index (CAI) and demonstrate its ability to predict adverse childhood experiences. Policymakers can build on the empirical results generated by the index to refocus support toward community-level interventions.

This introductory chapter provides a brief overview of the public narratives about the causes of adverse childhood experiences, the meaningful consequences of such narratives for policy, and the role of multi-sector collaboratives in advancing alternative narratives for policy change. Next, I introduce the CAI index as a tool for reframing narratives and bringing empirical evidence to bear on policy decisions. Then, I describe three quantitative studies designed to provide policymakers with empirical evidence that suggests community-level interventions are needed to prevent childhood adversity. Finally, I draw research conclusions and summarize the implications for child welfare policy.

Power of Public Narratives

Narratives are accounts of a sequence of events experienced by characters and are used by various actors to guide reasoning and inspire action (Polletta & Chen, 2009). When developing narratives, narrators select how to organize the story, present characters, and evaluate outcomes (Culler, 2000). Narrators rely on discursive strategies, such as emphasis or obfuscation, to achieve specific effects on an audience (Druckman, 2001; Van den Hoven, 2016). Narratives function to simplify complex life experiences (Entman, 1993; Goffman, 1974; Weaver, 2007) and emotionally engage listeners through relatable details (Green & Brock, 2000).

Narratives frequently repeated through many social channels and familiar to many community members can be described as “public narratives.” Dominant public narratives typically oversimplify complex problems, obscure perspectives, and rely on tropes that can harm those they portray (Rose, 2013). Dominant public narratives featuring families are typically racialized and classed, leading to negative consequences for poor, Black, Indigenous and Hispanic/Latino families (Barcelos & Gubrium, 2014; Campisteguy et al., 2018). These consequences are substantial because public narratives shape the interventions supported by public policy and funding (Niederdeppe et al., 2015; Thibodeau et al., 2015; Townsend et al., 2020). These dominant public narratives only unravel when social momentum accrues behind an alternative narrative that redefines a social problem and posits a new solution (Wainwright, 2019).

Inadequate parenting as an explanation for childhood adversity is typical of a dominant public narrative in that it features oversimplification, obscures perspectives, and uses harmful tropes. When maltreatment is narrated using race- and class-based behavioral tropes, the effect of social inequality and community disparities is obscured. Poor, Black, Indigenous and Hispanic/Latino families are more likely to live in distressed communities (Drake & Rank, 2009; Maguire-Jack et al., 2015; Mauer, 2014). Conditions outside families' control, like concentrated poverty, lack of community resources, and unstable housing (Freisthler et al., 2006), can lead to community distress that is misinterpreted as family neglect (Dubowitz, 2013). Such misinterpretations are typically fueled by stereotypes and tropes, such as the depiction of women of color as "welfare queens" with "numerous children [they] cannot support, who [are] cheating taxpayers to abuse the system to collect government assistance" (Gilman, 2013, p. 247). These stereotypes and perceptions play a key role in child welfare involvement, especially family separation (Roberts, 2002) for Black, Indigenous and Hispanic/Latino families, as poverty alone does not explain the increased risk these families experience as compared to Whites (Edwards, Beardall, et al., 2021; Roberts, 2002; White-Wolfe et al., 2021; Wulczyn, Gibbons, et al., 2013).

Finally, the inadequate parenting public narrative is tied to research and policies that direct resources toward solutions that cast parents as the problem. This dominant public narrative suggests that the primary solution to childhood adversity is changing parenting behavior, an issue to be managed within the family domain. Existing research contributes to this narrative, identifying family settings as the primary influence on child development and framing parents as primarily responsible for caring for their children's needs (Bullinger et al., 2019; Dubowitz, 2013). Such arguments discount an essential analysis of broader community processes. Child welfare policies further carry the inadequate parenting narrative by directing resources toward programs that attempt to modify parent behavior, such as programs that teach parenting skills.

An example of this process is the federal Family First Prevention Act of 2018, which provides funding for strategies that target parental behavior changes (Children's Defense Fund, 2018). The Act assumes that family-level strategies will address high neglect rates and other maltreatment. However, research shows that while behavioral interventions are beneficial in reducing physical abuse, they are ineffective at reducing the far more prevalent neglect problem (e.g., Eckenrode et al. 2017). The Act's focus on mediating parent behavior fails to address external circumstances beyond parent control, including oppressive social structures.

Despite mounting research suggesting that community stressors are important influences on maltreatment (Coulton et al., 2007; Drake & Pandey, 1996; Fong, 2019; Freisthler et al., 2006; Lotspeich et al., 2020; B. Smith et al., 2021; Wulczyn, Feldman, et al., 2013), policymakers have yet to adopt this conceptualization of the problem. Bullinger and colleagues (2019) speculate that child welfare policymakers continue to target family behavior modification because it is a domain within their influence, unlike community stressors which require coordinated inputs from many stakeholders and systems. Community coalitions, such as the many adversity, trauma, and resilience networks spread across the U.S. (Hargreaves et al., 2021), can play a pivotal role in advancing policy-level change using the Pair of ACEs framing. Additionally, further empirical evidence substantiating the part of adverse community environments could unify multi-sector partnerships, driven by a collective understanding, to coordinate resources for families.

Proposing an Alternative Narrative

This dissertation aims to investigate an alternative approach to mitigating childhood adversity. A powerful counter-narrative is emerging that incorporates a broader ecological focus on conditions that impact child outcomes. Several communities, defined as state, regional, or local groups, have formed multi-sector collaboratives to advance innovative policy work by promoting the narrative that community adversity causes family adversity (C. Young & Ellis, 2019). This approach acknowledges that community stressors overload parents' resources, and connects many stakeholders and systems to address childhood adversity jointly (Ellis & Dietz, 2017). These collaboratives are poised to influence community outcomes through pooled resources, monitoring, and evaluation (Kegler & Swan, 2012). In addition, multi-sector groups can collaboratively guide resource allocation to reduce neglect rates, such as by developing more affordable housing in underinvested communities (Fowler et al., 2017).

These local collaboratives face barriers in advancing a new narrative and implementing strategies that improve family outcomes. Targeting large-scale policy change requires local collaboratives to mobilize across geographic boundaries by sharing a well-articulated alternative narrative that poses community stressors as a threat to families across the nation (Nathanson, 1999). Unraveling the inadequate parenting public narrative entails generating a counter-narrative that acknowledges community adversity. Once the problem has been redefined, solutions can be reexamined. Parenting behavior interventions can be replaced with community-level interventions. However, further empirical evidence is needed to convince policymakers that community stressors are a viable target for intervention.

As a tool for summarizing multiple data inputs, indexes can uniquely promote alternative narratives while generating the empirical evidence needed to establish new framings it proposes. Like a public narrative, indexes function to simplify a complex topic. An index aggregates different measures of a multidimensional issue into a single quantitative metric (El Gibari et al., 2019), which can help narrate a problem by providing an empirical framework to establish links between complex phenomena and consequences, such as community factors and child outcomes (Acevedo-Garcia et al., 2014). Indexes are valued for their ability to help policy actors present new policy goals in simple terms that more readily engender public support. As such, proponents argue that indexes are useful in assisting policymakers in engaging stakeholders in discussions about critical issues, which are typically multi-faceted in nature (Acevedo-Garcia et al., 2014; El Gibari et al., 2019).

The current inadequate parenting narrative is largely supported by empirical evidence from an existing index, or composite measure, the Adverse Childhood Experiences (ACE) score. The ACE score simplifies the complex phenomena of childhood adversity into a single metric calculated by adding values for ten possible exposures to sources of family-level dysfunction (Felitti et al., 1998). Research indicates this score is associated with poor health and well-being outcomes across the lifespan (Anda et al., 2006)—a fact that has motivated widespread coalition and policy action (Hargreaves et al., 2021). For example, most U.S. states and counties now monitor adverse childhood experience (ACE) scores and use this information to guide investments in intervention strategies that target parent behavior change (Sacks & Murphey, 2018; Wu et al., 2022).

A new index is needed to combat this conceptualization of parents as the problem. I propose the Community Adversity Index (CAI) to reframe the problem of childhood adversity within the context of adverse community environments, reducing harm to poor, Black, Indigenous and Hispanic/Latino families. This index builds on the Pair of ACEs framing to position adverse community environments as a root cause of childhood adversity. An index is a unique tool that can strengthen an alternative narrative by making conceptual links to theoretical support, such as social determinants of health and neighborhood effects literature. Beyond its power to articulate the problem in a new way, the index also produces metrics that can be used to quantify and compare adversities across various communities. Further, examining the parts of the index, or subindices, can help to illuminate intervention priorities.

In developing this tool, I propose to answer the question, "How do adverse community environments contribute to the incidence of childhood adversity?" I do so over three studies, including two methodological and one substantive study. The first study draws on available county-level data to construct an index of community adversity.

The second study establishes the index's reliability through various criteria, including validity and sensitivity testing. Finally, the third study uses the Community Adversity Index to demonstrate that adverse community environments predict family separations. Overall, these studies offer empirical evidence that challenges public narratives claiming inadequate parenting is a primary cause of childhood adversity. In the next section, I will outline each of the three studies.

Studies and Conclusions

Study 1: Constructing the Community Adversity Index

In this chapter, I examine the community adversity domains suggested by Ellis and Dietz (2017) and their impact on childhood adversity. I connect these domains to theoretical support as a first step in developing an index. I then select available measures for each domain to construct the index using data from several datasets, including the American Community Survey and the Robert Wood Johnson County Health Rankings. I calculate Community Adversity Index scores for urban counties and establish a rank order to determine the highest- and lowest-scoring counties. Further, the domain, or subindex, score analysis reveals that counties with high and low adversity tend to feature high or low scores across all six domains. This suggests that no single domain, such as poverty, is driving placement in the county rankings. In addition, several adverse domains are commonly described as being confounded by poverty, meaning further analysis is required to isolate its effect.

Study 2: Validating the Community Adversity Index

In this chapter, I test whether and ultimately establish that the Community Adversity Index is a reliable measurement tool. To develop testing criteria, I draw on theoretical assumptions for measuring community-level risk, including literature on toxic stress, on operationalizing community, and on multiple risk theory. These tests use statistical analysis along with validity and robustness checks to ensure the index produces useful information. Results suggest that despite literature concluding poverty is collinear with other adversities; there is no evidence of multicollinearity between the domains in the sample data. In other words, poverty and each of the other domains independently contribute to community adversity. Further, in alignment with toxic stress theory, community adversity measures are associated with poor mental health days and social vulnerability. Finally, results indicate that the Community Adversity Index is robust to at least two different ways of operationalizing community: county or census-tract.

Study 3: Predicting Family Separation with the Community Adversity Index

In this substantive study chapter, I investigate whether community adversity explains family separations through foster care across a sample of U.S. counties. I analyze the relationship between several measures of community adversity and foster care entry. I find that the comprehensive Community Adversity Index predicts foster care entry better than poverty alone or a bundle of poverty and other standard economic measures. Further, community adversity predicts varying foster care entry rates across racial groups. I analyze the relationship between measures of community adversity and family separations using the same data featured in other chapters, along with Adoption and Foster Care Reporting System data. Results highlighted in this chapter indicate that the Community Adversity Index predicts foster care entry and does so better than two economically-focused measures of adverse community environments. Furthermore, the effect of community adversity on foster care entry varies across racial groups. Findings suggest that the disparity is greatest between White and Black populations, although predicted outcomes also suggest that reducing community adversity could decrease this gap. Future work to calculate race-specific Community Adversity Indices could produce results that further clarify the effect of adversity on Black and Hispanic/Latino children.[2]

Conclusions

The dissertation concludes with a summary of the three studies and suggestions for expanding on this limited research. The three studies suggest that the Community Adversity Index reliably quantifies adverse community environments and is useful in predicting childhood adversity, as measured by family separations. Estimates show that the Community Adversity Index, which features six domains, is a better predictor of family separation than community poverty alone. Further, estimates for the White, Black, and Hispanic/Latino populations confirm that adverse community environments have a significant and positive association with foster care entry across all racial groups. The three studies assist in shifting harmful narratives that blame parents by providing empirical evidence illuminating the association between adverse community environments and adverse childhood experiences. Results from this study indicate that child welfare policy could reduce the incidence of family separations by directing funding to community-level interventions.

[2] Available data would not allow for such an index to be created for Indigenous Populations. However, a custom, localized index could be created in coordination with tribal members.

CHAPTER 2

DEVELOPING THE COMMUNITY ADVERSITY INDEX

Introduction

Adverse childhood experiences persist in the United States despite government investment in intervention. Some scholars suggest that these interventions are ineffective because childhood adversity is typically falsely conceptualized as the result of inadequate parenting, typically labelled as *maltreatment* (Bullinger et al., 2019). This leads to policy solutions that target parent behavior. However, research shows that behavior interventions have had only a minor impact on maltreatment rates (e.g., Eckenrode et al. 2017). By contrast, a new body of research suggests that targeting community stressors effectively reduces abuse and neglect (Biehl & Hill, 2018; Fowler et al., 2017; Raissian & Bullinger, 2017; Rostad et al., 2020). This research has yet to be incorporated into child welfare policy.

Coalitions seeking to shift policy actors away from a singular focus on family intervention have begun to rely on the Pair of ACEs communication tool designed by Ellis and Dietz (2017). This tool is used to reposition childhood adversity within the framework of community adversity. It pairs adverse childhood experiences with a new concept called “adverse community environments.” Adverse community environments include concentrated poverty and other environmental conditions contributing to family distress. This work relies on a multidimensional rendering of the problem of childhood adversity that aims to help multi-sector groups “align large systems with one another—such as health care, city government, and education—and also with community-based partners” to “bolster strengths, fill gaps, and ultimately build child, family, and community resilience (C. Young & Ellis, 2019, p. 1).” This framing of the ecology of childhood adversity has evolved into a counter-narrative to the dominant narrative of inadequate parenting. Still, the inadequate parenting narrative continues to influence policy as it is a public narrative that is simple, well-recognized, and oft repeated.

Policy actors need to understand how community adversity is related to childhood adversity to know whether an ecological counter-narrative should be adopted. As a first step towards consolidating the evidence that a family’s ecosystem of support influences childhood outcomes, I develop a Community Adversity Index (CAI). The Community Adversity Index assists policy actors by integrating the abundant research suggesting that community-level forces contribute to adverse childhood experiences (as reviewed by Coulton et al. 1995, 2007). It relies on the framework identified by Ellis and Dietz (2017) that categorizes adverse community environments into six domains: poverty; discrimination; community disruption; lack of opportunity, economic mobility, and social capital; poor housing quality and affordability; and violence. Yet it makes a unique contribution by identifying measures for each domain, forming a metric of adversity that eases the task of quantifying a complex phenomenon for policy actors.

In this chapter, I examine the community adversity domains suggested by Ellis and Dietz (2017) and their impact on childhood adversity. I aim to better understand their influence and relative importance. In addition, I analyze how the Community Adversity Index varies across and within geographies. This analysis is made possible through using the single quantitative metric to rank counties by their relative adversity scores (El Gibari, Núñez, and Ruiz 2019). Still, the CAI components or domains can be disaggregated to investigate which stressors impact childhood adversity most. These simplified metrics offer insights for prioritizing child welfare and other family-focused policy interventions. Given that results suggest counties with high adversity feature high rates of poverty, violence, and discrimination, policymakers should implement multi-faceted strategies to improve the conditions for communities.

This chapter outlines the construction of the Community Adversity Index and its usefulness as a tool for convincing policy actors to adopt a counter narrative to replace the dominant narrative that suggests inadequate parenting is the primary cause of child maltreatment. Current policy conversations are dominated by a shared narrative centering on families as responsible for adverse childhood experiences, which I seek to unravel by proposing an index. I first explain how indexes are tools for generating a new narrative and empirically quantifying multidimensional problems like adverse community environments. Next, I describe the methods used to construct the Community Adversity Index, including summarizing the relevant theoretical and empirical literature. I then use the Community Adversity Index to analyze how adversity is distributed geographically and how the domains of community adversity group together. Finally, I explain how the Community Adversity Index assists policymakers in formulating a new, evidenced-based conceptualization of the sources of childhood adversity.

Indices

Developing an index is crucial to advancing an alternative to family-focused public narratives. Indices are valuable for their ability to help policy actors present new policy goals in simple terms that can more readily gain public support. An index that summarizes various streams of data to reframe a problem using a simplified metric can assist policymakers in making complex issues more easily understood (Acevedo-Garcia et al. 2014). Additionally, an index can accelerate the successful implementation of strategies by helping community leaders identify community cases to study, such as those with similar demographics but more effective interventions. Creating measures for all counties in the nation can also support the collective advancement of a new alternative narrative, which any local collaborative can employ with access to the index data.

Research shows that indices facilitate the advancement of new narratives. For example, the Human Development Index was developed as an alternative to former national measures of success (e.g., the gross domestic product) to advance a narrative that values people and quality of life more than a country's economic development (Deb 2015). Similarly, the County Health Rankings, an American index used to rank the health of counties relative to their state, is used to help stakeholders broadly conceptualize the social determinants of health and provide an alternative to narratives that propose intervening in individual health behaviors (Remington, Catlin, and Gennuso 2015).

Critics of this approach claim that an index can, like dominant public narratives, obscure parts of a problem. Other critics are skeptical of quantifying social phenomena that they claim defy precise definition, categorization, or aggregation given the various possible experiences across social groups. Some critics argue that relying on statistical analysis for decision-making demands a false trust in numbers from the public because statistics may not accurately capture problem elements. In this way, like the narratives they are designed to promote, indices may obscure part of a problem. This can lead to misunderstandings of complex social issues (Umbach and Bhuta 2018). For example, national-level aggregations hide local differences. Yet, there is some agreement that the complexities are better understood when a community coalition or diverse stakeholder group contributes to the development and interpretation of the index (Blanke and Walzer 2013; Dluhy and Swartz 2006). Therefore, I use a framework developed for coalitions, incorporating local or county-level measures.

I argue that the Community Adversity Index, while not precisely capturing all of the complexities of childhood adversity, will serve as a powerful tool for advancing a public narrative that contextualizes a family's experience within communities. The ease of using an index as a communication tool can be more important to policymakers than the tool's ability to precisely quantify a social phenomenon (Umbach and Bhuta 2018). This chapter presents the theoretical basis for the index, establishes the measures, and calculates the comprehensive metric. Then, I use the index to explore how adversity is distributed across urban counties and how adversity is bundled within each county-level community.

Methods

Empirical Strategy

I construct a composite measure of adversity following the methodology proposed by the Organization for Economic Cooperation and Development (OECD). Members of the OECD and the Econometrics and Applied Statistics Unit of the Joint Research Centre (JRC) of the European Commission developed a handbook with technical guidelines for creating composite measures or indices. The handbook suggests standards and best practices for developing high quality measures (OECD et al., 2008).

Following the recommended approach, I first establish a theoretical framework to support the analysis. To do so, I draw on the work of Ellis and Dietz (2017) and connect the concept of adverse community experiences to research on health, ecology, and neighborhood effects. Next, I select measures for each domain using guidance from the relevant literature. I then complete the remaining steps to build an index, including statistical procedures used to normalize the data (OECD et al., 2008). At this point, I aggregate the data for each county into an index that can be used to group and order counties by adversity levels. Finally, I use the index to rank counties according to levels of community adversity. This will be useful in identifying counties with greater levels of adversity and provide actionable information for policymakers on how to prioritize support (University of Wisconsin Population Health Institute, 2020).

Theoretical Model

An index depends on a theoretical framework that explains the multidimensional construct of focus. Theories are used to identify component parts and can be useful in suggesting domains or groupings of those parts. Once components are identified, an index constructor looks to existing literature to identify suitable measures. With empirical measures selected, the index developer then uses available data sources to begin to aggregate parts and develop a single composite measure or an index representing the multidimensional phenomena of study.

In the following sections, I use the Ellis and Dietz Pair of ACEs communication tool as a guiding framework for explaining adverse community environments. The claim that adverse community environments impact childhood outcomes is well supported in child welfare, neighborhood effects, and social determinants of health literature. However, the measurable impact of environments on outcomes is hard to communicate to policymakers because different disciplines use different vocabularies and measures to support this claim. I use the Pair of ACEs model to synthesize the literature across these three disciplines and unify the evidence into one comprehensive index. Later, I use the six parts identified by Ellis and Dietz to form the domains of the index and use studies of these domains to identify measures. Next, I identify available data to represent each measure. Finally, I use the data to construct the index and complete brief analysis of the whole index and its domains or parts.

Community Impacts on Family Outcomes

Ellis and Dietz (2017) claim that childhood adversity, often expressed as a composite measure of adverse experiences that take place in childhood, is linked to another composite measure—adverse community environments. While several research works have suggested composite measures for childhood adversity (Cronholm et al., 2015; Felitti et al., 1998; Wade et al., 2016), a composite measure for adverse community environments has yet to be developed. Ellis and Dietz lay the groundwork for developing a composite measure by defining adverse community environments as a composite of six domains, including poverty; discrimination; community disruption; lack of opportunity, economic mobility, and social capital; poor housing quality and affordability; and violence, as shown in Figure 1.

Figure 1

Pair of ACE's Framework

Note. Ellis & Dietz, 2017; Sumner M. Redstone Global Center for Prevention and Wellness, 2017. Reprinted with Permission.

Although not described in practitioner materials related to the Pair of ACEs, a broad research literature supports the concept of adverse community environments and claims that community adversity leads to family adversity. Three broad research areas related to community adversity offer support for the Pair of ACEs model: sociology, health (including public health and mental health), and child welfare. Combined, studies produced by these disciplines create a clearer picture of the factors that influence childhood adversity by providing theoretical models and empirical data. Sociologists typically focus on neighborhood-level drivers and other sources of influence on families. Health scholars look at the social contexts driving adversity and the health consequences across populations while considering how adversity impacts family and individual-level health. Child welfare researchers examine how economic hardships affect family outcomes. When synthesized, the following research supports the claim that childhood outcomes are shaped by the interaction between families and their community environments.

Sociology

Sociology provides robust research that suggests adverse community environments influence families. Sociologists study community stressors under the broader concept of "neighborhood effects," which refer to neighborhood sources of influence on families, such as concentrated poverty. In these studies, the neighborhood or community is a central focus for understanding social problems because they represent places where "geographically bound social interactions…shape socioeconomic outcomes of residents" (Ryabov 2020). Sociologists typically operationalize "neighborhoods" as geographic locations with boundaries determined by government agencies (e.g., school districts or the Census Bureau) that collect data within these districts.

Sociologists tend to understand social outcomes as resulting from social structures, including race and geography. Concentrated poverty and disadvantage are key neighborhood-level influences on social outcomes, particularly poor outcomes differentiated by race and class (Ryabov, 2020). Sampson and colleagues (2002) assess and review the neighborhood effects literature, finding that neighborhood-level poverty leads to poor outcomes for children, including poor development and reduced well-being. As Minh and colleagues (2017) show, studies link neighborhood poverty to behavioral problems, a lack of school readiness, and other developmental disadvantages in children and adolescents.

Sociologists argue that adverse community environments are comprised of several domains and suggest that negative outcomes typically "bundle together" in neighborhoods with “multiple forms of concentrated disadvantage” (Sampson et al., 2002, p. 446). Minh (2017) further suggests that institutional mechanisms contribute to adverse community environments and poor outcomes for families. For example, sociologists attribute poor housing as measured by “residential instability and low rates of home ownership” (Sampson et al., 2002, p. 446) to discriminatory housing policies. In particular, institutional practices are linked to much of the poor housing, residential segregation, and low rates of homeownership experienced by Blacks (Fischer & Massey, 2004). Zoning policies are another institutional mechanism that can impact children’s health by limiting beneficial resources like grocery stores and encouraging the establishment of detrimental resources like liquor stores (Chum, 2011).

Research in sociology focusing on neighborhoods and their impacts on development suggests that community stressors influence families through several pathways with lasting effects across the lifespan. Negative neighborhood effects can accumulate and impact “important transitions into adulthood” (Ryabov, 2020, p. 86) and substantially reduce life chances (chances of sufficient well-being, health, or economic success) for an individual (Sampson & Laub, 2018). Research building on cumulative disadvantage theory proposes that cumulative inequality, a phenomenon existing at the community level, also negatively impacts children because social systems serve as drivers of demographic differences that shape development and thus alter life course trajectories (Schafer et al., 2011). Therefore, sociology frameworks provide substantial support for the claim that adverse community environments contribute to poor outcomes at the family level.

Health

Several disciplines in the health discipline rely on theories suggesting adverse community environments impact family and child outcomes. Research in public health acknowledges both the ecology surrounding family health as well as social determinants of health, regularly using these concepts to examine community sources of stress. Bronfenbrenner (1986) first illuminated the contextualized environments or “ecological” influences that impact the ability of families to support positive child development. Bronfenbrenner’s landmark review explores how “intrafamilial processes are affected by extrafamilial conditions” (Bronfenbrenner, 1986) and classifies “extrafamilial conditions” by identifying specific environments that impact child behavior and social outcomes. Using a nested model to illustrate a system of concentric environments working together to shape child development across the life course, Bronfenbrenner identified five distinct sources of influence, including the “ecosystems” or community environments surrounding a child (Bronfenbrenner 1986).

Health research following this model examines health at the individual, family, community, culture, and policy levels and utilizes a range of levels of analysis varying from the micro to the macro levels. For instance, Horsley and Ciske (2005), among others, rely on this model to illustrate influences on child development from various external environments, including community; the authors note that this model is useful in shaping a broader policy agenda for family interventions.

Research in public health aligns with sociology in arguing that “address” (or geographic location) influences family outcomes. Studies on the social determinants of health suggest that unequal community contexts shape the health and well-being of families and children (Lucyk & McLaren, 2017; McCarty, 2016; National Academies of Sciences et al., 2017). Neighborhoods with lower access to healthy foods or health care providers, poor air and water quality, high unemployment, high crime, and other conditions experience high stress levels, poor health, and decreased well-being (Hofrichter, 2006; UCSF Center for the Social Disparities of Health, 2015). These poor outcomes are thought to be triggered by community-level stressors, such as perceived discrimination and witnessing violence, that can overstimulate the body's stress response (Wade et al., 2016).

Together, health literature across subdisciplines provides theoretical frameworks and empirical evidence describing how community stress impacts family and individual-level health. Health subdisciplines also suggest mechanisms for how this toxic stress manifests in negative outcomes for families and children, including determinantal changes in developing bodies and brains.

Child Welfare

Child Welfare literature borrows theoretical models from sociology and health literature when examining how adverse community environments impact family functioning. For example, Coulton and colleagues (1995) draw on sociology's neighborhood effects theoretical model (Sampson et al. 2002) and explore child maltreatment rates as a function of structural factors of select census tracts. In another example, Wulczyn and colleagues (2013) expand on research from social determinants of health (Lucyk & McLaren, 2017) and ecological models (Bronfenbrenner, 1986) to test the effect of ecological poverty on foster care entry.

Independent of these borrowed theoretical frameworks that aggregate adversities, Child Welfare research also examines singular community-level sources of stress that shape families' abilities to provide a supportive environment for child development. For example, Child Welfare research on community inequality suggests race is a strong predictor of access to resources beyond differences in socioeconomic status in the United States. For example, many Black, Indigenous and Hispanic/Latino families interfacing with the child welfare system live in communities with high concentrations of poverty and little access to resources (Dettlaff, 2014; Garcia et al., 2017; Mauer, 2014). This community-level inequality can negatively impact families and children (Eckenrode et al., 2014; Kravitz-Wirtz, 2016) and, as Pinderhughes and colleagues (2007) show, negatively impacts parent behavior.

Combined, this research suggests that adverse community environments influence child development and a family's ability to care for children. Many parents are challenged by neighborhood and community stressors that make it difficult to provide material care for their children. In addition, structural factors like policies and discriminatory practices make it especially difficult for families who are poor and racially marginalized to secure stable housing in well-resourced neighborhoods. These adverse community conditions can result in increased contact with child welfare.

Overall, reviewing work from these three disciplines demonstrates that abundant research supports Ellis and Dietz's claim that adverse community environments impact families. The typical stressors studied in this research also support that the domains they identified are appropriate for constructing a Community Adversity Index.

Adverse Community Environment Measures

With the theoretical framework in place to guide domain selection, the next step in developing the CAI is identifying measures for each index domain. I select variables by reviewing studies that highlight each domain. Below, I use studies across the three disciplines of sociology, health, and child welfare to identify suitable measures and available data sources for each domain.

Poverty

Wulczyn and colleagues (2013) point out that concentrated poverty or poverty experienced at the neighborhood level is an understudied risk factor in the child welfare field because most existing research examines poverty at the family level. The authors find county-level poverty is a predictor of foster care entry. More recent studies examining community-level poverty also suggest that it plays a key role in child welfare involvement. For instance, Eckenrode and colleagues (2014) demonstrate that county-level poverty positively correlates with child maltreatment rates. Raissian and Bullinger (2017) attempt to isolate poverty as a causal effect by examining state-level minimum wage and child maltreatment rates, finding that increasing minimum wages correspond with declining neglect cases.

The effect of poverty on families is even more pronounced for families of color. Wulczyn and colleagues (2013) find that county-level poverty predicts higher racial disparities in foster care entry rates. Maguire-Jack and colleagues (2015) further show that racial disparities in poverty align with racial disparities in maltreatment rates, suggesting it is important to study disaggregated poverty rates by race. Soss and colleagues (2008) underscore the need for careful exploration of the intersection of poverty, race, and child welfare involvement by demonstrating how “poverty governance” is implemented via federal policies that lead to the over-representation of families of color in the welfare system. This research supports my selection of measures for the poverty domain. Future research can improve on the current CAI by creating a race-specific index that features variables such as race-specific poverty rates that more precisely illuminate the differences in experiences between racial groups.

The size of the effect of poverty alone is difficult to compare to the effect size of poverty combined with other environmental stressors. This is partly because poverty is widely assumed to confound multiple domains, such as poor housing and lack of opportunity (Acevedo-Garcia et al., 2014; McCarty, 2016). Research often relies on simple measures of poverty and its obvious correlates to predict outcomes for families (Duva et al., 2011). Similarly, this dissertation will study these factors, although future sections will seek to distinguish whether poverty, poor housing, and lack of opportunity uniquely contribute to community adversity. Further, I will test how measures of poverty alone compare to measures that aggregate the impact of several domains. Such tests are supported by Ellis and Dietz’s (2017) theory that multiple domains contribute to parent overload.

Poor Housing Quality and Affordability

Scholars have examined the impact of unstable housing as an adverse community experience that can lead to family dysfunction, using rent burden rates and eviction rates to study the effects on families (Desmond, 2016; Hendey & Cohen, 2017). Desmond and Gershenson (2017) emphasize that public housing or other housing assistance is not provided for most low-income families. Therefore, low-income families spend between

50-70% of their income on private rentals (Desmond & Gershenson, 2017). Affordable housing is typically defined as housing that costs less than 30% of a family's income (Hendey & Cohen, 2017), which is a far lower proportion than most low-income families spend on housing. This high rent burden puts many families at risk for eviction and can cause a long-term struggle in the search for stable housing (Desmond, 2016). Families with eviction records may not be able to secure quality housing and can be forced to "accept substandard conditions and relocate to disadvantaged neighborhoods" (Desmond & Gershenson, 2017, p. 362). I will use county-level measures of rent burden and eviction rates as measures of poor housing.

Pinderhughes and colleagues (2007) suggest that renting and frequent housing changes can interfere with the ability of parents to build social capital and networks of support, which are critical for mitigating family stress. Wulczyn and colleagues (2013) consider high rates of renter occupancy as one of several measures of social disadvantage and show that county-level renter occupancy and other disadvantage measures correlate to county-level foster care entry with varying outcomes by racial group. Therefore, I will also use rent occupancy to measure poor housing.

Discrimination

Housing segregation is a frequently-used available measure of discrimination. Neighborhoods are typically segregated along racial lines (Massey et al., 2009; Rothstein, 2017); families of color tend to live in poorer, less-resourced communities than their White counterparts. Scholars link segregated neighborhoods to racial disparities in health outcomes, noting that these disparities exist even when accounting for economic status (Hofrichter, 2006). Research also suggests that "neighborhood and housing choices are too often constrained by private discrimination and public policies" (Hendey & Cohen, 2017, p. 1), suggesting that ethnic communities are not segregating themselves. For instance, Fischer and colleagues (Fischer & Massey, 2004) use housing audit data to demonstrate discriminatory practices that attempt to steer White and Black applicants toward housing in or near neighborhoods populated predominately by people of the same racial group. I will use housing segregation measures to construct the Community Adversity Index.

Violence

Available county-level indicators of violent crime predict childhood adversity, such as maltreatment and neglect. For example, one state-level analysis suggests that violent crime predicts child maltreatment fatalities, noting that when "poverty and crime decrease, fewer children die from maltreatment" (Douglas & McCarthy, 2011, p. 139). There are differing explanations for the correlation between community violence and family maltreatment. Some scholars attribute high exposure to neighborhood violence and crime to negative parenting outcomes, noting how warmth and discipline strategies are negatively impacted when parents feel they live in unsafe neighborhoods (Gonzales et al., 2011; Pinderhughes et al., 2007). Others posit that living in a neighborhood with high crime contributes to social isolation and the reduced availability of peer networks to support positive parenting (Ahmadabadi et al., 2018; Pinderhughes et al., 2007).

Child welfare agencies can deem parents neglectful and separate them from their children due to exposure to violence because "injuries, exposure to guns and intimate partner violence, and extreme risk-taking behavior may represent inadequate protection and supervision, threatening children's health, development, and safety" (Dubowitz, 2013, p. 4). Therefore, violent crime rates are an available county-level measure that I will use to construct the Community Adversity Index.

Community Disruption

Excessive drinking, overdose death, and incarceration are three measures of community disruption typically cited in research on incarceration and substance abuse. Norsati and colleagues (2019) bundle these forms of disruption together, citing punitive jail sentencing reform for substance abuse-related crimes as the cause for the growing number of incarcerated individuals. The health of a community is affected by incarceration, which can be “pivotal in shaping the trajectories of neighborhoods by removing prime working-age men from their local communities, separating families, and disrupting social networks” (Nosrati et al., 2019, p. 331). These effects are deeply felt in Black families; mass incarceration practices have made it commonplace for Black children to have an incarcerated parent (in 2000, more than 10% of African American youth had an incarcerated father, Western and Wildeman 2009).

Incarceration is imperative to examine because scholars describe it as a racialized punitive remedy for community disruption administered by state or local governments (e.g., Soss, Fording, and Schram 2008). There is also a close relationship between incarceration and welfare policies; both employ paternalistic and penalizing approaches to regulate behaviors (Schram et al., 2008; Soss et al., 2008). Communities implementing social control practices feature high numbers of incarcerated individuals (Soss et al., 2008) and correspondingly higher rates of children entering the “protective custody” (C. H. Foster, 2012) of government agencies. I will use incarceration rates as one measure of the adverse community environment domain of community disruption.

Other scholars disaggregate the community disruption problem and look at specific risk factors for child welfare involvement, such as the prevalence of alcohol and drug availability (Freisthler et al., 2007). A review by Freisthler and colleagues (2006) found that alcohol outlet density is correlated with child maltreatment. A later study looked at the number of opioid prescriptions in Tennessee as a measure of drug availability and found that rates of child maltreatment correlated with drug availability (Morris et al., 2019). In addition, the prevalence of drugs in a community is known to contribute to social disorganization and erode systems of social control, increasing the risk for child abuse and neglect (Morris et al., 2019). Given a review of child welfare data that shows "that a sizable majority of the families involved in child welfare services are affected by parental substance use disorders" (N. K. Young et al., 2007, p. 137), I will include county-level measures of excessive alcohol use and drug overdoses.

Lack of Opportunity

Ellis and Dietz (2017) suggest that adverse childhood experiences can be caused by a community's lack of opportunity, economic mobility, and social capital. Indicators of opportunity used widely by scholars include high school graduation rates and college attainment, which are important precursors to skilled employment and earning higher than minimum wage (Dong et al., 2015; Iversen & Armstrong, 2006; Ryabov, 2020; Smeeding, 2016). Economic mobility, or the ability to improve quality of life through increased earnings, is typically measured by employment rates and related employment measures such as earnings, access to health insurance, and regular work schedules (Iversen & Armstrong, 2006). Social mobility rates are generally low in the United States, with those starting at the bottom of income and education levels staying at the bottom and those starting at the top staying at the top (Smeeding, 2016). Mobility challenges vary by racial groups and are linked to disparities in the "intergenerational transmission of education, income and occupational prestige" (Ryabov, 2020, p. 95). In addition, neighborhood effects, including the average educational attainment of a community and unemployment rates, are tied to both mobility (Lyons & Pettit, 2011; Ryabov, 2020) and harsh parenting (Pinderhughes et al., 2007). Therefore, I will use unemployment and educational attainment to measure the lack of opportunity.

Income inequality is another commonly used indicator of opportunity and is partly explained by wage gaps between racial groups (e.g., Lyons and Pettit 2011). Income inequality is a measure resulting from a calculation that contrasts the income of the earners at the bottom and the top of the income range (Eckenrode et al., 2014). This gap between the richest and poorest family incomes is substantial and growing (income inequality increased by more than $100,000 between 1979 and 2010, Smeeding 2016). In the child welfare context, greater income inequality at the state and county level is a concern because it correlates with increased negative outcomes for children and families, including infant mortality, poor birth outcomes, and child maltreatment (Eckenrode et al., 2014; McLaughlin & Stokes, 2002). Eckenrode and colleagues (2014) also point to studies showing that high-income inequality leads to poor peer relations, thereby reducing available social capital for parents. I will use income inequality as a final measure of lack of opportunity.

In summary, at least one county-level measure is available for each adverse community environment domain. These measures allow for constructing an index and will result in aggregated Community Adversity Index scores for each United States county in the study.

Data

Level of Analysis

Neighborhood effects research usually uses Census tracts as its primary measure of community (Sampson et al., 2002), but studies that define neighborhood boundaries using other geographic units, like ZIP codes, tend to yield similar results (Freisthler et al., 2006). This study defines communities using county boundaries. Although country-level analysis is not as geographically precise as analysis at the census tract or zip code level, it has the advantage that administrative data are widely available at this level. To develop the CAI, I focus specifically on urban counties, which are large enough to have systems to support quality data collection. Sixty-four counties are classified as urban. These counties are located in 37 states and represent 29% of the U.S. population.

Urban counties in the United States share some similar features, so to understand their characteristics it is important to examine the absolute measures of the indicators that are later standardized and aggregated into the Community Adversity Index. Mean values for several descriptors (e.g., racial composition and population density) and each of the 16 indicators are included in Table 1 below. Where complete data are available for comparison with the typical U.S. county, analysis suggests that urban counties feature much larger populations (a million more than the U.S. average), smaller White populations (26% smaller), and larger Black and Hispanic/Latino populations (11% larger Black and 9% larger Hispanic). Urban counties also have greater population density (3557 people per square mile more dense), more renters (17%) who are more rent burdened (3%), more college-educated residents (11%), slightly fewer unemployed residents (.4%), and more adults who excessively drink than other U.S. counties (2.22).

Table 1

Description of the Sample of Urban Counties

Variable	Mean	SD	Minimum	Max
Descriptors				
Total population	1,377,110.31	1,447,704.65	133,647.00	10,038,388.00
White population percent	51.73	14.97	15.11	81.15
Black population percent	20.69	15.14	1.36	64.00
Hispanic population percent	17.93	14.18	1.44	65.62
Population density	3,776.20	5,415.05	240.20	37,347.52
CAI Indicators				
Percent poverty	12.82	3.89	5.68	21.71
Percent rent occupancy	43.83	8.99	28.71	68.71
Percent rent burdened	31.30	2.48	26.50	39.40
Eviction rate	2.91	2.40	0.00	11.44
Percent of households with severe housing problems	21.14	4.75	13.11	34.63
Income inequality rate	5.18	0.83	3.64	7.57
Percent of population with no high school graduation	19.00	7.18	3.30	44.06
Percent of population with no college	31.59	7.40	10.34	46.73
Percent unemployment	5.35	1.41	2.58	10.03
Total jail population rate per 10K in county population	34.68	17.38	3.26	88.36
Percent of adults who excessively drink	19.22	2.84	13.14	28.00
Number of drug overdoses per 10K in county population	200.37	111.72	57.19	748.31
Percent of people who are not White and live in segregated communities	45.06	12.29	23.60	71.71
Rate of violent crime incidents per 10K in county population	5,937.82	3,331.72	1,148.93	18,195.15

N = 128

Data sources

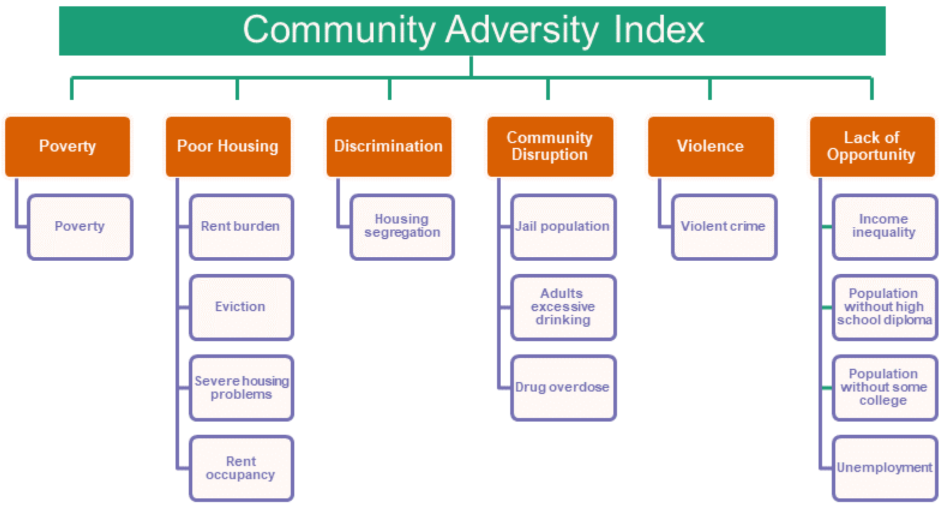
Data for this study were obtained from multiple datasets produced by government and non-profit agencies tracking health and well-being. I used data for 2014 and 2016 only, as other recent years did not have complete information for all required variables. Data on poverty, unemployment, renter occupancy, and population density were obtained from the American Community Survey (ACS) Five-Year Estimates, a survey administered by the United States Census Bureau since 2005. Data on residential segregation, alcohol misuse, and drug overdose were obtained from the County Health Ranking (CHR) datasets disseminated by the University of Wisconsin with support from the Robert Wood Johnson Foundation since 2010. CHR are sourced from the American Community Survey, the Centers for Disease Control Wonder Survey, and the Uniform Crime Reporting administrative database managed by the Federal Bureau of Investigation. Data on counts of children by age group and race and ethnicity were obtained from the Surveillance, Epidemiology, and End Results (SEER) program data produced by the National Cancer Institute using American Community Survey data. Incarceration data were obtained from the Vera Institute of Justice, a national advocacy group dedicated to ending incarceration. The Vera Institute sources this data from the U.S. Bureau of Justice Statistics and state corrections departments to facilitate incarceration research. Finally, eviction data were obtained from the Eviction Lab at Princeton University. Researchers developed the database using more than 82 million court records. These records were obtained through bulk requests to local courts, LexisNexis, and other data providers. The data are supplemented with the American Community Survey results related to poverty and rent burden.

Variables

I follow best practices for index development by selecting measures that are well-researched, freely available, reliable, and regularly updated (Dluhy & Swartz, 2006; Land, 2012; OECD et al., 2008). Selected variables and their sources are included in Table 17 in the Appendix and displayed in Figure 2 below:

Figure 2

Community Adversity Index Component Diagram of Domains and Indicators



Composite Measure Development

I develop the Community Adversity Index in three steps. I first normalize and standardize all variables to facilitate interpretability when aggregated. For domains with more than one variable, I then aggregate these variables into subindices. Lastly, I aggregate the subindices into a final composite measure.

Normalization

I transform skewed variables using square root or natural log functions to help normalize the data. I use the square root of poverty, unemployment, severe housing problems, and total jail population. I take the log of rent occupancy, income inequality, excessive adult drinking, drug overdose, and violent crime.

Standardization

The variables I use are measured on different scales (e.g., rates, percentages, counts). I therefore standardize each variable by taking z-scores as follows:

$$Z = \big((County\ Value) - (Average\ Value\ for\ Counties) \div (Standard\ Deviation\ Across\ Counties)\big)$$

Aggregation

When more than one measure is available for a given domain, the normalized and standardized variables are aggregated into a domain subindex using the arithmetic mean. For example, four measures of poor housing are available. A poor housing index is calculated as follows:

$$D_{poor\ housing} = \big(I_{rent\ occupancy} + I_{rent\ burden} + I_{eviction\ rate} + I_{severe\ housing\ problems}\big) \div 4$$

Where I = each Indicator in the domain and D = the Domain/Subindex, this procedure places equal weight on each indicator variable. Research suggests that this is the simplest form of aggregation, is appropriate for use with an emergent index, and that results do not typically vary when using other forms of aggregation (Land, 2012). When only a single variable is available, the domain or subindex equals that variable.

The Community Adversity Index is then obtained by aggregating the domains, again using the arithmetic mean.

$$\text{Community Adversity Index} = \left(D_{poverty} + D_{poor\ housing} + D_{lack\ of\ opportunity} + D_{community\ disruption} + D_{discrimination} + D_{violence}\right) \div 6$$

As each indicator's score (summary of average or single measure score) has been standardized, I expect community values greater than 0 (the median score) for the highest adversity scores and values less than 0 for the lowest adversity scores.

Distribution of Community Adversity

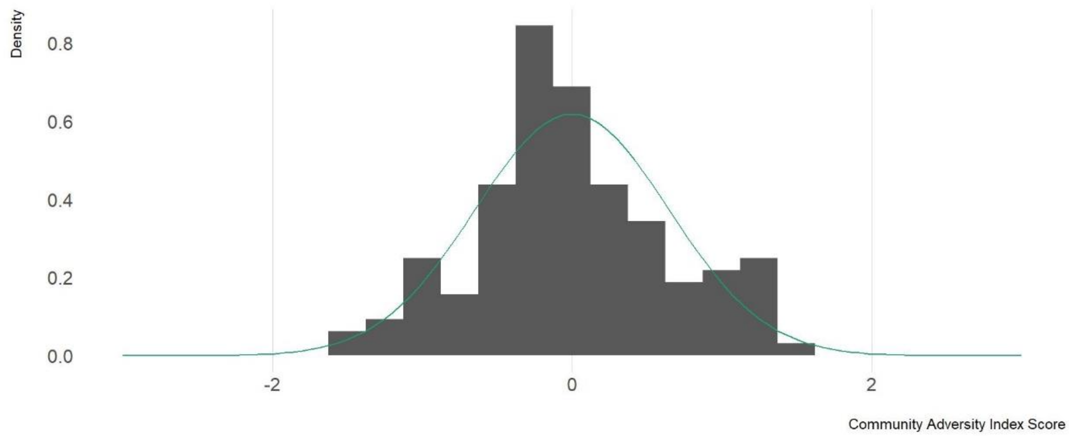
With the index constructed and a single composite measure now calculated, I can explore the patterns that appear across urban counties. I do so by ranking counties and identifying top- and bottom-scoring counties. Then I analyze how various adverse community environments cluster by examining the domain scores for the most and least adverse counties.

Numeric Distribution

Figure 3 shows the distribution of Community Adversity Index scores across urban counties. Each county's score is relative to all other urban counties. This means that a low score indicates low adversity relative to the rest of the sample but is not necessarily an indication of low adversity in an absolute sense. As is typical when data are standardized, roughly half the counties in this study experience average to high adversity relative to the other counties (median = -.045).

Figure 3

Community Adversity Index Scores: Distribution of Standardized Scores Across Urban Counties



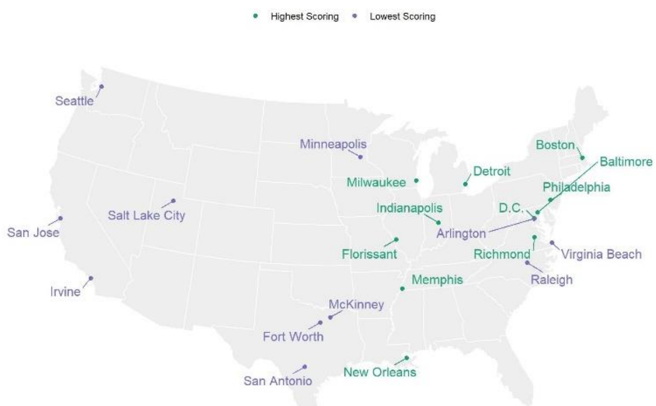
The distribution of scores diverges somewhat from a standard normal distribution (kurtosis = 0.120), however, a Jarque-Bera Normality Test suggests that this distribution is not significantly different from a normal distribution (JB = 0.235, $p = 0.8891$). The standardized data falls in a tighter range (min = -1.625, max = 1.452) than the typical ranges for standardized data (66% within one standard deviation, 95% within two standard deviations, and 99.7% within three standard deviations. The standard deviation is smaller than expected for a normal, standardized distribution (standard deviation = .645 rather than 1). Although there is some evidence that the urban sample data is not normally distributed, I expect it to better approximate the normal in future studies that increase the number of data points by incorporating more years or counties. For now, the data approximates a normal distribution enough for index purposes, especially if rank order is used instead of raw scores.

Geographic Distribution

A map showing the ten counties[3] with the highest and lowest adversity provides further information about how community adversity is distributed across urban counties in the United States. Here, I map the largest cities in each county to give readers a clearer geographic reference in Figure 4. The map shows that counties with higher adversity tend to be located in the eastern half of the United States. In contrast, counties with lower adversity are more typically in western regions.

Figure 4

Geographic Distribution of Highest and Lowest Scoring Counties



Several cities (e.g., Philadelphia, Detroit, Baltimore, Indianapolis, and Milwaukee) in high adversity counties are so-called rust-belt cities (areas with high de-industrialization and economic decline). Others (e.g., New Orleans, Memphis, and Richmond) feature long histories of slavery and ongoing racial segregation (the mean of national housing segregation is 31, and these cities' scores range from 56 to 65). Descriptive data about these high-adversity counties suggests they feature larger Black

[3] Note that there are more than 10 county names in the lowest and highest list as those displayed on the map represent both 2014 and 2016 and there was some variation in the list across years.

populations (average population of 45%). The average household income for these communities is $64,707, higher than the national average of $58,911. In contrast, some cities in low adversity counties are known for larger technology sectors (e.g., Raleigh, San Jose, and Seattle). They feature larger White populations (average population of 58%), smaller Black populations (average population of 16%) and average household incomes of $99,514. These trends align with research using other indicators of distress that suggests distressed communities are disproportionately Black. (Acevedo-Garcia et al., 2014) and further substantiate the claim that adverse community environments are not evenly distributed across geographies or racial groups.

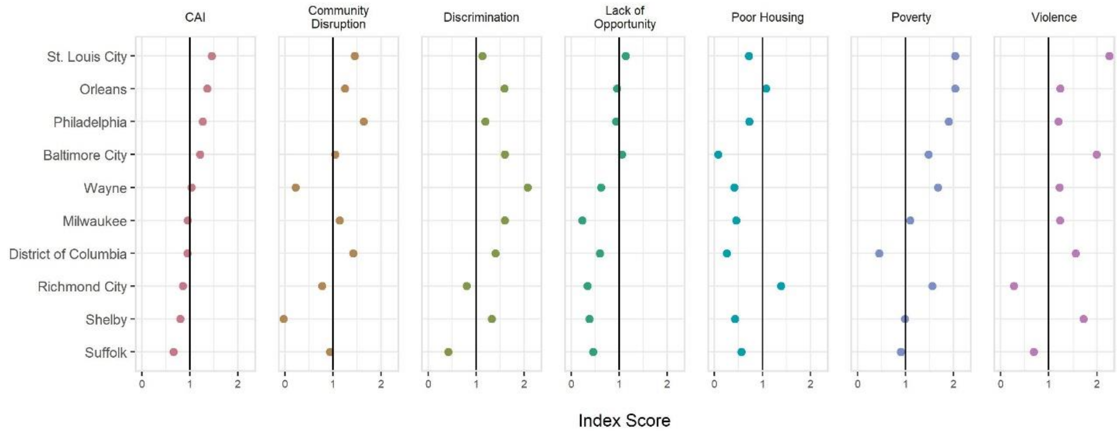
Domain Distribution

Community adversity can also be better understood by examining how the domain-level scores, or subindex scores, contribute to the ranking of urban counties in this study. Figures 5 and 6 show domain-level scores for the highest and lowest scoring counties for 2016. These figures make it easier to observe whether adverse community environments bundle together and provide further insight for policy actors on where to target intervention efforts. Both figures demonstrate that selected adverse community environments, represented by the domains or subindices, tend to share similar scores within a given county. Counties that score at the top or the bottom of the list show a similar general pattern of adversity: high-scoring counties tend to have above-average domain scores across all six domains, and low-scoring counties tend to have below average scores across all domains. The overall CAI score, in other words, does not appear driven by high adversity on a single subindex measure. This suggests that adverse community environments are interrelated and that a multi-faceted intervention would be most impactful.

In addition, some adverse community environments tend to score similarly. For example, in high-adversity counties, the domains of poverty, violence, and discrimination typically hold values greater than one standard deviation above the mean and typically group together as shown in Figure 5. In low-adversity counties, displayed in Figure 6, this same trio is typically scored at or near one standard deviation below the mean. This grouping suggests these are key interrelated intervention areas for communities with high adversity.

Figure 5

Counties with the Highest Adversity in 2016: How Adverse Community Environments Group Together

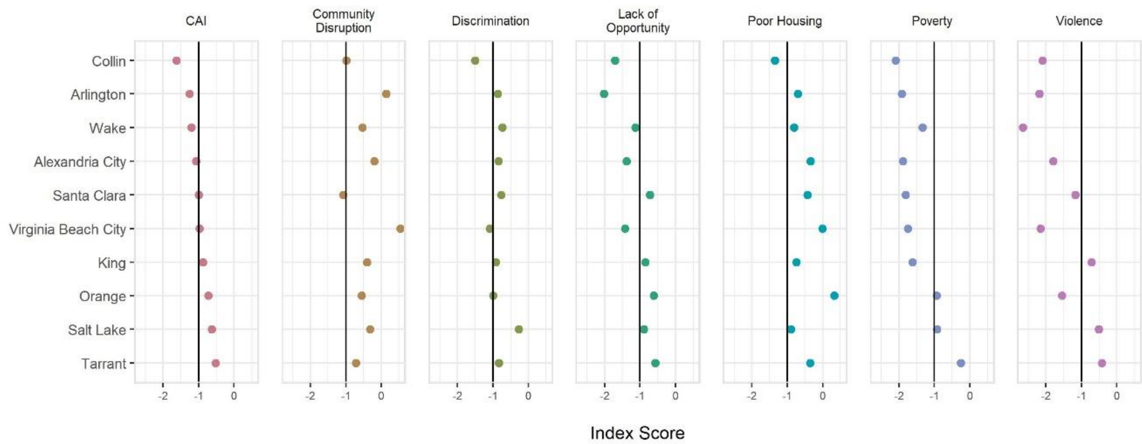


Note. Standardized data; 0 represents the mean, the line at 1 standard deviation demarks extreme scores to the right.

This shows that the index captures broader pathways into adversity than just poverty. While many counties feature extreme subindex scores in the poverty domain, in many cases, the poverty domain is not the most extreme scoring subindex. There are instances in the low adversity counties where the violence and discrimination domains have lower subindex scores than the poverty domain. In the case of Arlington, VA, and Tarrant, TX, although the poverty domain score is below average, other domains such as community disruption and discrimination are even more extreme. This is similar in high scoring counties such as Baltimore, MD, the District of Columbia, Milwaukee, WI, and Shelby, TN, where the violence, discrimination and other domains feature more extreme scores than the poverty subindex. Given the Community Adversity Index is created by calculating the arithmetic mean of subindex scores, this means that extreme scores in the poverty domain are not uniquely driving low or high CAI scores.

Figure 6

Counties with the Lowest Adversity in 2016: How Adverse Community Environments Group Together



Note. *Standardized data; 0 represents the mean, the line at -1 standard deviation demarks extreme scores to the left).*

Examining the best and worst ranked counties (see tables in the Appendix) demonstrates that county rankings tend to be consistent across time. Individual rankings fluctuate, but 90% of the counties are found in the best or worst lists at both time points. Poverty domain scores in particular do not vary much between years. However, domains like lack of opportunity and community disruption vary more substantially. This could reflect changes in local conditions and intervention efforts that have a greater impact on employment, education, substance abuse than on poverty. Such an observation is consistent with other research suggesting that poverty is difficult to change (for example Bird, 2013 on the difficulty of addressing generationally transmitted poverty).

Limitations

This study's design is influenced by data availability. Complete data for the wide range of indicators was not uniformly available across United States counties. Data availability can impact external validity; therefore, results are not generalizable to all United States counties. Other researchers have opted to sample states or regions where more complete data exists. Although studies that utilize data from a more limited region, such as a state, are generalizable to counties of various rural-urban status, results are difficult to generalize nationally. I desired a national perspective and opted to sample urban counties. While this decision means that results are not generalizable to rural areas, these data are more representative of geographies across the nation than studies that use limited regions.

Indicator availability also influences the results of this study. Although I was able to identify at least one indicator for every domain, ideal indicators would represent different facets of the broad domain category. The poor housing domain, for example, includes measures for poor housing that are well supported in the relevant literature. Other relevant measures, such as affordable housing stock or rates of housing insecurity were not available for use. Using a small set of available indicators means that the domain subindex score may not be adequately representing the magnitude of adversity in the poor housing domain. It also means that the Community Adversity Index score is underestimating the impact of specific negative environments. Prior research incorporating adverse housing data captures other relevant factors closely associated with housing. For example, low rates of home ownership are associated with low rates of wealth (Oliver & Shapiro, 1990). Poor housing can also be measured by how neighborhoods are situated in environments that have low access to healthy food outlets, public transportation, or parks (Kolak et al., 2020). Finally, measures that capture oppressive practices that impact housing, including the devaluation of properties in majority Black communities (Harshbarger, 2018) or gentrification of neighborhoods that result in loss of housing for families who are not White (Powell & Spender, 2003), are also important. These data are not available for every urban county, so I used measures like rent burden, eviction, severe housing problems, and rent occupancy rates to inform the picture of county-level poor housing. However, future research would benefit from policymakers' efforts to regularly collect other relevant housing data at the county-level.

Indicator quality also impacts the results of this study. Specifically, the measure used for discrimination, housing segregation, is an indirect measure that likely understates the extent to which discrimination contributes to community adversity. Housing segregation is typically a result of discriminatory practices, especially historical ones, but is not itself a measure of actual discrimination. It fails to capture discrimination in non-housing domains—like education, health care, and employment—that is widespread across counties, and it fails to capture individuals' experiences of discrimination. Survey instruments designed to directly measure discrimination have yet to be implemented across the United States to provide county-level measures. While I use an indirect measure of discrimination, I suggest future data development is needed for a direct measure of county-level discrimination, because research conducted with smaller populations suggests that the experience of stress resulting from discrimination has substantial impacts on families who must live in environments where oppression and racism are ever present (Carroll, 1998). I also strive to use existing literature to explain how indicators in other domains are influenced by institutional discrimination, as it is evident that discrimination is not a singular environment or domain, rather, it is present in all existing social institutions in the United States.

The adverse community environments proposed by Ellis and Dietz (2017) are limited to socially focused domains. Although environmental factors, such as poor water or air quality, can negatively impact child well-being, environmental issues are not included as a domain in the Ellis and Dietz framework. Still, research suggests that polluted environments generate stress. For example, a review of several studies investigating psychological impacts of various pollutants suggests anxiety and other mental health disorders are associated with exposure to major environmental pollutants, such as heavy metals (Ventriglio et al., 2021). Further, poor water or air quality can negatively impact child development. Outdated water infrastructure in Flint, Michigan, contributed to the widespread ingestion of lead—a substance known to disrupt cognition (Trejo et al., 2022). Children living near factories that generate air pollution are also more likely to develop asthma and allergies, conditions that can burden parents by requiring daily management, costly medication, and frequent doctor visits (Cook et al., 2021). This evidence of environmental harm to families suggests that the focus on social domains misses important sources of stress and adversity that shape the parenting context.

Therefore, the CAI scores may be underestimating stressors compounding on families, and further conceptual work should be done to expand the model to include other relevant domains.

Conclusion

This chapter builds on studies that suggest a broad range of community and societal factors contribute to stress and negatively impact families. The Community Adversity Index is unique in that it gives coalitions a tool for defining adverse community environments and quantifying them, both of which are useful for improving policymakers' understanding of this complex phenomenon. It establishes measures for six domains and offers a composite score for the combination of adversity present in urban counties. This simplifies the construct of adversity into a few key domains and a single aggregated score that is easy to synthesize and communicate.

Ranking the sixty-four urban counties in this study allows for an examination of the geographic distribution of high and low adversity counties. Geospatial patterning reveals that adversity is more prevalent in communities with high disinvestment and featuring larger Black populations. This finding is consistent with other research that suggests that hardship and distress are not evenly distributed across racial groups (Iceland & Sakamoto, 2022). The county-level Community Adversity Index provides a picture of how adversity is dispersed among the group of urban counties. However, future research is needed to understand how adversity is spread across rural and suburban counties. In addition, future research to determine how adversity is distributed within counties would provide county-level policymakers with actionable information about where to target interventions.

Still, a county-level Community Adversity Index provides policymakers with useful information about what type of interventions are needed because the tool makes clear which domains to prioritize for action. My analysis suggests that multi-faceted interventions that are intended to simultaneously address several domains would be the most effective at reducing Community Adversity Index scores; this is because communities with high scores typically feature high levels of adversity across all domains. Counties with the highest rates of adversity feature high rates of poverty, violence, and discrimination—a trio of interrelated hardships that contribute to distressed conditions that can span generations.

These convergent aspects of community adversity are difficult to impact through siloed efforts, although Ellis and Dietz (2017) posit that community coalitions could coordinate a collective response that effectively disrupts destructive systems. Their Building Resilient Communities model suggests that the work begins with creating a shared understanding of the problem of childhood and community adversity, encouraging multi-sector partners to pool resources, and engaging with community members to imagine new futures. The approach also puts relationships and agency at the center of efforts. For example, they promote collaboration and citizen action suggesting these two approaches offer effective pathways to creating new policies, practices, and programs that center the needs of families (Sumner M. Redstone Global Center for Prevention and Wellness, 2017). Certainly, it is reasonable to suggest that social action is needed to unravel the harmful social structures that create adverse community environments. This social action will be supported by using the Community Adversity Index that contributes to a shared understanding of sources of adversity as well as demonstrating where policy efforts need shifting.

Still, convincing policymakers to adopt the Community Adversity Index and community-level solutions to the problem of childhood adversity will require developing further evidence of the validity and utility of the instrument. In the next chapter, I test the reliability and validity of the CAI to further establish its reliability. Once I establish that the measure is well designed, I use it to empirically test how much family-level dysfunction is explained by community-level stressors. The fourth chapter tests the Community Adversity Index's utility in explaining family separation to foster care. If conclusions from this final chapter suggest adverse community environments explain adverse childhood experiences, coalitions will have further evidence for shifting policies away from preventing "inadequate parenting" and towards community-level prevention efforts.

CHAPTER 3

VALIDATING THE COMMUNITY ADVERSITY INDEX

Introduction

Adverse Community Environments are communities with a high concentration of poverty, violence, discrimination, and/or low access to resources (Ellis & Dietz, 2017). These communities typically feature reduced education and employment opportunities, stymied economic development, and limited social support for health and well-being (Sumner M. Redstone Global Center for Prevention and Wellness, 2017). Research on the social determinants of health suggests that such adverse environments harm children and families (Kolak et al., 2020; Lucyk & McLaren, 2017). This is echoed in sociological research on neighborhood effects that proposes that environmental stressors like concentrated poverty curtail child well-being (Gonzales et al., 2011; Sampson et al., 2002). Evidence suggests that these community-level stressors contribute to hardships that constrain the ability of parents to provide optimal care for their children (Fowler & Schoeny, 2017; Marcal, 2018; Raissian & Bullinger, 2017).

However, community stressors remain under-acknowledged by child welfare policymakers who administer the support that helps keep families safely together. Instead, by focusing on strategies such as parenting classes, policymakers imply that parents are responsible for preventing adverse childhood experiences (Testa & Kelly, 2020; White et al., 2019). Maltreatment is prevalent across communities, partly because of a failure to recognize how community contexts can compromise parenting (Bullinger et al., 2019). In this chapter, I argue that policymakers seeking to coordinate adequate support to parents need to adopt the problem framing of Adverse Community

Environments. I aim to facilitate this by providing policymakers with a reliable measurement tool that quantifies community adversity.

The preceding chapter introduces the Community Adversity Index (CAI) as a tool for helping policymakers integrate new problem definitions and solutions. In this chapter, I draw on various empirical tests to examine whether the index is a reliable measure of community adversity and performs as expected by adversity and toxic stress response theories (Gillespie et al., 2009; Lucyk & McLaren, 2017; Sampson et al., 2002; Wade et al., 2016). These tests validate the CAI and demonstrate its robustness given various configurations.

I develop five criteria that substantiate the Adverse Community Environments concept using frameworks already established in the Adverse Childhood Experiences literature. I create these criteria by relying on theoretical assumptions about the primary sources of influence on child well-being. For example, I use multiple risk literature to develop a correlation test between adversity domains. Next, I use stress response theory to examine the role of toxic stress and demonstrate how the Community Adversity Index is associated with poor mental health and compromised resilience. In addition, I test how changes in indicators and levels of analysis impact the robustness of the CAI. Combined, empirical results suggest that the Community Adversity Index is a valid and robust tool for helping policymakers identify and quantify sources of adversity.

Approaches to Measuring Adversity

Adversity typically is conceptualized as an individual experience that may have harmful effects across the life course, especially if the adversity begins in childhood. Parenting is a central mediating factor in many adversity studies, where parents are presented as either agents of harm or as buffers against it. However, research adopting an ecological framework—such as social determinants of health (Phelan et al., 2010) or neighborhood effects (Sampson et al., 2002)—suggests that parent behavior is not an exogenous variable. Instead, parent behavior is mediated by the surrounding environment. Research on the effect of community poverty, for instance, suggests that the incidence of child maltreatment is higher in communities where poverty rates are higher (Coulton et al., 1995; Drake & Pandey, 1996; Farrell et al., 2017; Kim & Drake, 2018; B. D. Smith et al., 2021). Beyond poverty, Coulton (1995) and Lery (2009) demonstrate that child neglect or abuse are also associated with impoverishment, parents' childcare burden, and residential instability, among other factors.

Other quantitative studies measuring the impact of community adversity on adverse childhood experiences have focused on socioeconomic stressors experienced at the community level (Lotspeich et al., 2020; Wulczyn, Feldman, et al., 2013). There are few studies examining environmental factors beyond economic measures. These works propose social disorganization (Barnhart & Maguire-Jack, 2016; Freisthler, 2004) or proximity to social support (Maguire-Jack & Klein, 2015) at the community level also shapes the context of parenting. The unifying premise of these various arguments is that maltreatment occurs when sources of community stress overload parents and compromise their ability to provide optimal care for children (Belsky, 1993; Caldwell et al., 2021). This perspective presents childhood adversity as rooted in adverse community environments and suggests that a change is needed in delivering child welfare services.

In this chapter, I synthesize the literature on multiple risk theory, toxic stress, sources of community stress, and how community is operationalized to develop five reliability tests for the CAI. I begin by summarizing existing theories explaining how to measure combined adversity and propose a criterion that examines whether CAI domains are sufficiently correlated to measure under the umbrella concept of adversity. Then, I describe how the toxic stress framework is helpful in testing the CAI validity. I propose two validity criterion tests that look for associations between community adversity and poor mental health as well as between community adversity and reduced resilience. Next, I highlight research on the influence of proximate environmental stressors on families and propose a criterion to test whether the CAI with a large set of indicators performs better than the CAI with a restricted set of indicators. Finally, I explore how community is operationalized and propose a criterion that examines whether aggregated measures of county adversity are skewed by high scores in the smaller communities they contain.

Using a Measure of Multiple Risks

Multiple factors in families' social ecology can support or hinder a parent's ability to provide optimal care to children. Environmental influences, such as concentrated wealth or poverty, can meaningfully shape opportunities for positive youth development (Acevedo-Garcia et al., 2014). Here I focus on the community-level risk factor—a phrase I use interchangeably with adverse community environments—that can compromise parenting and negatively impact child well-being. Many of these community-level risk factors are conditions of material hardship (Yang, 2015). However, social processes such as community violence (Aisenberg & Ell, 2005) or poor community organization (Daley et al., 2016) are also considered community-level risk factors. Risks to families include poor mental health, increased vulnerability to stressors, and/or place families in a state of deprivation. These conditions make it difficult for families to thrive.

Several mechanisms are proposed through which community-level stressors can erode parental capacity (Ceballo & Hurd, 2008).Distress can overload a parent's ability to attune to their child's needs (Arditti et al., 2010). Deprivation can force parents to limit care if they are unable to stretch existing resources to provide adequate nutrition, supervision, or medical care (Slack et al., 2004). Regardless of the mechanism, parents can be viewed as responding to stressors rather than making poor choices. Further, independent of parent choices, community-level adversity directly impacts children. For example, children living in low opportunity neighborhoods are more likely to have poor health outcomes (Acevedo-Garcia et al., 2014).

The constellation of community-level risk factors shaping the family context typically occur concurrently and inter-relate. For example, concentrated poverty and community violence empirically co-occur in urban areas (Pratt & Cullen, 2005). While the mechanism explaining why poverty and crime co-occur is not settled, several theories exist for how they relate. For example, crime has been described as relief from deprivation, a result of poor social organization, and the outcome of police officer profiling of low-income neighborhoods (Aber et al., 1997; Pratt & Cullen, 2005; Raphael & Winter-Ebmer, 2001; Stein & Griffith, 2015).

Environmental risk factors typically accumulate in ways that overburden parents and are detrimental to a child's well-being. When multiple risk factors are aggregated, they appear to have a stronger association with poor child outcomes than single stressors alone, and demonstrate a more substantial dose-response effect on poor childhood outcomes (for a review see Evans, Li, and Whipple 2013). Further, Evans and colleagues (2013) suggest that risks representing more than one domain (e.g., school or community) can be particularly detrimental because they can overload an individual's ability to adapt to competing sources of stress. Ellis and Dietz (2017) similarly propose that resilience is compromised when several key adverse community environments impact the parenting context. Given the strong correlations between risk factors that comprise community adversity, it is necessary to study these factors as a group.

In recognition of the multiple related sources of risk and the potential for additive risk, the CAI aggregates multiple risk indicators across six domains: poverty, poor housing, community disruption, incarceration, lack of mobility, discrimination, and violence. This approach captures a broad scope of negative environmental influences on families that likely correspond to a more pronounced dose-response relationship, where greater community adversity is associated with increased family breakdown. Creating a composite measure of multiple risks assumes that the component domains are related to their umbrella construct but should not be so strongly correlated that they provide redundant information. This consideration of collinearity is necessary, given research suggesting poverty is highly correlated with other adversities (Duncan et al., 2017). Therefore, the relationship between domains should be assessed empirically and constitutes the first criterion used to validate this approach.

> Criterion 1: CAI domains are sufficiently correlated to measure the umbrella concept of adversity yet are not redundant

Toxic Stress as an Underlying Framework

Adverse community environments render families vulnerable through exposure to multiple risks that cause harm. Various mechanisms perpetuate harm, including increased likelihood that consequences of poverty are misconstrued as parental neglect, increased contact with mandated reporters across punitive systems, and parental overload through toxic, or persistent and compounding, stress. Here, I discuss the link between adverse community environments and stress.

The "Stress Process Framework" offers a potential theory for explaining how extra-familial stressors are associated with adverse childhood events. Stress is generally described as the mental and physical reactions to adversity (Chetty et al., 2014). Garner (2013) proposes that stress erodes mental health through biological mechanisms and uses the "Stress Process Framework" to explain how negative biological responses result in compromised mental health. Proponents of this framework suggest that stressors generated by either "disruptive events or … more persistent hardships" (Pearlin, 2010, p. 208) activate the amygdala and prefrontal cortex, as well as the body's other stress response systems (Bremner, 2006). When the brain and body are stressed, it is difficult for people to adapt to or cope with challenges (Merrick et al., 2017).

Similarly, researchers propose that toxic stress—or stress that is compounded, persistent, or extreme (Clifton et al., 2022)—can cause compromised mental health.[4] Toxic stress can occur when multiple adverse community environments trigger the stress response that overloads an individual's ability to cope or solve problems (Arditti et al., 2010; Garg et al., 2019). For example, one study examines how the "cascade of difficulties characterized by neighborhood worries, provider concerns, bureaucratic difficulties … and the inability to meet children's needs" leads to maternal distress

[4] Although toxic stress is thought to contribute to mental health disorders (e.g., schizophrenia) for some populations, researchers suggest that the general population suffers from the harmful consequences of toxic stress in ways that do not meet the criteria for a disorder diagnosis but can still constitute poor mental health (Murray et al., 2012).

(Arditti et al., 2010, p. 142). Blumenthal (2021) suggests that mothers who face persistent community-level stressors like poverty and unemployment can face reduced cognitive capacity to solve problems, plan, or relate to children. Environmental stress triggers are thought to lower parent efficacy, and increase child maltreatment risk (Pinderhughes et al., 2007; Slack et al., 2004). However, more research is needed to understand the specific pathways through which community adversity could result in maltreatment.

Still, when adverse community environments are prevalent, toxic degrees of community-level stress, or stress experienced by many families, is a likely result. Research on family-level stress suggests an association with poor mental health. For example, family-level poverty and other hardships are linked to substance abuse, depression, and suicide (Goodman & Huang, 2002; Hoffmann et al., 2020). Research also suggests that reduced socioeconomic status, poor housing, joblessness, and other material hardships contribute to poor mental health (T. H. M. Moore et al., 2017). These associations between individual-level stressors and mental health are likely due to toxic stress.

Research connecting community adversity to stress likewise supports the claim that multiple adverse community environments cause poor mental health (Clifton et al., 2022). The CAI domains represent several persistent, community-level sources of toxic stress that research suggests are linked to poor mental health and reduced resilience. For example, the community disruption domain includes a measure of rates of community-level substance abuse that is known to be interrelated with poor mental health (Aas et al., 2021). The lack of opportunity domain includes a measure of community unemployment that is thought to contribute to rates of suicide (Haw et al., 2015). If the CAI meaningfully captures community risk factors for this stress, then the CAI should be a predictor of poor mental health across communities. As a second test of the CAI's validity, I examine the empirical association between the CAI and measures of poor mental health.

> Criterion 2: The CAI will be positively correlated with a measure of poor mental health.

Poor mental health can be expressed as the inability to maximize personal potential, cope with stress, or make meaningful employment or community-focused contributions (World Health Organization and Calouste Gulbenkian Foundation, 2014). If poor mental health includes the inability to cope, it follows that community adversity would also compromise resilience. Ecological resilience or community-level resilience is defined as the ability of a community to experience a disruption or shock and re-establish functioning while maintaining nearly the same formation and make-up (Wassénius & Crona, 2022). Empirical work examining community-level resilience is primarily concerned with disaster response. Disaster research asserts that under-resourced or challenged communities find it difficult to adequately respond to or recover from intense stress due to lowered resilience (Flanagan et al., 2018). Reduced resilience, also termed vulnerability, is typically presented as a composite of economic, demographic, and housing indicators. These same indicators are frequently cited in research on collective efficacy that suggests neighborhoods with limited resources can also feature neighbors with limited abilities to help each other cope with everyday stress (H. Foster & Brooks-Gunn, 2009). The CAI similarly aggregates data about community features that Ellis and Dietz (2017) suggest restrict resilience, such as community poverty, high rates of incarceration, and discrimination. Together, material and social constraints reduce resilience when community adversity is high. Thus, if the CAI meaningfully captures community adversity, it should predict reduced resilience across communities.

> Criterion 3: The CAI will be positively correlated with a measure of resilience.

Sources of Community Stress

Bronfenbrenner's ecological systems framework suggests that a child is most influenced by their families *and* communities (Bronfenbrenner, 1986). Community influence on families is increasingly being recognized (Felitti et al., 1998; White et al., 2019). Many studies suggest that community stressors experienced in childhood are associated with poor health outcomes and reduced opportunities across the life course (Acevedo-Garcia et al., 2014; K. E. Smith & Pollak, 2020). These studies suggest many community-level stressors, including poverty, unemployment, typical family composition, and income inequality are associated with constraints on child development (Brown & De Cao, 2018; Coulton et al., 1995; Eckenrode et al., 2014; Kim & Drake, 2018; Lery, 2009; Maguire-Jack & Klein, 2015). Combined, studies using these frameworks suggest that adverse community environments influence child well-being.

Here, I add to the research on adverse community environments influencing families by proposing a set of aggregated domains and indicators. The CAI uses a comprehensive set of domains proposed by Ellis and Dietz (2017). However, it is important to test the how the index performs with fewer domains, given that most empirical studies typically use a subset of these domains that are limited to measures of socioeconomic status. Therefore, I create a second composite measure of community adversity called the CAI Socioeconomic Status, or CAI-SES, which is a reduced version of the CAI. By formulating a second community adversity score with measures that are nested within the larger composite measure, I can test whether the CAI is robust to a change in indicators.

Criterion 4: The full CAI will perform similarly to the reduced CAI-SES.

Operationalizing Community

Research examining community stressors begins with determining a bounded geography that represents the community. This choice can shape study conclusions in meaningful ways (Boing et al., 2020). For example, data on community stressors measured at the county level could mask the experience of concentrated disadvantage in smaller geographies like neighborhoods (Sampson et al., 2002). Still, data for units smaller than counties, such as census tracts, zip codes, or other aggregations, are frequently unavailable. Therefore, researchers face tradeoffs between data availability and geographic precision in mapping the community.

Many researchers operationalize community based on available data, making theoretical support for operationalizing community secondary to the decision (Caldwell et al., 2021). However, various theories exist for determining which proximal environmental factors influence family behavior. For example, research suggests that parent networks and social services are accessed from larger geography than the neighborhood (Belanger & Stone, 2008; Beyers et al., 2003). In this case, the county more accurately represents the geography a parent regularly traverses to access support. Research on how environmental influences constrain parenting options focuses on the economic conditions that cluster near the family residence, such as the prevalence of community poverty, unemployment, and low educational attainment (Lotspeich et al., 2020). In this case, the census tract, zip code, or other parent-defined space better operationalizes the "community" environment. Ideally, community stressors research would be conducted at multiple geographic levels when data are available (Caldwell et al., 2021; Sampson et al., 2002).

The Community Adversity Index aggregates stressors meaningfully influenced by county-level resource allocation and management. For example, county-level policies are primarily responsible for distributing economic assistance, coordinating health and social services, and managing courts and jails (Boing et al., 2020). The county may also more accurately capture the broader community culture that expands across neighborhoods operationalized as census tracts or zip codes.[5] Borders of such smaller geographies are also typically permeable to stressors from neighboring communities (Caldwell et al., 2021; Lery, 2009; Sampson et al., 2002). An additional advantage of selecting county-level analysis is that more community stressors can be examined because more administrative data are available at this level. For these reasons, I chose to operationalize communities as counties for the majority of my analysis.

However, ecological researchers recommend collecting econometrics[6] at both the county and census tract level (Caldwell et al., 2021; Sampson et al., 2002) because social processes and resources vary between the two geographies. This is partly due to housing

[5] The boundaries of neighborhoods are usually established using data from Census tracts (Sampson et al., 2002), although results from studies that measure neighborhood boundaries using Census tract data are usually very similar to results from studies that use other methods, like ZIP codes, to define neighborhood boundaries (Freisthler et al., 2006; Lery, 2009).
[6] Sampson and colleagues (2002) use this phrase to describe the metrics representing various ecosystems surrounding families.

segregation and other racialized socio-political factors contributing to neighborhood-level differences. Such differences between neighborhoods can be obscured in county-level aggregations. In order to conduct a robustness check to examine whether and how community adversity scores vary across county-and tract- levels, I use available data to calculate a CAI-SES score for both levels.[7]

> Criterion 5: The reduced CAI-SES applied at the census tract-level will demonstrate a distribution of adversity that confirms the county-level CAI does not obscure skewed scores at the neighborhood level.

Methods

There is a lack of consensus across disciplines about how to analyze an index's reliability (Sürücü & Maslakçi, 2020). This lack partly explains why index developers typically stop at theoretical construction and neglect to conduct sensitivity or validity tests (Bakkensen et al., 2017). To test the criteria I proposed above, I draw on strategies proposed across various studies. I draw on Evans (2013) to guide correlation testing for multiple risk measures. I also draw on research related to the Social Vulnerability Index (Flanagan et al., 2011), Child Opportunity Index (Acevedo-Garcia et al., 2014), Child Well-Being Index (Land, 2012), and Human Development Index (Beja, 2021) for guidance on how to conduct sensitivity and validity tests.

I use five tests to corresponding to each of the five criteria proposed above. To test the first criterion, I begin with a correlation analysis for measures of the CAI subdomains. Such correlation testing provides evidence that the domains are associated with each other and with the umbrella construct they collectively define (Evans et al.,

[7] Data is not available to calculate the full CAI at both the county- and tract-level.

2013). Although association is expected and a sign that the variables operate together as part of a large construct (in this case, adversity), excessively high correlations can indicate multicollinearity (Alin, 2010). Multicollinearity would indicate that subdomain measures are redundant and not appropriate to include in a broader index—doing so would, essentially, allow a subdomain to "count twice". This is important as my interpretation of results assumes that each variable in the composite measure is independent.

For the next two criteria, I use two tests of criterion validity. Criterion validity tests whether given variables or constructs are empirically related to the index in theoretically expected ways (Salkind 2007). As such, this validity testing helps determine how well a constructed measure adequately captures the phenomenon of study (Heale & Twycross, 2015). The two tests used will assess criterion validity using predictive and concurrent validity. Predictive validity examines how well one construct predicts another in cases where theory expects an association (Salkind, 2010a). Concurrent validity examines how two different measures of a similar or related concept correlate (Frey, 2018). For example, Acevedo-Garcia et al (2014) suggest that child opportunity should be empirically linked to neighborhood quality. Using a measure of home values as an indicator of neighborhood quality, the authors use regression analysis to validate the Child Opportunity Index by showing that home values are correlated or concurrent with similar ranges of the index. I will employ a similar method to evaluate the association between CAI and poor mental health days.

Concurrent validity examines how an index correlates to another credible instrument or composite measure of similar or related concepts (Salkind, 2010b).

Acevedo-Garcia et al (2014) examine the concurrent validity of the Child Opportunity Index by examining its correlation with residential segregation. Likewise, a study of the Human Development Index and the Multi-dimensional Poverty Index shows that these constructs have a negative correlation, as expected by theory (Beja, 2021). I will similarly use regression analysis to determine if the CAI is concurrent with the Social Vulnerability Index.

For the fourth and fifth tests, I will assess the CAI's sensitivity to alternative specifications. Sensitivity tests establish the robustness of an index. A robust index does not produce substantially varied results when the developer makes minor changes to how the index is constructed (Tate, 2013). For these tests, I reconstruct the index twice. In one version, I restrict the domains and variables used to calculate the full CAI and create a new, more parsimonious index called the CAI-SES. For the CAI-SES, I choose variables mostly related to socioeconomic status, for which relationships with well-being outcomes are well-documented (Adler & Snibbe, 2003). Then, using the CAI-SES, I again reconstruct the index by changing the unit of analysis from county to census tract. The final criterion tests each use one of these reconstructed indices to assess robustness.

Specifically, for criterion 4, I compare the CAI and the CAI-SES to test whether the more parsimonious version of the CAI has equal criterion validity. I regress the CAI-SES on poor days of mental health and social vulnerability. I then examine the association strength between each index and the adverse outcome. Next, I calculate an Akaike Information Criterion (AIC) score for each model that assesses how well the regression model fits the empirical data. Lower AIC scores are superior and a difference of 10 or more between models indicates better model fit (Portet, 2020). Taken together, this information helps to determine if comparable results are produced despite a change in indicators. Comparable results provide support for the robustness of the index.

For criterion 5, I conduct a second sensitivity test by using a version of the CAI-SES with an alternative operationalization of community.[8] I compare the distribution of the CAI-SES using county-level measures to the distributions of the CAI-SES that use census level data. If the CAI-SES is overly sensitive to variation at the census level, counties showing high skew at the census level could contribute to inflated CAI-SES scores. Here, I examine the distribution of tract level scores. This confirms that the county level CAI does not generally obscure disparities at the neighborhood level.

Data

This study relies on the 2014 and 2016 data described in the previous chapter drawn from 128 counties across the two years. These counties come from 37 states and hold 29% of the U.S. population. Summary statistics for each variable are noted in the previous chapter.

I add to these data additional indicators: the average number of poor mental health days over the past 30 days for individuals ages 18 and older and the Social Vulnerability Index. Poor mental health data were provided by the Robert Wood Johnson Foundation's County Health Rankings, sourced from the Behavioral Risk Factor Surveillance System survey. Table 2 provides summary statistics for this variable.

[8] Tract-level data are only available for the CAI-SES.

Table 2

Poor Mental Health Days Summary Statistics for 2016 and 2014 Combined

Variable	Mean	Standard Deviation	Minimum	Maximum
Poor days of mental health	3.70	0.47	2.50	4.99

N = 128

Data from the Social Vulnerability Index (SVI)—a composite measure of resilience—were sourced from the Centers for Disease Control. The SVI is calculated using fifteen Census variables. These indicators are standardized and then aggregated, with the final composite score providing a percentile ranking between .01– 1.0 (Flanagan et al., 2011). Although data are available for all U.S. counties in 2016 and 2014, I filter the data to include only the 128 counties in this study. Summary statistics for this variable are provided in Table 3.

Table 3

Social Vulnerability Index Summary Statistics for 2016 and 2014 Combined

Variable	Mean	Standard Deviation	Minimum	Maximum
SVI	0.60	0.19	0.10	0.92

N = 128

In order to compute the CAI-SES at the tract-level, I draw additional census tract-level data from the American Community Survey to recalculate a new version of the CAI for a smaller geography. This data set provided the socioeconomic variables used in the county-level CAI and allowed for a partial recalculation of the CAI. Tract-level variables and their summary measures are shown in Table 4 below.

Table 4

Summary Statistics for Tract-Level Variables Sourced from the American Community Survey

Variable	Mean	Standard Deviation	Minimum	Maximum	Standard Error
Total Population in Census Tract	4373.23	2123.16	28	40616	10.47
Percent White	45.73	30.20	0	100	0.15
Percent Black	18.94	26.87	0	100	0.13
Percent Hispanic	24.61	25.78	0	100	0.13
Population Density	9317.69	14541.66	0.42	490596.60	71.72
Percent Poverty	18.15	13.83	0	100	0.07
Rent Burden	48.97	14.88	0	100	0.07
Population Without High School Degree	76.19	10.55	36.77	100	0.05
Population Without Some College	72.45	8.58	9.09	100	0.04
Percent Unemployed	9.87	6.71	0	100	0.03
Income Inequality (Gini Index)	42.78	6.75	6.44	81.15	0.03

N = 41,105

Test 1: Correlation Analysis

Approach. In this section, I examine various measures of domain correlation to ensure that the domains are correlated but no domain is duplicative. Index domains should be moderately to strongly correlated (R = .4–.9) to each other (Acevedo-Garcia et al., 2014). Collinearity (R ≈ 1) between domains, however, could indicate that measures of separate domains are too similar to include in the index. I calculate the variance inflation factor to determine if the combination of domains is multicollinear with a given measure (Craney & Surles, 2002).

Results. Correlation analysis displayed in Table 5 demonstrates that the six CAI domains are all positively correlated with each other. Given that theories suggest each domain represents a measure of overall adversity, these positive correlations were anticipated.

Table 5

Correlation Table of Community Adversity Domains

	Lack of Opportunity	Poor Housing	Community Disruption	Poverty	Discrimination	Violence
Lack of Opportunity	1.00					
Poor Housing	0.66***					
Community Disruption	0.28**	0.21*				
Poverty	0.80***	0.70***	0.41***			
Discrimination	0.54***	0.23**	0.44***	0.56***		
Violence	0.71***	0.46***	0.47***	0.77***	0.57***	1.00

*$p < .05$. **$p < .01$. ***$p < .001$

As Table 5 shows, correlations between domains tend to be moderate to high, although there are instances where correlations fall below this threshold. The violence domain is moderately correlated with poor housing (.45), community disruption (.47), and discrimination (.57). The violence subindex is strongly correlated with lack of opportunity (.71) and poverty (.77), which is consistent with other research linking these domains (Pratt & Cullen, 2005). Poor housing follows a similar trend, with relatively high correlations to lack of opportunity (.68) and poverty (.71). Lack of opportunity is moderately to highly correlated with most of the other subindices, except for community disruption. For most domains, the correlation range is .54–.84, but for community disruption, the correlation falls to 0.30.

Poverty, a domain with a single measure, is highly correlated with poor housing (.71), violence (.77), and lack of opportunity (.78) and is moderately correlated with the community disruption (.41) and discrimination (.56) domains. This finding is consistent with other research that posits community poverty is strongly linked to increased rates of adverse outcomes (Duncan & Brooks-Gunn, 1997; Phelan et al., 2010).

Two domains show lower correlations with other adverse community environments. The community disruption domain has the lowest correlation with the other domains, with a range of .21–.47. Discrimination also shows a low to moderate (.30–.56) correlation with the other five domains. This weaker correlation could be tied to the single measure used to calculate this domain. The measure selected, housing segregation, is one of the only available county-level measures of discrimination. This domain might show more correlation with the others if the measure was strengthened by combining it or replacing it with another more direct measure of discrimination. It could also indicate that these domains are relatively independent of the other measures and contribute to overall adversity via their independent pathways.

Overall, this evidence suggests that these domains are empirically related to each other, as implied by the umbrella construct of community adversity. Given that the correlations between domains are high in this data, it is necessary to examine measures of multicollinearity to determine whether any combination of the domains provides redundant information. Variance inflation factors (VIF) are calculated from an OLS regression model that regresses the combined domains on the CAI. As Table 6 demonstrates, none of the VIFs meet the standard threshold for multicollinearity.

Table 6

Variance Inflation Rates

Index Component	Lack of Opportunity	Community Disruption	Poor Housing	Poverty	Discrimination	Crime
Variance Inflation Factor	3.59	1.37	2.55	4.45	1.9	2.94

Note. 5–10 is considered evidence of multicollinearity (Craney & Surles, 2002).

The correlation and variance inflation measures suggest that the composite CAI can provide a more complete understanding of community adversity than a single measure, such as the poverty rate.

Test 2: Predictive Validity Analysis

Research suggests that community adversity is linked to poor mental health outcomes (Goodman & Huang, 2002; Hoffmann et al., 2020; T. H. M. Moore et al., 2017). Therefore, as a test of predictive criterion validity, it is reasonable to assume that the CAI should be positively correlated with a measure of poor mental health.

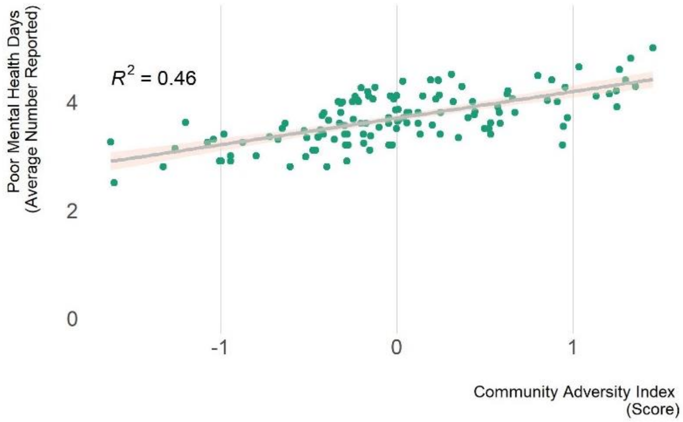
Approach. I use a bivariate OLS regression to investigate the relationship between the CAI score (independent variable) and average poor mental health days reported by county residents (dependent variable).

Results. The regression coefficient for the CAI is statistically significant [b = 0.49, 95% CI (.40, .58), $p < 0$], indicating that for every one-unit difference in the CAI, the average number of poor mental health days reported changes by .49 days. The model explains approximately 46% of the variance in poor mental health in this sample (R^2 =

.46). Figure 7 provides a visualization of this association. The evidence suggests that the CAI has some predictive validity: it correlates to another measure of a similar construct (Salkind, 2010a).

Figure 7

Predictive Validity Analysis: Association Between Community Adversity Index and Poor Mental Health Days



Test 3: Concurrent Validity Analysis

The SVI, like the CAI, seeks to quantify community factors that restrict resilience. Therefore, as a test of concurrent criterion validity, I examine the association between the SVI and the CAI. The SVI includes indicators that are connected to persistent stress and compromised abilities. Three indicators (poverty, unemployment, and high school attainment) are also used in the CAI. The overlap in shared indicators and the concern for resilience suggests the two instruments are likely to be positively correlated.

Approach. I conduct a bivariate OLS regression to test for an association between the CAI (independent variable) and the SVI (dependent variable). I also examine top-ranking counties for each index to investigate whether counties that score high on vulnerability tend to have high adverse environments scores.

Concurrent validity testing is limited by using an index that shares similar indicators with the CAI. I chose to use the Social Vulnerability Index when testing the full CAI despite the shared indicators, as the number of shared indicators was proportionately small compared to the total indicators in each index, and the SVI data were available for all counties in my study. However, the use of this index makes results less conclusive when comparing the SVI and the CAI-SES because these two indices share a more considerable proportion of indicators. The reliability of validity testing results could be improved by finding an additional composite measure of local resilience.

Results. The regression coefficient for the CAI is positive and statistically significant [*b* = .49, 95%, CI (.41, .57), $p < .05$], indicating that for every one-unit difference in CAI score, the Social Vulnerability Index score is expected to change by .49 points. The model explained approximately 54% of the variance in the SVI for the sample ($R^2 = .54$). Figure 8 shows this association.

Figure 8

Concurrent Validity Analysis: Association Between Community Adversity Index and Social Vulnerability Index

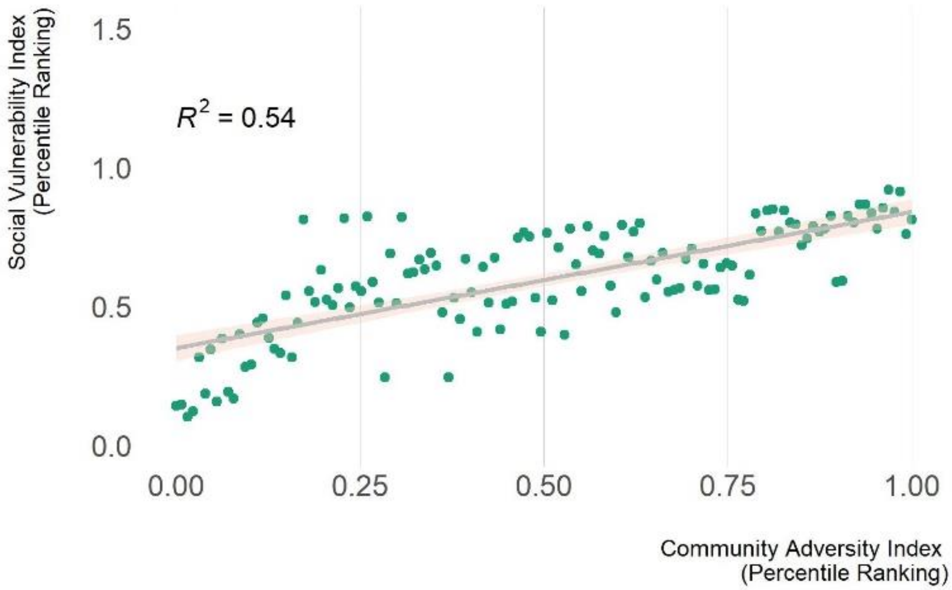


Table 7 lists the most vulnerable and most adverse counties according to the CAI and SVI. The highlighted counties show counties appearing in both lists. Five counties appear in the top ten for both the most vulnerable and adverse counties. Nine counties overlap in the top fifteen. The overlapping counties share many similarities: all have relatively large Black populations (38% on average), have average incomes at or below the national average, and all are in the eastern half of the United States. Interestingly, New Orleans has the highest CAI score but is not in the top fifteen scores for the SVI. This county has been vulnerable to disaster in recent years, suggesting that the SVI may miss important resilience-restricting factors better captured in the CAI.

Table 7

Comparison of the Highest-Ranking Counties in the Community Adversity Index and Social Vulnerability Index

	State	County	CAI	State	County	SVI
1	MO	St. Louis City	1.00	PA	Philadelphia	0.92
2	LA	Orleans	0.99	MI	Wayne	0.87
3	PA	Philadelphia	0.97	NJ	Essex	0.85
4	MI	Wayne	0.94	MD	Baltimore City	0.84
5	WI	Milwaukee	0.93	FA	Miami-Dade	0.83
6	DC	District of Columbia	0.91	WI	Milwaukee	0.83
7	VA	Richmond City	0.91	CA	Riverside	0.82
8	TN	Shelby	0.87	TX	Bexar	0.82
9	MA	Suffolk	0.87	MO	St. Louis City	0.81
10	IN	Marion	0.85	IN	Marion	0.80
11	VA	Norfolk City	0.83	TN	Shelby	0.79
12	NJ	Essex	0.82	CA	Los Angeles	0.79
13	FA	Miami-Dade	0.80	CA	Sacramento	0.78
14	NY	New York	0.79	VA	Norfolk City	0.77
15	OH	Cuyahoga	0.76	VA	Richmond City	0.77

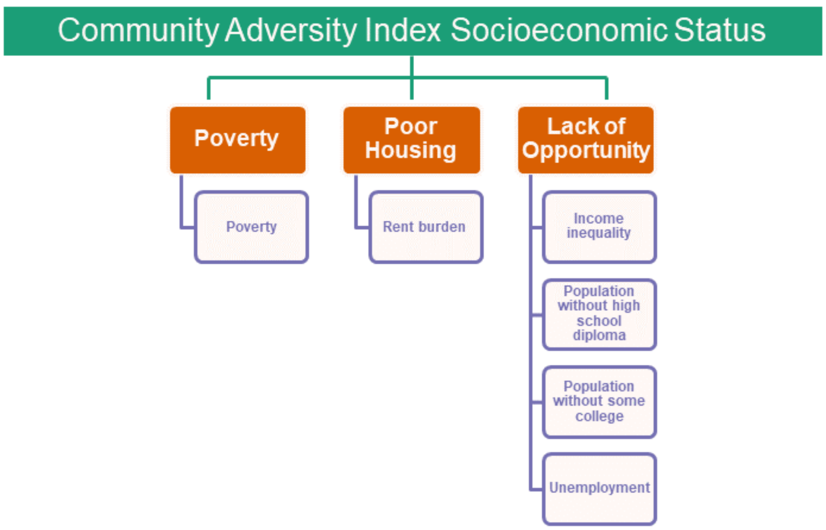
Test 4: Indicator Selection Sensitivity Analysis

The Community Adversity Index offers a comprehensive picture of multiple domains influencing community-level adversity. While the substantial number of domains (6) and indicators (14) in this composite measure contribute to its comprehensiveness, a more parsimonious measure may prove useful when assessing geographies with fewer data points available (e.g., census tracts). To develop a more parsimonious CAI, I draw from prior research on socioeconomic status and health that suggests that socioeconomic indicators are highly associated with health outcomes (Adler & Snibbe, 2003; Duncan & Brooks-Gunn, 1997; Phelan et al., 2010) to determine which variables to include in a reduced model. As second criterion, I select variables for which data is widely available for analysis across counties and at the tract level. I call this new index the Socioeconomic Status Community Adversity Index, or CAI-SES.

This reduced index includes the following domains and indicators as shown in Figure 9 below:

Figure 9

Community Adversity Index Socioeconomic Status Component Diagram



The following analysis examines whether the CAI and the reduced CAI-SES are similarly associated with a correlated outcome and index. Similar associations provide evidence that the CAI is robust to changes in indicators.

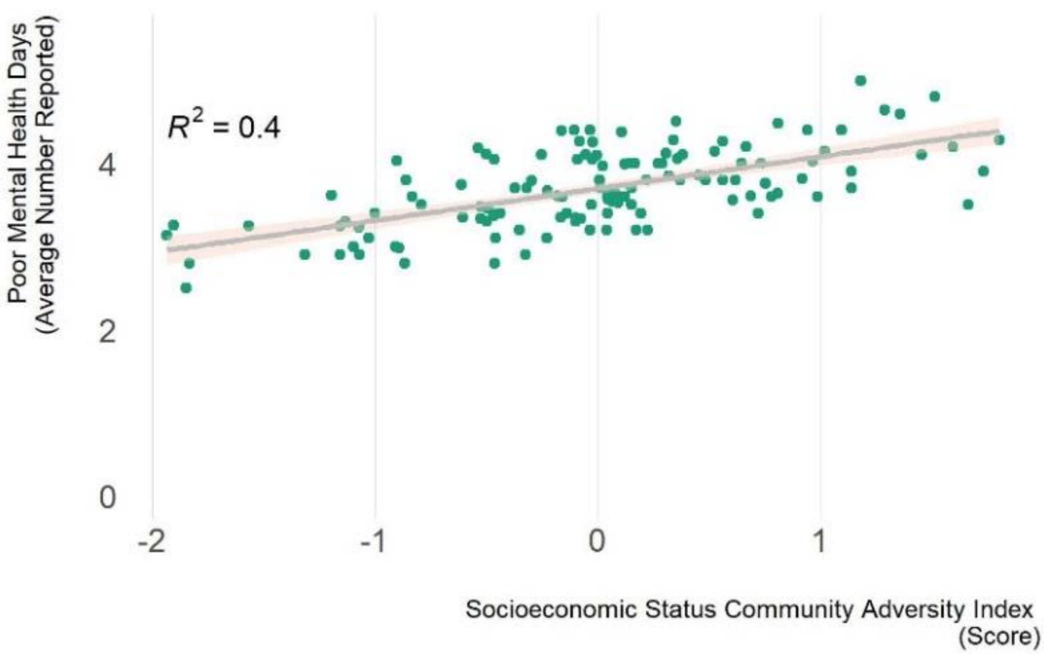
Approach. I use measures of model fitness to assess the sensitivity of the CAI to a change in indicators. I will do so by conducting the criterion validity tests with the CAI-SES and comparing results with prior analysis of the full CAI. I begin by conducting regression analysis to measure how well the CAI-SES correlates to poor mental health days and the Social Vulnerability Index. Then, I compare AIC scores between models to determine whether one model demonstrates more predictive and concurrent validity.

Similar scores would support the interchangeability of the indices and demonstrate that the CAI is still sensitive to detecting adversity even given fewer indicators.

Results. The data shown in Figure 10 suggest that the full CAI is a better predictor of poor mental health days than the CAI-SES. The CAI-SES explains only 40% of the variation in poor mental health days, while the CAI explains 46%. In addition, the CAI model (AIC = 97) provides a better fit to the data than the CAI-SES model (AIC = 109).

Figure 10

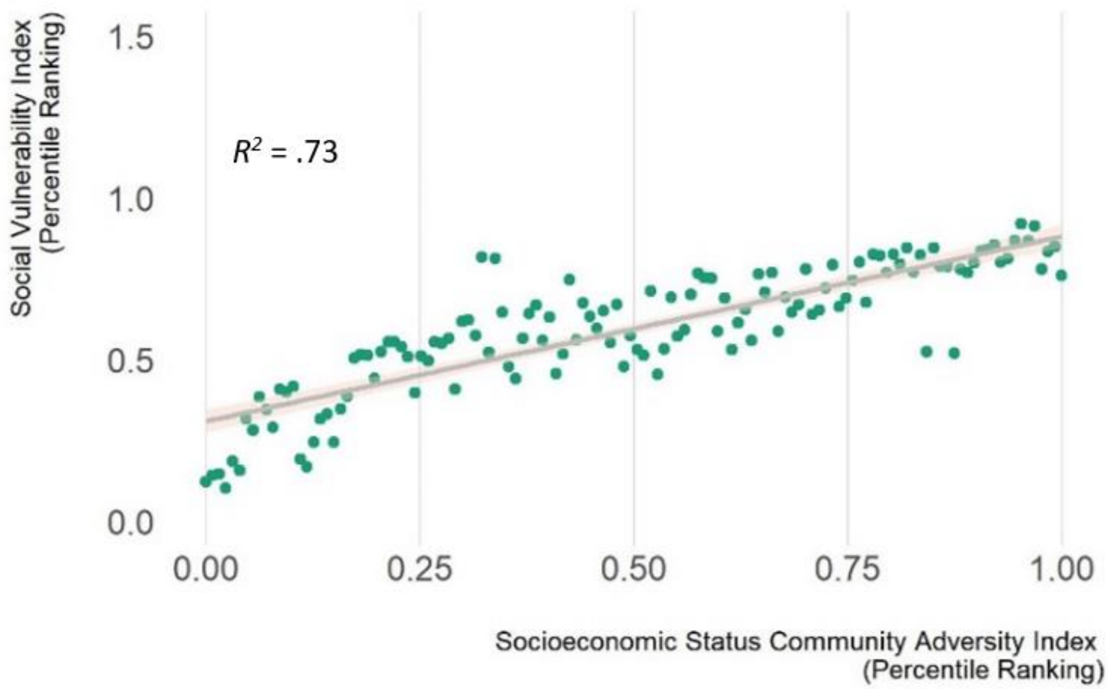
Association Between Community Adversity Index Socioeconomic Status and Poor Mental Health Days



By contrast, the data in Figure 11 suggest that the CAI-SES (R^2 = .73) is better than the CAI (R^2 = .54) at explaining the variance in Social Vulnerability Index Scores. In this case, the AIC estimates also suggest that the CAI-SES model (AIC = -219) is superior to the CAI model (AIC = -150). However, these results should be interpreted cautiously since both versions of the CAI model share indicators with the SVI. Conclusions could be drawn more easily from an alternate concurrent validity test that compares the CAI and the CAI-SES to another index using dissimilar measures.

Figure 11

Association Between Socioeconomic Status Community Adversity Index and Social Vulnerability Index



The lack of clear evidence that either model is superior and that each index is moderately correlated with these measures of criterion validity suggest that the index performs well, even when measures used are restricted. Similar performance suggests that the index is robust to changes in indicators.

Test 5: Level of Analysis Sensitivity

Theories underpinning the CAI index, such as neighborhood effects and ecological framework theories, argue that child development is affected by more proximal environments than the county. In addition, research demonstrates that structural discrimination, such as housing segregation, contributes to an uneven distribution of wealth and resources within counties (Levy, 2022). Capturing these more proximal communities requires a geographically narrower unit of analysis than the county level. The census tract provides one such unit.

Operationalizing the community as a county is a design choice that limits the generalizability of the CAI's results to counties. In the previous chapter, I used theory to support my choice of operationalization, identifying the county as geography of shared neighborhood environments and processes driven by county-level policy and service administration. However, county-level indicators aggregate data across neighborhoods that could have vastly different adverse community environments. This means that county-level indicators can obscure variation at the neighborhood level. Researchers have sought to identify which bounded geographies are most influential to family circumstances by examining multiple geographies simultaneously (e.g., Lery 2009). Therefore, I created the CAI-SES to analyze patterns at both the county and tract levels. This analysis was restricted to a smaller set of indicators than the full CAI includes, so results suggesting that variations are relatively consistent within the studied counties may not be generalizable to the composite measure that includes more domains. This is important to note, as domains that include indicators of discrimination and incarceration are absent in the reduced CAI. These adversities can have a meaningful effect on county and neighborhood (tract) settings.

I test the sensitivity of the CAI to changes in units of analysis by operationalizing communities as census tracts and recalculating the CAI at this level. This test allows me to examine the geographic patterns of adverse community environments for census tract within given counties. To conduct the test, I again use the CAI-SES because only this reduced measure includes indicators available at both the county and the tract level. I then use the CAI-SES to determine how the distribution of adversity at the tract level influences the county level measure.

Approach. Aggregating data from a smaller unit of analysis to a larger unit of analysis requires summarizing multiple data points into a single geographically aggregated estimate, which results in a loss of information. A county level measure provides an estimate of average experience across the county, which can obscure considerable variation at the tract level. A county with two tracts scoring 0 and 4 on a given metric, and a county with tracts scoring 2 and 2 on the same metric will both have an average county-level score of 2. Yet the first county has a much more prominent disparity between tracts, which implies that individuals' experiences of "community" in that county varies greatly. Therefore, it is essential to evaluate how well the county level CAI-SES captures the variation at the tract level.

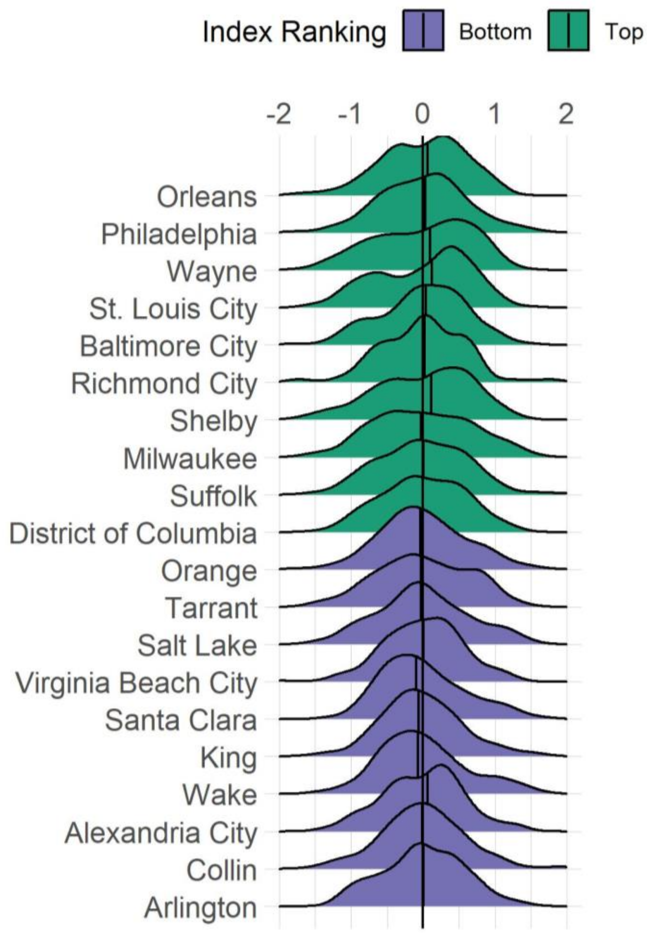
I use tract level data to calculate CAI-SES scores for each census tract in the sample counties. Then, I examine the distribution of these scores for evidence of skew that would suggest that the aggregate county level score is being influenced by extreme tract level scores in ways that reduce the usefulness of aggregate measures. If standardized within-county tract-level CAI scores are roughly symmetrically distributed around zero, this will suggest that using an aggregate county-level measure does not overly obscure within-county variation in community experiences, and, especially, does not give undue influence to higher or lower scoring outliers at the tract level.

Results. Examining counties with the highest and lowest CAI-SES scores provides insights into tract level score patterns. Figure 12 includes frequency distributions of census tract CAI-SES scores for the highest- and lowest-scoring counties and includes a line marking the median score for tracts. High-ranking counties (with high adversity) are shaded green, and low-ranking counties are shaded purple. As expected, the figure shows that the mean tract-level CAI score within counties is typically near 0. This suggest that extreme tract values are not a major concern and are unlikely to introduce bias in county-level CAI-SES scores.

When tract-level CAI-SES score distributions are skewed, in four out of 20 cases (Wayne, St. Louis City, Shelby, and Alexandria City), they are skewed slightly to the right—even in cases where the CAI score is low. This further suggests that county-level scores are not systematically driven by tract-level outliers. Still, future research could examine counties with skewed distributions further to reveal more subtle patterns of adversity in these communities. For example, spatial analysis would reveal whether adversity concentrates in specific tracts with shared boundaries or whether adversity is more evenly distributed within counties. Such tract level research could be helpful in informing policymakers who make decisions about where to invest intervention funds.

Figure 12

Tract-Level Distribution of Community Adversity Index Scores



Conclusion

The impact of community-level stressors on children's well-being is well documented in health and sociology literature. However, child welfare policy has yet to include community-level interventions in major funding initiatives. I argued that policymakers seeking to coordinate effective support for parents need to identify and measure Adverse Community Environments. I presented the CAI as a tool for taking inventory of community-level adversity and proposed to conduct several validity tests to assure policymakers of its reliability.

Drawing on validity and sensitivity tests used in other index development studies, I demonstrated the ability of the CAI to describe and identify adverse community environments. I examined the association between the CAI and county levels of poor mental health and resilience to demonstrate the criterion validity of the index. Additionally, drawing on research related to housing segregation and distributive injustice, I found that the CAI is sensitive to effects at both the county and tract level.

To evaluate whether the CAI meets a series of proposed validity criteria, I conducted five tests using 2014 and 2016 data from the American Community Survey, Eviction Lab, Incarceration Trends, Robert Wood Johnson County Health Rankings, and the Centers for Disease Control's Social Vulnerability Index. I examined the correlations between the index domains for the first test and ruled out multicollinearity. Next, I regressed the CAI on the average number of poor mental health days reported at the county level to establish evidence of predictive validity. For the third test, I again used simple linear regression to determine if the CAI and the Social Vulnerability Index, a measure of constrained community resilience, were correlated. This test sought to establish concurrent validity, or correlation between two indices measuring a similar construct. For the fourth test, I tested the index's sensitivity to choice of subdomain indicators by creating the Socioeconomic Status Community Adversity Index (CAI-SES) and submitting it to the same tests as the CAI. Finally, I computed the CAI-SES at the census tract level to determine the instrument's sensitivity to choice of units of geographic analysis. Each of these tests relied on theories that suggest the ecology or community surrounding a family can contribute to parenting distress and result in adverse childhood outcomes. Key findings follow.

Despite research that suggests poverty is a domain that overlaps with other adversity domains, such as poor housing (Garnham et al., 2022; Tunstall, 2013), variance inflation factor testing suggests that the domains in this data are independent.

I found that the CAI was positively correlated with the average number of poor mental health days reported for each county. I interpreted this to mean that the CAI sufficiently represents the construct of adversity as it conforms to previous research that suggests ecological adversity is associated with poor mental health.

Findings also demonstrate that the CAI was positively correlated with the Social Vulnerability Index. This correlation suggests that the CAI and SVI are measuring related constructs. In the next chapter, I will examine how high rates of adversity correspond with reduced resilience by examining how community adversity is associated with poor family outcomes, such as family separation.

By comparing the CAI and CAI-SES to determine the index's sensitivity to a change in indicators, I found that a reduced CAI is helpful in contexts where limited data availability prevents computing the complete index.

In the final test, I operationalize community at a smaller unit of analysis to test the CAI's sensitivity for geographies of varying sizes. Findings suggest that the CAI is appropriately robust to the level of analysis as demonstrated by the absence of skew and fairly normally distributed tract-level adversity.

Overall criterion results suggest that the CAI is a valid and sensitive tool with the potential to help policymakers identify intervention opportunities that provide meaningful support to families living in urban communities in the United States. The five tests provide evidence that the index is well-constructed, as the tests here suggest it adequately captures community adversity. Sensitivity tests assure policymakers that community adversity identified at the county level captures enough of the broadly shared community needs to establish which counties to prioritize for intervention support.

This work's essential contribution is that it advances the Pair of ACE's communication tool by defining and quantifying adverse community environments—an initial concept that Ellis and Dietz (2017) loosely articulated and left unmeasured. In addition, the CAI is a tool for policy actors who can now empirically measure adverse community environments and determine where to direct limited intervention resources. With the new concept defined and reliable ecological metrics, it is now possible to shift policy framing away from parent behavior interventions and towards material support that changes the conditions in which parents care for children.

CHAPTER 4

PREDICTING FAMILY SEPARATION WITH THE COMMUNITY ADVERSITY INDEX

Introduction

Community-level adversities, such as concentrated poverty and neighborhood violence, constrain parenting and negatively impact children and families (Aisenberg & Ell, 2005; Barnhart & Maguire-Jack, 2016; Wulczyn, Gibbons, et al., 2013). Advocates have termed these adversities *adverse community environments* (ACEs), a concept purposely designed to draw attention beyond existing public narratives centered on a similar, individual-level idea with the same acronym: *adverse childhood experiences* (ACEs). This "Pair of ACEs" (Sumner M. Redstone Global Center for Prevention and Wellness, 2017) promotes an inclusive understanding of how child abuse or neglect can result from the toxic stress and material hardships parents suffer. By incorporating both ACEs, research can situate child maltreatment trends that disproportionately affect Black, Indigenous and Hispanic/Latino groups within the context of racially structured differences in community environments.

Adverse community environments can hinder a family's ability to care for their children. Ellis and Dietz posit that several domains of adversity, beyond just poverty, can accumulate and overload parents. This argument is partly explored by studies that look at the singular impact of various community-level factors, such as community poverty, income inequality, and poor housing, to explain rates of child abuse or neglect (Chandler et al., 2020; Eckenrode et al., 2014; Maguire-Jack & Klein, 2015). Removing the child from home and placing them into foster care, or separating families, is a response that child welfare agencies use to protect children from purported harm. Yet, this response disrupts parent-child bonds in ways that have profoundly negative impacts on child development (Roberts, 2002; Sugrue, 2019). These disruptions are disproportionately experienced by Black and Hispanic/Latino children, who are separated from their families at higher rates than White children (Dettlaff & Boyd, 2020; Maguire-Jack et al., 2015). Family separation is an especially damaging outcome of community-level adversity. However, there is scant research assessing how cumulative measures of environmental adversity predict the separation of Black and Hispanic/Latino families.

This dissertation presents the Community Adversity Index (CAI) as a comprehensive tool for measuring adverse community environments. The CAI provides an easy-to-understand metric that can help policymakers assess the intensity and composition of local adversity. In this chapter, I examine the CAI's usefulness in predicting child welfare outcomes. Specifically, I use the CAI to answer the question, "Does community adversity explain family separations across a sample of U.S. counties, and does it do so better than previously studied economic measures?" Further, I analyze how the CAI helps to explain racially disparate outcomes in child welfare by asking, "How does community adversity predict rates of family separation across racial groups?"

Using several datasets, including the American Community Survey (ACS) and the Adoption and Foster Care Analysis and Reporting System (AFCARS), I examine how measures of community-level adversity are associated with counts of foster care entry. To do so, I obtain estimates using generalized linear models appropriate for count data. I begin by examining county populations as a whole and determining how well the CAI and other measures of community hardship (e.g., poverty) predict family separation.

Comparing hardship measures and their association with family separation helps to further demonstrate the value of the CAI as a cumulative measure of adversity. Next, I explore how the CAI and hardship measures predict family separation for White, Black, and Hispanic/Latino children.[9]

Results of this study suggest that the CAI is positively associated with county-level measures of family separation. The CAI is a superior predictor of family separation compared to community poverty and the CAI-SES, a reduced-form index of adversity introduced below that focuses on poverty and other measures of socioeconomic status. The CAI is positively associated with family separation across racial groups, although the strength of the association varies. The empirical evidence provided by this study offers policymakers compelling information. It supports a new problem framing, positing that adverse community environments (rather than individual "inadequate" parents) warrant interventions.

In the following sections, I provide an overview of family separation and its relationship to environmental stressors. Next, I explain the methods I use to empirically test the associations between county-level adversity and foster care entry rates. Then, I present results that suggest community adversity is strongly associated with family separation for the general population and across White, Black, and Hispanic/Latino populations. The chapter concludes with a discussion of policy implications, including

[9] Data is not presently available to conduct a similar study for Indigenous Peoples. However, the absence of data does not equate to an absence of problematic family separations for Indigenous Peoples. Although unique protections to prevent the removal of Indigenous Peoples to foster care are outlined in the Indian Child Welfare Act, a disproportionate number of Indigenous Peoples' children (2.6% of the foster care population but just 1% of the population of US children) are represented in foster care (Children's Bureau, 2020; National Center for Juvenile Justice, 2019).

using the CAI to reformulate interventions funded by the Family First Prevention Services Act.

Disproportionality and Current Child Welfare Debates

Child welfare scholars typically propose that disproportionality is caused by one of two pathways. One argument suggests that differences in community conditions—notably the greater likelihood of living in high poverty neighborhoods (Drake & Rank, 2009; Mauer, 2014)—contribute to higher risk of child welfare system involvement for Black, Indigenous, and Hispanic or Latino children (Maguire-Jack et al., 2015; Merritt, 2009; Putnam-Hornstein et al., 2013). However, some counter-intuitive or mixed results across several studies exploring the relationships between race, socioeconomic measures, and poor child outcomes have led some scholars to challenge this argument (Drake et al., 2009; Wulczyn, Gibbons, et al., 2013). Some scholars point to this evidence and suggest that bias is another more important pathway contributing to the overrepresentation of some racial groups in the child welfare system.

Researchers proposing bias as a pathway investigate the perceptions, actions, and decisions of child welfare agents. For example, researchers suggest that bias in the form of perceptions and judgements lead to child welfare actors interpreting visible signs of poverty as evidence of poor parenting. These researchers hypothesize that child welfare actors view Black, Indigenous, Hispanic or Latino families through a White-centered racial frame that holds all parents to a privileged, White standard of well-resourced parenting (Cooper, 2013; Merritt, 2020). Further, bias may contribute to increased child welfare and other mandated reporter surveillance. These agents act on discriminatory and racist beliefs that cast people who are low-income or belong to specific racial groups as more likely to need monitoring and intervention (Edwards, 2019; Edwards, Beardall, et al., 2021; Roberts, 2022). Scholars that dispute bias as a pathway attempt to undermine this argument by suggesting that disproportionality in child welfare outcomes mirrors disproportionate outcomes across multiple systems, pointing back to concentrated risk as the source of generalized poor outcomes for families (Drake et al., 2011).

Frustrated by this dichotomous debate, still other scholars argue that neither of these proposed pathways sufficiently explains disproportionality on their own and contend that both are part of the larger problem of racism (Dettlaff et al., 2021). Similarly, this chapter emphasizes multidimensional root causes in order to step away from the limiting pursuit of a single explanation for racial disparities. Community stressors are empirically explored as a contributor to varied outcomes by racial group, while bias is theoretically considered as a contributing factor to high rates of neglect.

Family Separation as a Function of Community Adversity

Family separation—removing a child to foster care due to substantiated reports of abuse and/or neglect—is a traumatic event for children that is typically framed as a necessary system response to family-level problems. While removal is intended to protect a child from harm, the experience of separation puts children at risk for poor developmental and behavioral outcomes (Doyle, 2013; Lawrence et al., 2006). Further, without intervention and support, these consequences can impact health outcomes during childhood and throughout the life course (Anda et al., 2006; Brummelte, 2017). Policy and practice efforts that aim to prevent family separation typically do so by focusing on improving parenting skills or behaviors. These individual-focused efforts discount the role of racialized differences in community hardship that structure parenting opportunities. Further, disproportionate hardship often fuels child welfare system staff bias. This occurs when hardship status is construed as the result of poor choices and used as a justification for limiting or removing parents' role as guardians of their children's well-being. However, a growing body of research suggests that rates of child maltreatment (which include both neglect and abuse) are the result of community-level issues that structure family opportunities and experiences (Coulton et al., 2007; Drake & Pandey, 1996; Fong, 2019; Freisthler et al., 2006; Lotspeich et al., 2020; B. Smith et al., 2021; Wulczyn, Feldman, et al., 2013).

Adverse community environments render families vulnerable to system-level bias and racism through three mechanisms. First, scholars and advocates argue that child welfare agents cannot distinguish between neglect and poverty and therefore punish parents for being poor by removing their child from the home (Font & Maguire-Jack, 2020; Pressley, 2020). Only half of U.S. states explicitly try to prevent child welfare agencies from using poverty as a basis for separating families, but such policies remain vulnerable to case worker subjectivity because neglect is typically loosely defined (Sarah Catherine Williams, et al., 2022). Increased community hardships would therefore tend to lead to increased misattribution of neglect for families, net of family-level poverty.

Second, community adversity also increases the presence of welfare, charitable, and surveillance actors whose perceptions are often driven by bias. Once drawn into closer contact with welfare or other agencies that monitor families (e.g., police or schools), parents are vulnerable to increased engagement with mandated reporters who interpret visible signs of poverty as poor parenting (Edwards, 2019; Fong, 2020; Roberts, 2022). Further, child welfare's coordination with other systems can create pathways for engagement with poor families who are not under investigation. For example, parents accessing economic support find themselves under increased surveillance as evidenced by the high number of families receiving cash aide who later become involved with Child Welfare (Courtney et al., 2005). Further, parents struggling with engagement in the justice system experience increased risk of child welfare engagement, including termination of their parental rights if they are incarcerated (Johnson & Waldfogel, 2002).

Finally, racially structured community conditions can create compounding adverse community environments that overload parents by exhausting resources, overburdening parental abilities, or pushing parents toward coping strategies that harm children (or are interpreted as doing so by child protection agencies). Environmental adversity can trigger the family stress response (Neppl et al., 2016), leading parents to use strategies deemed harsh or neglectful by mandated child abuse reporters. In particular, substance use, a maladaptive coping strategy that is noted with as much as 30% of neglect cases, leads to caseworkers taking more punitive action against parents (Freisthler et al., 2017; Laslett et al., 2012; N. K. Young et al., 2007). Yet, even when caseworkers offer parents placement in treatment programs, the goal is typically to stop the coping behavior—not to reduce the source of stress that demanded the coping strategy be employed in the first place. Still, several studies posit that parent behavior is sensitive to stress from community-level adversity. For example, reported child maltreatment rates increased in communities where unemployment is high—a finding that suggests further consideration of the mechanisms contributing to parent stress (Brown & De Cao, 2018; Sedlak et al., 2010). Conversely, when low wages are increased for families, child maltreatment decreases—another finding that warrants investigating the role of toxic stress and its alleviation on child outcomes (Raissian & Bullinger, 2017).

Research should investigate family separation more critically to more precisely understand adverse community environmental stressors, including discrimination, that overload parents and cause family separations. Available data on family separation supports such inquiries. Specifically, foster care data collected by the federal government includes information on a child's race, and time and place of removal. These data can be linked to community-level measures of adversities that are also measured with time and geographic identifiers.

What are the specific stressors that compound on families? Poverty is the most studied, followed by poverty along with other socioeconomic stressors. Ellis and Dietz (2017) make the case that the set of influential domains includes poverty and socioeconomic distress, but they propose community adversity includes other socially focused domains. Testing for associations between family separation and poverty alone, poverty along with other socioeconomic stressors, and poverty combined with socioeconomic stressors as well as social domains can help to illuminate which of the various compositions of adversity is most impactful.

Poverty is accepted as predictor of family separation because it impacts the ability of parents to provide stable housing, supervision, food, and other necessities for their children (Anderson, C., et al., 2022; Slack et al., 2004). Although the consequences of poverty are apparent at the family-level, family success is further limited when poverty is widespread. When hardships are widespread in a community, neighbor and kin networks are unlikely to have resources to share with other families in crisis. Community resources (e.g., afterschool programs) are likely to be limited or absent, and families may not have the time or opportunity to create social networks that support mobility (e.g., employment networks) (Ackert et al., 2019; Oliver & Shapiro, 1990; Sampson et al., 2002; Wulczyn, Feldman, et al., 2013). I will use a measure of community poverty to test for positive associations with family separation to confirm patterns in my data align with existing research.

Poverty combined with other socioeconomic adversity presents multiple sources of stress that can compound the risk for family separation. Extant research suggests that child maltreatment rates are sensitive to income inequality, unemployment, the educational attainment of parents, and other similar factors that cause economic related hardship (Eckenrode et al., 2014; Wulczyn, Gibbons, et al., 2013) Economic adversities are the most studied community-level stressors, likely because they are the most apparent and data are widely available. Here, poverty and poor socioeconomic status spanning a community concentrate hardship in ways that make it visible and leave parents susceptible to neglect allegations (Ards et al., 2012; Roberts, 2002). Such research supports the claim that family separation is typically rooted in systemic economic factors, not parent-level failures. I will use a composite measure of poverty plus socioeconomic indicators, the CAI-SES, to better understand its relationship to family separation in my data.

I propose a third hardship measure that moves beyond poverty and economic indicators. I argue that research that analyzes economic community characteristics in isolation produces results that obscure important sources of adversity. For this reason, it is important to look at standard socioeconomic measures conjointly with an expanded set of domains known to impact families. This is accomplished by predicting family separation using the CAI with its six domains of adverse environments. The CAI's domains include poverty, socioeconomic domains, as well as measures of community disruption, discrimination, and violence.

I have suggested that three measures of community adversity are critical to understanding family separation. Selecting measures of family separation is equally important. Associations between adversity and family separation disaggregated by racial groups are likely to yield differing results given structural factors create varying experiences for different racial groups. For instance, Black and Hispanic/Latino families are more likely to concentrate in disinvested neighborhoods experience because of housing segregation—a racialized adversity that resulted from discriminatory lending practices and forced homogenous communities (Owens, 2019; Rothstein, 2017). Still, other racialized social structures facilitate the concentration of adversities in communities where people of color live. For example, the experience of carceral saturation, or a high number of incarcerated community members in a given neighborhood, is a more common experience for Black than White children (Roehrkasse, 2021). These community-level adversities can attract the attention of police and mandated reporters, and can trigger implicit biases from child welfare representatives (Dettlaff et al., 2021; Edwards, 2019; Roberts, 2022). Further, the burden of risk created by multiple sources of stress is greater for people of color who also endure the stress of discrimination throughout daily interactions (Carroll, 1998). Such distinct and racialized differences in adverse experiences make it important to study how the association of community adversity and family separation vary across racial groups.

Community population data, in combination with foster care data, make it possible to gain insights into racial group population rates and disproportionalities. I use the CAI to test the claim that family separation is partly a result of community-level stress. In the following sections, I also make a new contribution to child welfare literature by examining how White, Black, and Hispanic/Latino rates of foster care entry, specifically, are associated with community adversity.

Data and Methods

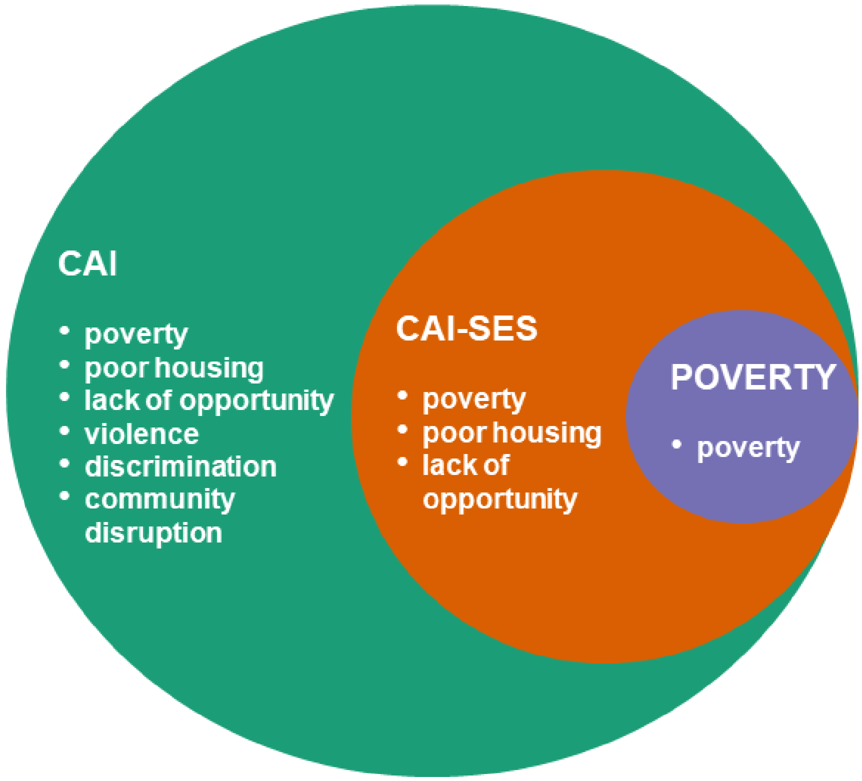
Empirical Strategy

I use generalized linear regression modeling (GLM) to examine the association between the community adversity index and rates of entry to foster care. I create separate models for four county-level populations of children: the general population, as well as White, Black, and Hispanic/Latino communities. This allows me to examine how empirical estimates of community adversity explain family separation in general and for each specific population. I expect to see variations in empirical estimates because the distribution and experiences of community-level adversity in the United States are distinct across racial groups.

I create three sets of models that use an increasingly broad approach to measuring hardships. The first model uses poverty alone, the second uses the CAI-SES, a composite measure that includes poverty plus additional socioeconomic status (SES) variables, and the third model uses the CAI, a composite measure that combines poverty, the CAI-SES, and other hardships. Figure 13 displays the groups of hardship and their summary index name (e.g., CAI or CAI-SES). By creating models with various measures of community adversity, I can compare the effects of community-level hardship across constructs with empirical support (poverty and indicators of socioeconomic status) with the newly constructed CAI that captures a wider set of influential domains.

Figure 13

Nested Measures of Community Adversity



Data

Analyses continue to draw on sources described in the chapters on the development of the Community Adversity Index and the Community Adversity Index Socioeconomic Status. These composite measures were developed using data from the American Community Survey, the Eviction Lab, County Health Rankings, Vera Institute of Justice, as well as the Surveillance, Epidemiology, and End Results (SEER) Program. Data used in this chapter are from 2014 and 2016.

In addition, I obtain foster care entry data from the Adoption and Foster Care Analysis and Reporting System (AFCARS). Federally funded child welfare agencies in the United States provide annual reports on children (youth under 18) placed into foster care. Data are reported at the child-level and include race, age, geographic identifiers, key service dates (entry, length of stay, and exit), reasons for removal, and other useful information for understanding child welfare outcomes. Because a federal mandate requires agencies to report this data regularly, these data are the most comprehensive source of foster care information available in the United States.

I aggregate the AFCARS child-level data and create county-level measures. I use Federal Information Processing Standard (FIPS) codes to collapse child-level data into county-level summaries. However, the AFCARS data only includes county-level identifiers for counties with more than 1,000 youth in foster care. County identifiers are available for 224 counties across 2014 and 2016, including 111 counties that appear in 2014, 113 in 2016, and 105 in both years. While these counties represent about 4% of all United States *counties*, they contain 40% of the child population and 44% of children who entered foster care during this period. Unlike analysis in previous chapters that focused on urban counties, the counties in this sample include a mix of small or midsized, suburban, and rural communities representing all four Census regions of the country. Tables 8 and 9 display a selection of variables describing this sample of counties.

Table 8

Descriptive Statistics for Sample Counties

	Mean	SD	Median	Min	Max	Range
County child population	275,258	301,323	186,383	41,268	2,436,171	2,394,903
White child population	109,343	79,811	90,715	22,859	475,378	452,519
Black child population	46,710	53,586	26,637	1,682	331,361	329,679
Hispanic child population	95,413	178,022	35,759	1,310	1,504,703	1,503,393
Percent of county population White	59.20%	17.48%	62.34%	15.11%	91.68%	76.57%
Average household income	$74,102.18	$14,880.90	$70,240.46	$51,059.69	$135,686.80	$84,627.11
Population density	2062.13	4157.35	1121.89	32.09	37347.52	37315.43
County foster care entry rate	44.73	23.49	41.35	9.43	143.08	133.65
White foster care entry rate	31.62	21.35	27.15	0.66	127.96	127.30
Black foster care entry rate	72.64	41.96	65.76	17.27	394.60	377.33
Hispanic foster care entry rate	38.03	23.91	32.15	2.60	157.78	155.18

N = 224; rates are per 100,000 children

Table 9

Geographies Featured in Sample Counties

Region	Midwest	Northeast	South	West
	55	33	64	72
Urbanicity	Small/Mid	Suburban	Urban	
	79	44	101	

N = 224

Dependent Variables

The dependent variables for this study are foster care entries drawn from an annual, aggregated county-level count of entries for 2014 and 2016. In 2014, 117,820 children entered foster care in the counties included in this sample. This number decreased slightly to 116,943 children in 2016. I calculate a separate foster care entry rate per 100,000 children for each of the four groups of interest: county, White, Black, and Hispanic/Latino.

Independent Variables

Models use a variety of independent variables. When estimating associations between county-level poverty and foster care rates, I use the percent of county poverty from the American Community Survey. To test for an association between foster care entry and the CAI-SES, I use a composite measure that includes poverty and several more measures of socioeconomic adversity. Finally, to examine the relationship between foster care entry and the CAI, I use a composite measure that includes poverty and the measures included the CAI-SES, as well as measures that further capture other domains of community adversity, including violence, community disruption, and discrimination.

Controls and Exposure

Certain county features, including racial composition and population density, tend to be associated with adverse community environments and child foster care entry rates. The racial composition of communities is thought to be a social determinant of health (Schulz et al., 2002) because communities with high concentrations of White populations are typically highly segregated, “systemically isolating [people of color] from resources and opportunities” (Mendez et al., 2016, p. 692). In several studies, child welfare researchers have examined the association between racial composition and child welfare outcomes, noting fewer entries to foster care in states with smaller White populations (C. H. Foster, 2012; Russell & Macgill, 2015). County-level analysis of child maltreatment further suggests that population percentages are associated with report rates. However, the effect can be positive or negative depending on the racial group that constitutes the majority of the population (B. D. Smith et al., 2017). I measure racial composition using the percentage of the county population that is White.

Population density, a measure of the number of people per square mile of land, is included as an additional control because it is considered a measure of concentrated social risk (Carnegie et al., 2022). In addition, prior research on child maltreatment outcomes shows that counties with high population density feature higher rates of Black and Hispanic/Latino child maltreatment than counties that are less densely populated (Maguire-Jack et al., 2015). I log transform population density to limit skew, or normalize it, an approach consistent with Smith et al. (2017). Percent White and population density are included as controls in all models.

Imputation/Missing

Data are available to calculate the CAI and CAI-SES for the sample of identified counties in the AFCARS dataset, except for 11 (5%) eviction rate data points and 10 (4%) jail population counts. As noted in Chapter 2, eviction data was imputed using cold deck imputation. Here, I inserted data points from sources beyond the Eviction Lab dataset. When counties do not feature a county jail, I use an estimate calculated by multiplying the state prison population by the population proportion of the county compared to the state. While this allows models to use the entire sample of counties, it may overstate the prison population in more urban counties, as prisons tend to locate in rural areas disproportionately.

Models

I use truncated negative binomial regression models that are appropriate for use with dependent count variables (non-negative integers) that show substantial overdispersion (a significant difference between the mean and variance of the distribution). I opt to model a truncated distribution to account for the censoring introduced by the systematic removal of counties from the AFCARS data with fewer than 1,000 children in foster care. No zeros are observed in the data, so the data are truncated at 0 to ensure predicted values are greater than 1.

Because child removal counts will vary as a function of the number of children in each county, each model uses the group-specific child population (0–18) as an exposure. The child population is used to calculate entry rates per 10,000 youth and make meaningful comparisons between counties in the sample.

To account for the 105 cases where the same county appears twice in the two years of cross-sectional data, standard errors are clustered by county. Tables report estimates using the incidence rate ratio (IRR). To facilitate interpretations, I provide figures showing the predicted entry count per 10,000 children by group for a range of given values.

Model Interpretation

I estimate coefficients to understand the effect of community hardships on child foster care entry across racial groups. Understanding these estimates, however, requires focusing on both *relative* and *absolute* estimated differences in entry rates across groups. For example, several studies show that poverty is associated with a greater *relative* increase in foster care entry rates for White than for Black or Hispanic/Latino children. White-Wolfe and colleagues (2021) show poverty has a larger relative effect on foster care entry for White children, while Drake and colleagues (2009) similarly find that the correlation between child maltreatment and poverty is sharper for Whites than Blacks. Explanations for such counter-intuitive results include rural-urban differences (Wulczyn, Gibbons, et al., 2013), class differences (Drake & Rank, 2009), and differences in historical or present-day challenges that may have a "steeling" effect on Black children, as evidenced by child welfare outcomes that are seemingly unaffected by increased hardship (Fagan & Novak, 2018). These explanations typically assume that larger relative increases in foster care entries for White children indicate that White children are in some way "more" impacted by poverty than children from other groups are. As will be shown below, considering absolute differences in rates of entry suggests a different interpretation. To understand the magnitude of a stressor's impact on entry rates, I present estimates using *relative* (IRRs) measures and examine *absolute* (entry rate and population count) differences between groups.

Results

Comparing Community-Level Adversity Measures

Here, I present the results of models examining the association between three measures of community-level adversity and foster care entry. Table 3 provides county-level estimates (using incidence rate ratios or IRR) from truncated negative binomial models of foster care entries for the county population of children. Model 1 is a baseline model using only the outcome and controls, including log population density, percent of the population that is White, and year. Model 2 includes the CAI. Model 3 includes the CAI-SES, a measure of adversity related to socioeconomic status. Model 4 features a measure of county-level poverty.

The model estimates[10] provide evidence that the CAI explains family separations across U.S. counties, and it does so better than two measures of economic hardship, as displayed in Table 10. The coefficient for the CAI (IRR = 1.785, $p < 0.001$) explains more of the variation in county-level foster care entry than the CAI-SES (IRR = 1.446, $p < 0.001$) or poverty (IRR = 1.317, $p < 0.001$). Model fit testing using Bayesian Information Criteria also suggests that the reduction in BIC is the greatest between the

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[10] Racially unequal distributions of adversity are addressed here with the control for racial composition (measured as percent of county population that is White). Coefficients across models increase in affect size and more become significant when the control for racial composition is included, thus suggesting that accounting for racial composition is critical to estimating the effect of adversities and reducing uncertainty in estimates.

baseline model and the model with the CAI (ΔBIC = 67) as the key independent variable. This indicates that the CAI model better captures actual observed trends in the data than the other proposed models. In terms of incidence rates, for each standard deviation change in the CAI, foster care entry rates per 10,000 children are predicted to increase by 78%.

Table 10

Truncated Negative Binomial Models for the County Population

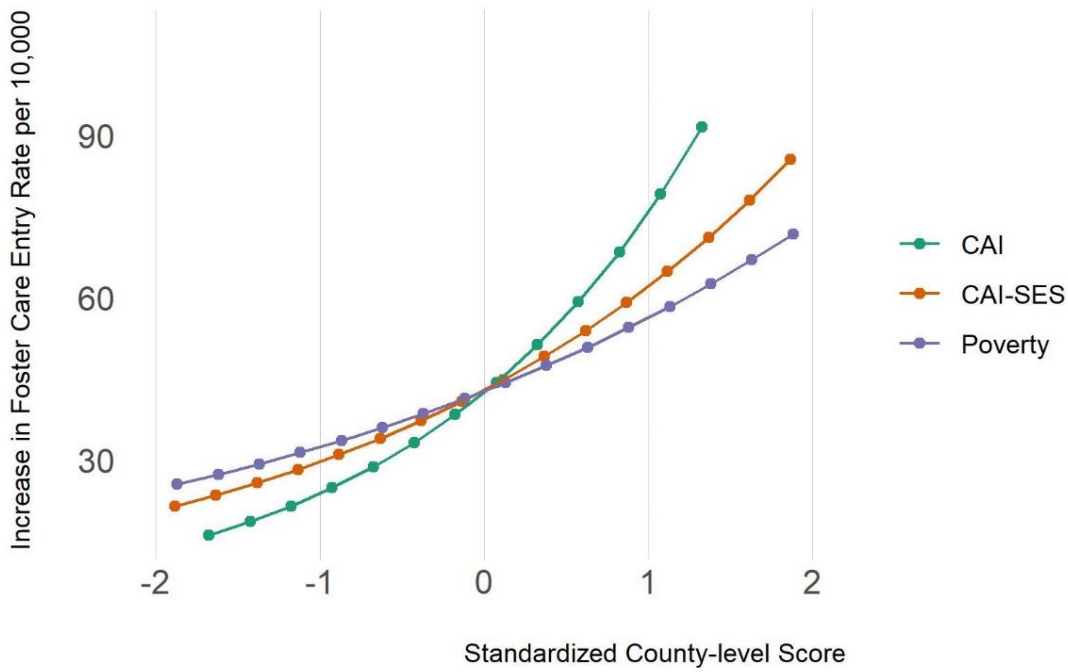
	Model 1		Model 2		Model 3		Model 4	
County Entry Rate								
CAI			1.785	***				
			-0.159					
CAI-SES					1.446	***		
					-0.113			
Percent Poverty							1.317	***
							-0.081	
Population Density (log)	0.985		0.906	*	0.985		0.973	
	-0.045		-0.044		-0.04		-0.04	
Percent White	1.008	***	1.014	***	1.017	***	1.015	***
	-0.002		-0.002		-0.003		-0.003	
Constant	0.003	***	0.004	***	0.002	***	0.002	***
	-0.001		-0.001		-0.001		-0.001	
Year (2016)	1.05		1.063	**	1.096	***	1.064	*
	-0.03		-0.024		-0.029		-0.026	
Alpha (log)	0.233	***	0.172	***	0.192	***	0.183	***
	-0.03		-0.023		-0.021		-0.023	
N	224		224		224		224	
AIC	3326		3256		3282		3270	
BIC	3343		3276		3302		3290	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 14 uses predicted entry rates to illustrate the relationship between the three models, further showing that the CAI has a stronger positive association with county foster care rates. This data suggests that the CAI, an index of six domains of community adversity, has a larger impact on foster care entry than the CAI-SES (a subset of socioeconomic adversity) or county-level poverty alone.

Figure 14

Predicted Foster Care Entry Rates for the County Population as a Function of Measures of Community Adversity Using Regression Models



The potential impact of reducing the measures associated with the Community Adversity Index is more easily understood when the coefficient is applied to the actual population numbers in my sample of counties. Table 11 shows that the actual foster care entry rate per 10,000 youth in my sample is 38. The CAI's coefficient (IRR = 1.79) in my model suggests that a one standard deviation decrease in the CAI would decrease the rate by 79% and become 21. This considerable decrease in the entry rate translates to a reduction of 103,610 youth entering foster care.

Table 11

Populations and Rates for Actuals and Potential Reductions for the County Population

Population Group	Number in Population 2014–2016	Number Entering Foster Care 2014–2016	Actual Foster Care Entry Rate Per 10,000	Effect of 1 Standard Deviation Decrease in CAI	Foster Care Entry Rate Resulting from Decrease in CAI	Number Entering Foster Care With Decrease in CAI	Reduction in Foster Care Entries Given Decrease in CAI
County Child Population	61,699,394	234,763	38	1.79	21	131,153	103,610

N = 224 counties; rates and population numbers are rounded

In the next section, I separately examine variation in measures of community-level adversity for the White, Black, and Hispanic/Latino populations. I find that the CAI, CAI-SES, and poverty perform consistently across racial groups, with the CAI having the largest impact on foster care entry rates.

Modeling Community Adversity for White, Black, and Hispanic/Latino Populations

As shown in Table 12, the county poverty rate, CAI-SES, and CAI are all significantly and positively associated with foster care entries for the White population. These findings are consistent with previous work that suggests foster care entry for White children correlates to measures of economic hardship (White-Wolfe et al., 2021; Wulczyn, Gibbons, et al., 2013). The CAI has the largest impact on White foster care entry, with a standard deviation increase in CAI associated with a 74% increase (IRR = 1.745, $p < .001$). The rate of entry is also affected by the CAI-SES, which combines poverty and other measures of economic hardship, indicating that a standard deviation increase in CAI-SES is associated with a 56% increase (IRR = 1.556, $p < .001$) in White foster care entries. The county poverty model suggests that a standard deviation increase in county poverty is associated with a 36% increase (IRR = 1.365, $p < .001$) in White foster care entries. This pattern of association across models suggests that the most compounded adversity, as measured by the CAI, has the greatest effect on entry rates for the White population.

Table 12

Incidence Rate Ratio and Standard Error Estimates from Models of White Foster Care Entry

	Model 1		Model 2		Model 3		Model 4	
White Entry Rate								
CAI			1.745	***				
			-0.222					
CAI-SES					1.556	***		
					-0.146			
Percent Poverty							1.365	***
							-0.108	
Population Density (log)	0.808	***	0.738	***	0.813	***	0.803	***
	-0.036		-0.026		-0.032		-0.031	
Percent White	1.009	**	1.014	***	1.019	***	1.017	***
	-0.003		-0.003		-0.004		-0.004	
Constant	0.007	***	0.01	***	0.004	***	0.005	***
	-0.002		-0.003		-0.001		-0.002	
Year (2016)	1.086	*	1.086	*	1.129	**	1.09	*
	-0.044		-0.036		-0.044		-0.039	
Alpha (log)	0.328	***	0.266	***	0.269	***	0.26	***
	-0.046		-0.038		-0.034		-0.037	
N	224		224		224		224	
AIC	2838		2792		2794		2788	
BIC	2855		2813		2814		2808	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13

Incidence Rate Ratio and Standard Error Estimates from Models of Black Foster Care Entry

	Model 1		Model 2		Model 3		Model 4	
Black Entry Rate								
CAI			1.381	***				
			-0.134					
CAI-SES					1.267	*		
					-0.14			
Percent Poverty							1.206	**
							-0.082	
Population Density (log)	1.036		1.002		1.05		1.041	
	-0.058		-0.06		-0.057		-0.057	
Percent White	1.003		1.006	*	1.009	*	1.008	*
	-0.002		-0.003		-0.004		-0.003	
Constant	0.005	***	0.005	***	0.003	***	0.003	***
	-0.002		-0.002		-0.001		-0.001	
Year (2016)	1.033		1.039		1.055		1.033	
	-0.045		-0.044		-0.047		-0.043	
Alpha (log)	0.232	***	0.215	***	0.215	***	0.21	***
	-0.032		-0.032		-0.03		-0.031	
N	222		222		222		222	
AIC	2620		2604		2605		2600	
BIC	2637		2625		2626		2621	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimates provided in Table 13 suggest that all three measures of community adversity are significantly and positively associated with foster care entries for the Black population. All models show an improvement in fit over the baseline model (ΔBIC > 10) but otherwise similarly fit the data (ΔBIC ≤ 5). The poverty model suggests that a standard deviation increase in county poverty is associated with a 21% increase (IRR = 1.206, $p < .01$) in Black foster care entries. The CAI-SES model indicates that this bundle of socioeconomic-status measures corresponds to a 27% increase (IRR = 1.267, $p < .05$) in Black foster care entries. The CAI model shows the strongest association and suggests that a standard deviation increase in the CAI is associated with a 38% increase (IRR = 1.381, $p < .001$) in Black foster care entries.

Although results for the Black population are similar to those for the White population, the relative effects of poverty, CAI-SES, and the CAI are smaller for the Black population. This is consistent with other research that also found measures of community adversity had a starker relative impact on White populations (Kim & Drake, 2018; White-Wolfe et al., 2021; Wulczyn, Gibbons, et al., 2013). Although the IRR is smaller for Black than White populations in these instances, examining the absolute differences reveals that the consequence is graver for the Black population. In an upcoming section, I calculate foster care entry rate disparities and foster care population counts to make it more apparent how community adversity affects black children.

Table 14 provides estimates from models examining associations for the Hispanic/Latino population. Estimates suggest that the county poverty rate and the CAI are significantly and positively associated with foster care entries for the Hispanic/Latino population. Somewhat surprisingly, the CAI-SES is not. The county poverty model suggests that a standard deviation increase in the county poverty rate is associated with a 16% increase (IRR = 1.161, $p < .05$) in foster care entries for Hispanic/Latino children. The model with the CAI suggests that a standard deviation increase in the CAI is associated with a 31% increase (IRR = 1.315, $p < .05$) in foster care entries for Hispanic/Latino children. The CAI appears to have a similar effect on Hispanic/Latino populations (IRR= 1.315) as compared to Black populations (IRR = 1.381), although this effect is substantially smaller when compared to the impact on White populations (IRR = 1.745). However, none of the community adversity and Hispanic/Latino population models substantially improve fit over the baseline model. Community adversity does not appear to explain variation in foster care entry rates for the Hispanic/Latino population to the same extent as for White and Black groups. Still, the consistency of results across the three community adversity measures supports the claim that the county poverty rate and the CAI predict foster care entry for Hispanic/Latino children, even if it is to a more limited extent.

Table 14

Incidence Rate Ratio and Standard Error Estimates from Models of Hispanic/Latino Foster Care Entry

	Model 1		Model 2		Model 3		Model 4	
Hispanic Entry Rate								
CAI			1.315	*				
			-0.158					
CAI-SES					1.192			
					-0.108			
Percent Poverty							1.161	*
							-0.071	
Population Density (log)	0.986		0.951		0.994		0.99	
	-0.039		-0.038		-0.038		-0.037	
Percent White	1.013	***	1.016	***	1.018	***	1.018	***
	-0.003		-0.003		-0.004		-0.003	
Constant	0.002	***	0.002	***	0.001	***	0.001	***
	-0.001		-0.001		0		0	
Year (2016)	1.079	*	1.087	*	1.102	*	1.087	*
	-0.04		-0.039		-0.042		-0.039	
Alpha (log)	0.297	***	0.282	***	0.287	***	0.282	***
	-0.035		-0.032		-0.032		-0.031	
N	224		224		224		224	
AIC	2578		2569		2573		2568	
BIC	2595		2589		2593		2589	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Variation in the measures of model fit produced by this study's models could be partly explained by the lack of race-specific formulations of the CAI.[11] This will be further explored in future studies as described in the discussion.

[11] The CAI is calculated using county-level measures for the county population as a whole. Here, I am not using race-specific hardships to predict race-specific entry rates (e.g., Hispanic/Latino Poverty Rates to predict Hispanic/Latino Foster Care Entry). For this type of analysis, see White-Wolfe et al. 2021.

Predicted Entry Rates for White, Black, and Hispanic/Latinos

The models of White, Black, and Hispanic/Latino foster care entry rates (per 10,000 children) are easiest to interpret by plotting the association between population rates of foster care entry and each of the three measures of community adversity. The truncated negative binomial models described above generate foster care entry predictions at selected values of each measure of community adversity, along with controls for population density, percent White, and year. Figure 15 shows foster care entry rates as a function of the CAI, Figure 16 as a function of the CAI-SES, and Figure 17 as a function of county poverty.

Figure 15

Predicted Foster Care Entry Rates by Population as a Function of Community Adversity Index Scores Using Regression Models

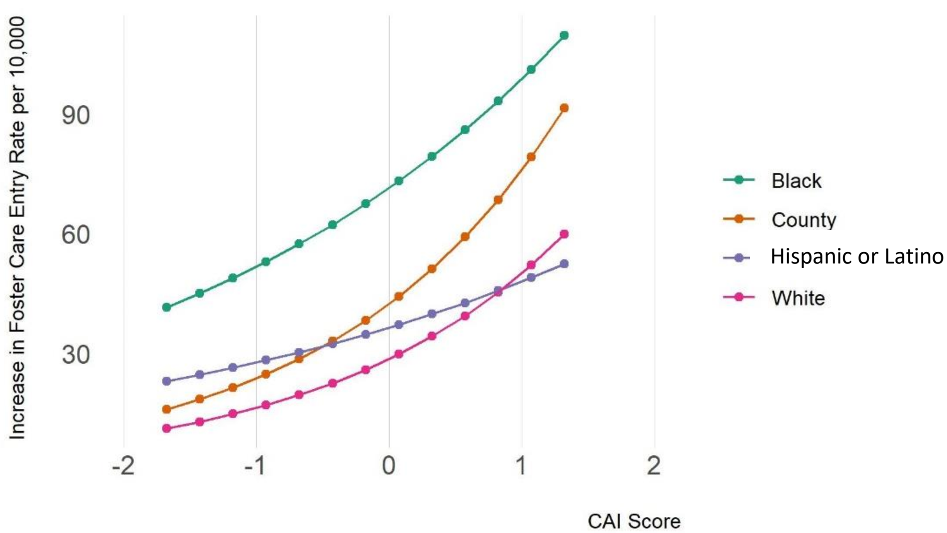


Figure 16

Predicted Foster Care Entry Rates by Population as a Function of Socioeconomic Status Community Adversity Index Scores Using Regression Models

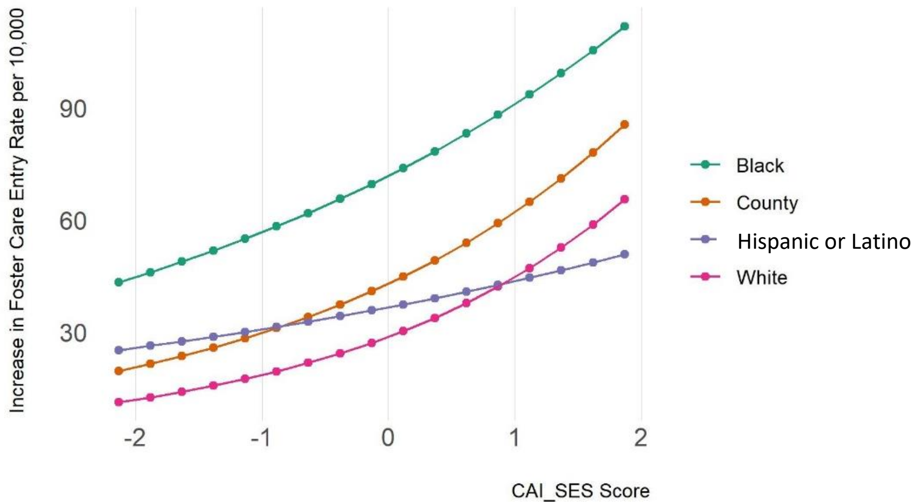
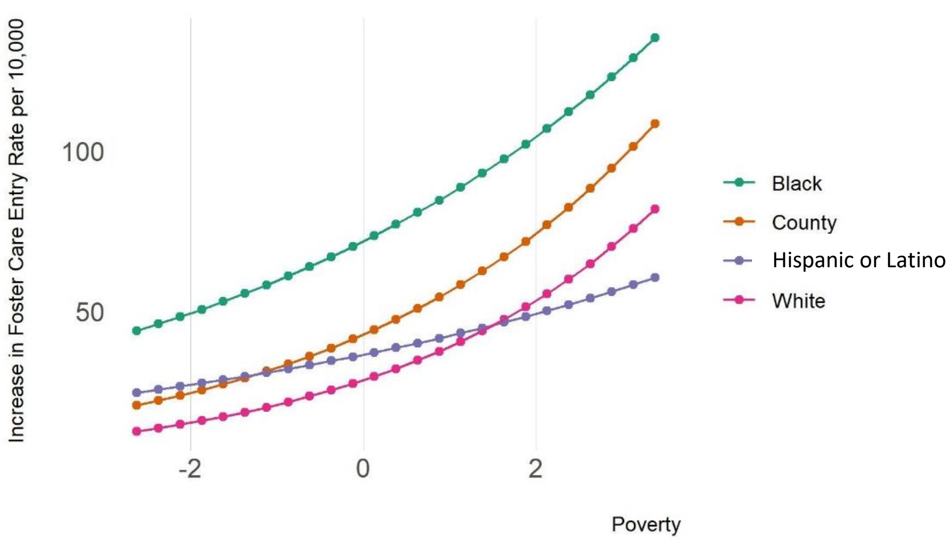


Figure 17

Predicted Foster Care Entry Rates by Population as a Function of Community Poverty Using Regression Models



The figures show that all three measures of adverse community environments are positively correlated to foster care entry across populations. These correlations are significant across all measures and groups, except for the relationship between CAI-SES and Hispanic/Latino foster care entry rates. The findings frame community-level adversity as an important predictor of foster care entry.

Disaggregating the foster care entry rates to show the effects of community adversity by county, White, Black, and Hispanic/Latino populations further reveals that the effect varies across populations. The variation follows a typical pattern across all measures of community adversity, with Black foster care entry rates well above those for the overall county population and White foster care rates well below those for the county. Hispanic/Latino rates are consistently above county and White rates at low levels of adversity. At elevated levels of adversity, Hispanic/Latino rates are lower than White or county rates.

These figures allow a better understanding of the trends captured by the IRR in the regression models. For example, when foster care entry rates are predicted for the lowest observed values of the CAI (-1.67), the foster care entry rate per 10,000 people for Black populations is 41.59, 11.28 for White populations, and 23.09 for Hispanic/Latino populations. Here we measure a disparity of more than 30 entries per 10,000 children between the lowest rate of entry for the White population at 11.28 and the highest rate of entry for the Black population at 41.49. At the highest value of the CAI (1.32), foster care entry rates per 10,000 people are 109.62 for Black populations, 59.93 for White populations, and 52.47 for Hispanic/Latino populations. The absolute racial disparities widen as communities face increasing adversity. This is especially true of the differences measured at the highest level of adversity that show the largest entry rate differences between the Black and White populations (approximately 50 entries) and Black and Hispanic/Latino populations (more than 50 entries).

A table of actual and potential rates and populations provides further insight into the existing disparities and the potential impact of the CAI. As shown in Table 15 below, Hispanic/Latino children make up the largest portion of foster care entries in our when considered as an absolute number—rather than a rate per 10,000—followed by Black children. The greatest disparity in actual entry rates is between the White and Black population (difference of 40 entries per 10,000 children). The White population has the lowest entry rate for all groups (27 per 10,000 children). However, if the CAI were reduced by one standard deviation, the entry rate would decrease across all populations and substantially reduce foster care entry. This reduction would close the disparity gap between Black and White populations, moving from a disparity between the actual rates of 40 entries to a predicted disparity of 33. Although the Hispanic/Latino foster care population would dramatically reduce if the CAI were reduced, the burden of foster care entry would continue to be highest for Hispanic/Latinos. In addition, the disparity between White and Hispanic/Latino rates would potentially increase by ten entries. These numbers suggest that although reducing the CAI would not eliminate inequalities, it could still reduce the total number of family separations.

Table 15

Populations and Rates for Actuals and Potential Reductions by Racial Group

Population Group	Number in Population 2014-2016	Number Entering Foster Care 2014-2016	Actual Foster Care Entry Rate Per 10,000	Effect of 1 Standard Deviation Decrease in CAI	Foster Care Entry Rate Resulting from Decrease in CAI	Number Entering Foster Care With Decrease in CAI	Reduction in Foster Care Entries Given Decrease in CAI
Black Child Population	10,371,921	69,075	67	1.38	48	50,054	19,021
White Child Population	24,293,294	65,515	27	1.75	15	37,437	28,078
Hispanic Child Population	21,747,917	71,486	33	1.30	25	54,989	16,497

N = 224 counties; rates and population numbers are rounded

Discussion

Limitations

The findings presented here are limited by the measures used to calculate adversity. Each measure of adversity, including the CAI, CAI-SES, and community poverty, relies on indicators reflecting the general county population. Notably, the White and general county population coefficients are nearly equal across adversity measures. However, these facts should not be interpreted as the White population being more susceptible to adversity. Instead, the fact that the White population’s slope tracks the general county population’s slope is representative of the fact that counties in this study have a mean of nearly 60% White community members and 40% White child populations. This suggests that findings are limited by using county-level aggregated measures of adversity that reflect the experience of the majority (White) population in this sample of counties. Therefore, the CAI may not adequately reflect the effect of adversity on other racial groups. In previous works, I use race-specific indicators, such as the Hispanic/Latino poverty rate, to improve predictions of foster care entry for Hispanic/Latino children. Future research can address this limitation by calculating race-specific CAI scores.

Further, results are only generalizable to the counties included in this sample. Small and rural counties are underrepresented in this study, meaning that environmental differences in rural contexts, such as higher poverty and low access to resources, are not well accounted for in these findings. This limitation could be addressed if the National Data Archive of Child Abuse and Neglect (NDACAN) changed its standards to allow for sharing county identifiers for data aggregated at the county level. Along with other researchers, I advocate that NDACAN release county-level aggregates to support future ecological research across U.S. counties.

Summary of Findings

Adverse Community Environments predict family separations across a sample of U.S. counties. The observed relationship in this data sample conforms to the proposed theoretical links between community adversity, parent overload, and childhood adversity. The Community Adversity Index, a composite measure of six adverse community-level domains, is strongly associated with county-level foster care entry rates. It explains entry rates better than other economic measures typically used in studies of community-level stressors. The CAI is more predictive than the reduced CAI-SES, comprised of measures related to socioeconomic status. The CAI also predicts with greater accuracy than poverty alone. Results from these models suggest that reducing the CAI could dramatically reduce the number of foster care entries.

All measures of community-level adversity are positively associated with foster care entry for all racial groups. The strength of this association varies across racial groups, a finding that aligns with my hypothesis and literature suggesting that social structures drive racialized housing and resource distribution (Owens, 2019; Wulczyn, Feldman, et al., 2013). The association between the CAI and foster care entry is significant and positive for all three racial groups studied. The positive association between the CAI-SES and foster care entry is also significant for White and Black populations, although not significant for Hispanic/Latino populations. Poverty is significantly and positively associated with foster care entry for all racial groups.

Adverse community environments only partly explain racial disparity in foster care entry rates. At equal levels of community adversity, foster care entry rates remain higher for Black children than Hispanic/Latino and White children. This finding is consistent with previous research (White-Wolfe et al., 2021; Wulczyn, Gibbons, et al., 2013). Predicted foster care entry rates are highest for the Black population for all measures of community adversity, a finding typically attributed to racialized social structures and systems (Curtis & Denby, 2011; Dettlaff et al., 2021; Dettlaff & Boyd, 2020; Raz et al., 2021).

The substantial variation in effect for Hispanic/Latino populations, as compared to White and Black populations, is an unexpected result and worthy of further investigation. A secondary analysis of my data sample shows that Hispanic/Latino foster care entry rates vary the most across counties (mean = 319, sd = 746). These rates of Hispanic/Latino foster care entry also correlate in surprising ways to the six domains of the Community Adversity Index. Hispanic/Latino foster care entry has an inverse relationship with three of the six adversity domains—community disruption, violence, and housing segregation. These unanticipated results could be due to overdispersion, making it difficult to identify patterns in the data. Other research noting such anomalies in the Hispanic/Latino experience have theorized that differences in immigrant status and cultural assimilation complicate generalizations about the Hispanic/Latino population (Teruya & Bazargan-Hejazi, 2013). Although beyond the scope of this study, additional data incorporating more U.S. counties and specifying Hispanic/Latino subgroup membership could address shortcomings in the sample data.

Policy Implications

Each of the major findings in this study presents implications for policymakers. This study provides expanded evidence that community adversity is predictive of family separation, reinforcing the need to replace the existing public narrative. The data presented here makes clear that the inadequate parenting narrative fails to acknowledge that community adversity overloads parents. Armed with the CAI, coalitions can spur a new public narrative by working to amend existing policies. Changing rhetoric at the policy level is a key strategy for coalitions in shifting norms, or attitudes and beliefs (Galbiati et al., 2021). For example, coalitions could propose to update the Family First Prevention Services Act to reflect a new problem framing that recognizes the "interdependence of children with their families and communities" (Marshall Mason & Dadi, 2019, para. 15). Further, my results indicate that expanding the Family First Act's list of allowable interventions to include strategies that reduce community-level hardships could drastically reduce foster care entries. Redirected funding, for example, could increase affordable housing options and decrease the number of family separations caused by unstable housing.

Considering results that suggest the CAI is more predictive of family separation than poverty alone, solutions that improve conditions for families must move beyond targeting anti-poverty strategies. Critics of the fragmented federal programs that offer eligibility-based support to families suggest that increased coordination of economic assistance—including housing, job placement, education, and childcare, among other concrete support—could lower the incidence of maltreatment, especially neglect (Anderson, C., et al., 2022). For example, several federal agencies created a whole-of-government interagency agreement to coordinate resources to address adversity in childhood for children outside the United States (USAID, 2012). A similar arrangement to coordinate federal Health and Human Services programs could benefit American families. Still, the need for improved coordination of services extends beyond federal government agencies and includes county-level nonprofits, businesses, and schools. Therefore, effective coordination approaches, such as the Building Resilient Communities coalition model, could additionally be scaled up to increase support for local families (C. Young & Ellis, 2019).

There are also important policy implications related to the finding that the effect of community adversity varies across racial groups. Results indicate a greater relative effect of community-level adversity for White foster care entry as evidenced by coefficients; however, in absolute terms, greater numbers of Black and Hispanic/Latino children are impacted by the effect of community adversity. Further, coefficients suggest that a reduction in the CAI leads to substantially reduced foster care entries for all populations. Reducing the CAI could reduce entry rates by approximately 30% or 16,497 children for Hispanic/Latino populations, 38% or 19,021 children for Black populations, and 75% or 28,078 children for White populations. Differences in effects by racial group suggest that different interventions are needed for each group. For example, targeted universalism, or setting a universal goal while using varied strategies with different target populations, is gaining traction as a practical social policy approach to address disparities in well-being outcomes (powell et al., 2019). Alternatively, as discussed in the limitations section, the current iteration of this index may be less effective in measuring adversity for Black and Hispanic/Latino populations, and future research should include a revised CAI that includes race-specific measures. Improved metrics will be useful in designing strategies to achieve the universal goal of ending family separation.

Finally, estimates of foster care entry rates vary substantially for equal measures of community-level adversity across each racial group studied. This suggests that the selected measures of community adversity do not fully explain disparities in foster care entry rates. For equal values of community adversity, there is minimal overlap in foster care entry rates across racial groups. Black children experience the highest rates of family separation for all values of community adversity. Although previous research proposes that such outcomes are a result of welfare system-level bias (Dettlaff & Boyd, 2020; Roberts, 2002) or differences in risk for various racial groups (Bartholet, 2009; Dettlaff et al., 2011), scholars are more recently acknowledging that systems and the resources they allocate are racialized (Delgado & Stefancic, 2001; Ray, 2019). This racialization is evident in the health and well-being disparities that result across education, social service, health, and legal outcomes. Anti-racist efforts are needed at multiple levels to improve outcomes equitably. For example, evidence suggests that intense community engagement and systems change strategies can disentangle the unjust treatment of families (González, 2020; Wallerstein & Duran, 2010). Community engagement, especially with those who have lived experience, is increasingly recognized as a useful strategy in addressing the root causes of racialized experiences because it helps to make discrimination and racism identifiable and preventable (Shiman et al., 2021; Tajima et al., 2022).

Overall, this chapter suggests that the Community Adversity Index is a powerful tool for defining and quantifying the adverse community environments that contribute to family separation. Coalitions can use the index as a tool to influence policymakers who rely on empirical evidence to guide decision-making. The Community Adversity Index clarifies that poverty and other community-level hardships predict family breakdown. Predicted values suggest that reducing community adversity could substantially reduce foster care entry rates. Therefore, policymakers need to replace the inadequate parenting narrative with a new narrative that illustrates how preventable community-level problems overload parents. To do so, policymakers can begin by updating the Family First Prevention Act with new provisions to fund community-level interventions. Additionally, disparities between White, Black, and Hispanic/Latino children in foster care entry outcomes despite a reduction in the CAI suggest that community-level adversity and other racialized experiences must be addressed to keep families together.

CHAPTER 5

CONCLUSION

Adverse community environments compromise the well-being of American children and families. Child welfare policy has primarily promoted child well-being by encouraging parent behavior change and skill-building support. However, this focus on addressing inadequate parenting fails to acknowledge the impact of community-level hardships that create toxic stress levels for parents and also directly translate into adversity for children. Researchers posit that community-level hardships—such as poverty, unemployment, and income inequality—affect child maltreatment rates (Brown & De Cao, 2018; Coulton et al., 1995; Eckenrode et al., 2014; Kim & Drake, 2018; Lery, 2009; Maguire-Jack et al., 2015). In this dissertation, I examine how adverse community environments impact adverse childhood experiences by assessing empirically how these environments are associated with detrimental child welfare outcomes.

Based on decades of failed parent-level interventions, researchers are beginning to recognize that persistently high levels of neglect and high racial disproportionality in child welfare engagement are not exclusively the result of inadequate parenting (Bullinger et al., 2019). While compelling, such research has yet to be applied to child welfare policies and to influence funding mechanisms. As Ellis and Dietz (2017) suggest, policymakers need a new framework for conceptualizing the problem of childhood adversity before they can be persuaded to implement community-level solutions. Ellis and Dietz (2017) work with local coalitions to disrupt public narratives that hold parents responsible for changing family-level conditions. They offer an alternative narrative that suggests adverse community contexts create toxic stress for parents and their children.

Although local adversity and trauma networks have adopted this new framing, it lacks broader empirical support needed to advance from practitioner circles into state and national public policy implementation.

This dissertation takes up part of this task by proposing an index that supports an alternative public narrative that argues community conditions lead to poor outcomes for children and families. I do so by providing empirical measures of community adversity. I sought to define and quantify adverse community environments throughout the chapters of this dissertation. Each substantive chapter has a distinct goal. Chapter 2 proposes to connect existing theoretical models to define adverse community environments and offers an index to empirically measure variation in community adversity across geographic units. Chapter 3 empirically demonstrates that the index is well-constructed by demonstrating that it has criterion validity and the measures it yields in terms of identifying where adversity is greater are robust to minor changes in its construction. Chapter 4 empirically tests how community adversity is associated with one measure of childhood adversity. This is further expanded to examine how childhood adversity varies by racial groups for equal values of community adversity. Overall, this research provides evidence for integrating adverse community environments into childhood adversity problem descriptions and solutions. Further, the index and its results offer coalitions a new tool for influencing policymakers' allocation of resources in childhood adversity interventions.

Chapter Contributions

In Chapter 2, I propose an index that gives coalitions a tool for defining adverse community environments and quantifying them. This tool is intended to elevate policymakers' understanding of this complex phenomenon. Building on the initial work by Ellis and Dietz (2017) to define adverse community environments, chapter 2 proposes to form a quantifiable measure of adversity based on the suggested definition. I use the key domains they identify to construct a single aggregated score that is easy to synthesize and communicate to different stakeholders. Using data from a collection of publicly available administrative datasets featuring well-being and demographic indicators, I establish measures for six domains and offer a composite score for the combination of adverse community environments in U.S. urban counties.

Further, I analyze how adversity is distributed and demonstrate how various domains of adversity tend to bundle together for this sample of counties. My analysis reveals geospatial patterning that suggests hardship is more prevalent in communities featuring high disinvestment or segregation as well as larger Black populations. It also suggests that communities with high scores typically feature high levels of adversity across all domains, meaning multi-faceted interventions could be the most effective at reducing Community Adversity Index scores.

In Chapter 3, I argue that the CAI is a credible tool with the potential to help policymakers identify intervention opportunities for reducing adversity in U.S. urban counties. Using data from administrative datasets and additional measures of poor mental health and vulnerability, I demonstrate that the CAI is a valid and robust index. Validity tests provide evidence that the index is well-constructed, suggesting it adequately assesses community adversity. Robustness tests hold that changes in the indicators do not overtly sway community adversity scores. Similar scores result from using the complete set of adversity domains or the set limited to socioeconomic status. Furthermore, score variation at the census tract level also does not appear to skew county-level adversity scores. Therefore, policymakers can reliably use the CAI to prioritize intervention support.

After developing the index and ensuring its reliability, I use it to predict a particularly harmful outcome of childhood adversity: family separation. This final substantive chapter examines the role of the CAI, CAI-SES, and poverty on family separation as measured by foster care entry. Although previous works establish community poverty and community-level indicators of socioeconomic status as drivers of family separation, the CAI, a comprehensive measure of six adversity domains, can better encapsulate a potential cause of parental overload. Using truncated negative binomial models, I investigate associations between various measures of community adversity and foster care entry. Results indicate that the CAI explains more of the variation in county-level foster care entry rates for the general population than either community poverty or the CAI-SES.

Further, I examine how White, Black, and Hispanic/Latino foster care outcomes vary given predicted levels of community adversity. Results suggest that the CAI has varying associations with Black, Hispanic/Latino, and White entry rates, with the greatest entry rate disparities between Black and White populations. Further, when rates are converted to counts, Hispanic/Latino children make up the largest number of children in foster care. Estimates for this sample of counties suggest that reducing community adversity could substantially reduce the number of family separations for all racial groups while shrinking disparities between White and Black populations.

Future Research

I propose extending this research by developing race-specific Community Adversity Indices. Using values that measure adversity as it is uniquely experienced by varying groups will result in a more precise understanding of how environmental factors impact family outcomes. For example, research that relies on race-specific measures of poverty shows that the range of county poverty rates for White children shares little to no overlap with the range of rates for Black children—a fact that is obscured by general county population rates (White-Wolfe et al., 2021). Race-specific data are available for many of the indicators used to calculate the CAI. For example, most indicators provided through the American Community Survey can be disaggregated by race or ethnicity, including poverty, unemployment, and rent occupancy. Incarceration data are also available for Black and Hispanic/Latino populations. Housing segregation data are also available for various racial groups. Combined, these indicators could provide a more refined view of the community-level adversity experienced by Black or Hispanic/Latino populations. These measures quantify poverty, lack of opportunity, community disruption, and discrimination. More precise measures could improve the index's ability to explain racially disparate rates of family separation.

However, developing an Indigenous Peoples' specific version of the CAI is not presently possible given poor data availability in national datasets. Still, coordinating with Indigenous community members to develop localized measures of adversity could prove useful in quantifying the many harmful systems and social structures that combine to limit the well-being of Indigenous Peoples. Such an approach could entail gathering local indicator data from systems holders, such as poor housing data from housing assistance agencies. This quantification could drive policymakers to distribute reparations or renewed investments to benefit Indigenous Peoples.

This research could also be enriched by expanding the socially focused domains proposed by Ellis and Dietz (2017). Abundant research suggests that environmental stressors compound on families through contributing to poor health (Evans & Kantrowitz, 2002; Hajat et al., 2015). In order to render a more comprehensive picture of the sources of stress in the ecosystem of families, future research will include a new environmentally focused domain that uses presently available air and water quality county-level indicators.

This dissertation does not resolve the empirical question of how or by what mechanism community adversity impacts child outcomes. I do not test the claim that child maltreatment is the unfortunate result of parents overloaded by toxic environmental stressors. Emerging research examining the impact of adverse communities on child development indeed suggests that harmful environments can impact parenting and lead to negative outcomes for children (Center on the Developing Child, 2007). More work is needed to analyze the multi-level associations between adverse community environments, toxic stress for parents, and adverse childhood experiences. This can be accomplished using data from the Fragile Families and Child Wellbeing Study that includes indicators reflecting community environments, parenting behaviors, and reported harm to children. A multi-level analysis, utilizing an ecological framework that considers the interconnectedness of child, family, and community, would provide a more complete picture of these associations.

As a final potential investigative inquiry, I propose doing a cluster analysis of the counties in my study. Using an approach such as latent profile analysis and K-means clustering, it is possible to create county classifications, or groupings of counties with similar features. Such research could provide further information about how the CAI domains typically bundle together given county characteristics, such as racial composition. In addition, it would be possible to quantify how many counties fall within a classification type. For example, it would be possible to determine whether 50% or more of counties with above-average CAI scores typically feature high poverty, violence, and discrimination. Results from such a study would be valuable to policymakers and others designing interventions.

Implications for Action

In direct alignment with this dissertation, several organizations have called to emphasize community adversity to reduce family separations. For example, the Centers for Disease Control (CDC) suggest that family health is primarily tied to socioeconomic conditions. They promote a list of evidence-based, community-level strategies to prevent maltreatment (Fortson et al., 2016). Another organization, Chapin Hall, is working to highlight the effectiveness of broadly distributed economic support as a child maltreatment reduction strategy. They cite the CDC's recommendations and mounting research that suggests anti-poverty strategies effectively reduce maltreatment, urging better coordination of government-funded economic support to families (Weiner, D., et al., 2020). The American Association of Pediatrics, another professional group, identifies the Family First Prevention Services Act as a prime policy target. They recommend that the Act be expanded to include "additional service categories and investment in primary prevention services that enable families to avoid child welfare involvement (*Reimagining Child Welfare*, 2021, Chapter Recommendations).” These organizations further recommend using geographic data to monitor adverse community environments. Finally, they propose engaging families and other stakeholders in reimagining solutions to ensure children, families, and their communities thrive.

Here, the utility of the Community Adversity Index becomes clear. The CAI provides a tool for understanding and quantifying adversity for various geographies, including counties and census tracts. It provides empirical evidence that community adversity is associated with family separation. New sense-making is supported as the CAI builds on literature and theory demonstrating how adverse community environments overload parents. Poverty is centered as part of the problem, but the compounding impact of multiple adverse domains is also acknowledged. Identifying multiple sources of adversity provides support for engaging cross-sector coordination in solution development. Further, it demonstrates that the problem of family separation requires the partnership of stakeholders well beyond child welfare.

I turn next to the coalitions that aim to dismantle the current problematic policy narratives and limited interventions that result. There are more than 300 adversity, trauma, and resilience networks in the United States. Although many of these networks have focused on building awareness of adverse childhood experiences (Hargreaves et al., 2021), they are poised to move to the second phase of community organizing: building on problem identification and moving into solution development. The CAI can assess local geographies, put forth an alternative narrative, and provide a point of dialogue for parent and other stakeholder engagement.

Table 16 puts advocate recommendations and the CAI into conversation. It also proposes how coalitions can use the CAI to support specific action steps. While intense effort is needed to bring this dialogue to the attention of coalition leaders, the growing consensus of advocates and researchers indicates that the timing is right to elevate the findings of this dissertation into a national strategy for action. Moving forward, I plan to share my research and make a call to action by collaborating with the Mobilizing Action for Resilient Communities staff, who coordinate dissemination of capacity-building resources for adversity, trauma, and resilience networks

Table 16

The CAI Connects Recommendations and Action

Policy and Practice Recommendations	Predict geography specific impact of community stressors using local data[12]	Promote interconnectedness of children with families and communities[13]	Partner with families to solve challenges	Expand responsibility for child and family well-being beyond child welfare[14]	Support families by reorienting collective resources
CAI's Contribution	Defines and quantifies community adversities; predicts family separation	Connects parental overload to adverse community environments	Proposes sources of parent overload for parents to corroborate	Demonstrates that multiple risk domains contribute to family separation	Shows that adversities compound, meaning cross -domain interventions are needed
Now: Coalitions Use CAI to Influence Policy	Use the CAI to assess geographies (counties or census tracts)	Present CAI to families to test for resonance and activate parental agency	Unravel the "inadequate parenting" narrative and center community-level stress	Impact all domains of influence using CAI-informed, cross sector partnership	Demand coordination of local, state and federal resources

[12] This specific recommendation was stated in a Chapin Hall COVID-19 issue brief (Weiner, D., et al., 2020).
[13] This recommendation was providing in the context of scholars reviewing family separations at the border, although the concept holds in the child welfare context (Marshall Mason & Dadi, 2019, para. 14).
[14] This specific recommendation was stated in a Chapin Hall COVID-19 issue brief (Weiner, D., et al., 2020).

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APPENDIX A

SUPPLEMENTARY TABLES

Table 17

Selected Variables

Adverse Community Environment Construct	Variable	Description	Data Source
POVERTY	County Poverty Rate	Percent of the population with income in the past 12 months below the poverty	American Community Survey, 5-year estimates
POOR HOUSING	County Eviction Rate	An eviction rate is the number of evictions per 100 renter homes in an area.	Eviction Lab sourced from court records, public eviction records, and American Community Survey data
	County Rent Burden Rate	Median gross rent as a percentage of household income, max is 50%	Eviction Lab sourced from court records, public eviction records, and American Community Survey data
	Severe Housing Problems	Percentage of households with at least 1 of 4 housing problems: overcrowding, high housing costs, or lack of kitchen or plumbing facilities	Robert Wood Johnson Foundation County Health Rankings
	Renter Occupancy	Percent of head of households renting	American Community Survey, 5-year estimates
DISCRIMINATION	Housing Segregation	Measure of non-White/White housing segregation	Robert Wood Johnson Foundation County Health Rankings
COMMUNITY DISRUPTION	Percent Incarcerated Pretrial	Derived from Total Jail Pretrial Population/ Total County Population	Vera Institute of Justice Incarceration Trends dataset
	Excessive Drinking	Percentage of adults that report excessive drinking	Robert Wood Johnson Foundation County Health Rankings
	Drug Overdose Deaths	Number of drug overdose deaths (or mortality rate due to overdose)	Robert Wood Johnson Foundation County Health Rankings
LACK OF OPPORTUNITY/ ECONOMIC MOBILITY	High School Graduation (diplomas/ enrollment)	Calculated average freshman graduation rate	Robert Wood Johnson Foundation County Health Rankings
	Percent Unemployed	Percent of the population age 16+ unemployed and looking for work (2008)	American Community Survey, 5-year estimates
	Some College	Percent of adults aged 25-44 years with some post-secondary education	Robert Wood Johnson Foundation County Health Rankings
	Income Inequality	Ratio of household income at the 80th percentile to income at the 20th percentile	Robert Wood Johnson Foundation County Health Rankings
VIOLENCE	Violent Crime Rate	Violent crimes/aggregate population * 100,000	Robert Wood Johnson Foundation County Health Rankings

Table 18

Counties with Highest Community Adversity Scores 2016

Rank	County	Lack of Opportunity	Poor Housing	Community Disruption	Poverty	Discrimination	Crime	CAI
1	St. Louis	1.13	0.71	1.45	2.03	1.12	2.26	1.45
2	Orleans	0.96	1.07	1.25	2.03	1.59	1.24	1.36
3	Philadelphia	0.93	0.73	1.64	1.90	1.19	1.20	1.26
4	Baltimore	1.06	0.08	1.05	1.48	1.60	1.99	1.21
5	Wayne	0.62	0.41	0.21	1.67	2.07	1.22	1.03
6	Milwaukee	0.23	0.45	1.14	1.09	1.59	1.23	0.95
7	District of Columbia	0.60	0.25	1.42	0.45	1.40	1.56	0.94
8	Richmond	0.34	1.38	0.77	1.55	0.80	0.27	0.85
9	Shelby	0.37	0.43	-0.03	0.99	1.32	1.72	0.80
10	Suffolk	0.45	0.56	0.93	0.90	0.42	0.69	0.66

Table 19

Counties with Highest Community Adversity Scores 2014

Rank	County	Lack of Opportunity	Poor Housing	Community Disruption	Poverty	Discrimination	Crime	CAI
1	Philadelphia	1.53	0.70	1.13	1.90	1.36	1.35	1.33
2	St. Louis	1.02	0.67	0.70	2.03	1.22	2.14	1.30
3	Baltimore	1.52	0.03	1.01	1.48	1.67	1.78	1.25
4	Orleans	0.52	1.19	1.16	2.03	1.66	0.93	1.25
5	Wayne	1.28	0.43	-0.02	1.67	2.17	1.25	1.13
6	Richmond	0.86	1.34	0.75	1.55	0.92	0.37	0.97
7	District of Columbia	0.99	0.06	0.95	0.45	1.58	1.61	0.94
8	Milwaukee	0.64	0.41	0.56	1.09	1.68	1.09	0.91
9	Shelby	0.84	0.28	0.09	0.99	1.44	1.64	0.88
10	Suffolk	0.94	0.51	0.43	0.90	0.42	0.83	0.67

Table 20

Counties with Lowest Community Adversity Scores 2016

Rank	County	Lack of Opportunity	Poor Housing	Community Disruption	Poverty	Discrimination	Crime	CAI
1	Collin	-1.71	-1.34	-0.99	-2.09	-1.51	-2.10	-1.62
2	Arlington	-2.02	-0.70	0.14	-1.93	-0.86	-2.19	-1.26
3	Wake	-1.14	-0.81	-0.53	-1.33	-0.73	-2.66	-1.20
4	Alexandria	-1.38	-0.34	-0.20	-1.89	-0.84	-1.80	-1.07
5	Santa Clara	-0.73	-0.43	-1.07	-1.81	-0.77	-1.18	-1.00
6	Virginia Beach	-1.43	0.00	0.54	-1.74	-1.09	-2.15	-0.98
7	King	-0.85	-0.74	-0.40	-1.62	-0.92	-0.72	-0.88
8	Orange	-0.62	0.33	-0.55	-0.94	-1.00	-1.55	-0.72
9	Salt Lake	-0.89	-0.90	-0.31	-0.92	-0.27	-0.51	-0.63
10	Tarrant	-0.57	-0.35	-0.71	-0.25	-0.83	-0.42	-0.52

Table 21

Counties with Lowest Community Adversity Scores 2014

Rank	County	Lack of Opportunity	Poor Housing	Community Disruption	Poverty	Discrimination	Crime	CAI
1	Collin	-1.44	-1.42	-1.09	-2.09	-1.44	-2.14	-1.60
2	Arlington	-1.62	-0.70	-0.41	-1.93	-1.07	-2.23	-1.33
3	Wake	-0.89	-0.85	-1.02	-1.33	-0.84	-1.31	-1.04
4	Alexandria	-0.78	-0.44	-0.40	-1.89	-0.64	-1.90	-1.01
5	Virginia Beach	-1.05	-0.12	0.29	-1.74	-0.98	-2.07	-0.94
6	Santa Clara	-0.35	-0.38	-0.94	-1.81	-0.92	-1.25	-0.94
7	King	-0.61	-0.74	-0.12	-1.62	-0.93	-0.77	-0.80
8	Orange	-0.34	0.22	-0.40	-0.94	-0.95	-1.64	-0.67
9	Salt Lake	-0.58	-0.86	-0.36	-0.92	-0.50	-0.68	-0.65
10	Hennepin	-0.57	-0.87	-0.45	-1.24	-0.16	-0.33	-0.61

APPENDIX B

AUTHOR’S PERMISSION FOR FIGURE USE

Holly White-Wolfe

From: Ellis, Wendy <wendye@email.gwu.edu>
Sent: Monday, November 1, 2021 5:36 AM
To: Holly White-Wolfe
Subject: Re: Pair of ACEs Paper?
Attachments: Pair of ACEs Tree_300dpi.tif

Holly

Congratulations on a very well written thesis. I have attached the proper image that you can use that also has a reference in it.

Good luck!

Wendy

Wendy R. Ellis DrPH, MPH
Assistant Professor, Global Health
Director, Center for Community Resilience
Sumner Redstone Global Center for Prevention & Wellness
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On Sun, Oct 31, 2021 at 1:14 PM Holly White-Wolfe <hwhitewo@asu.edu> wrote:

> Dear Dr. Ellis,
>
> It has been some time since we last connected. I hope sincerely that you and your family have been well. Certainly your work is even more imperative and relevant given the recent pandemic.
>
> Please allow me to reacquaint us. I am a graduate student at Arizona State University, and I was inspired to go back to school at age 42 after working on the Robert Wood Johnson Mobilizing Action for Communities grant in 2015-2018. You were one of the advisors for our work, and I was connected to you through our mutual friend Leslie Lieberman.

The Pair of ACEs model you shared with us spoke deeply to me and it has been the focus of my research for the past three years. You are also a model for me as a woman who I believe also sought her PhD later in life.

I am using your Adverse Community Environment construct to create a multidimensional index called the Community Adversity Index. I believe such an index will be a powerful tool in advancing the work of ACEs networks who are targeting Child Welfare policy. Such networks are faced with the challenge of developing a counter narrative to inadequate parenting and finding empirical supports to convince policy makers to redirect material supports to families rather than simply prescribing parenting classes or treatment programs. I believe your Pair of ACEs tool is powerful for developing the counter narrative and that the Community Adversity Index will strengthen the message to policy makers by using data to demonstrate where policy makers can meaningfully intervene on factors that impact childhood adversity. (More details are provided in my prospectus, attached.)

I've completed my draft analyses of the CAI and early results suggest that it is a credible measure as it correlates with another measure of community resilience (Social Vulnerability Index) and the number of days of poor mental health. I am now in the process of finalizing my first two dissertation chapters. Next, I'll use this index to see how well it predicts entry to foster care and other foster care outcomes.

Your work has been instrumental in my life and I am wondering if I may humbly ask permission to use your Pair of ACEs graphic and the following reference below in my dissertation works. I would also like to request to use this image in any subsequent publications I may be able to secure. Would you please consider allowing me to use your graphic and confirm the citation below?

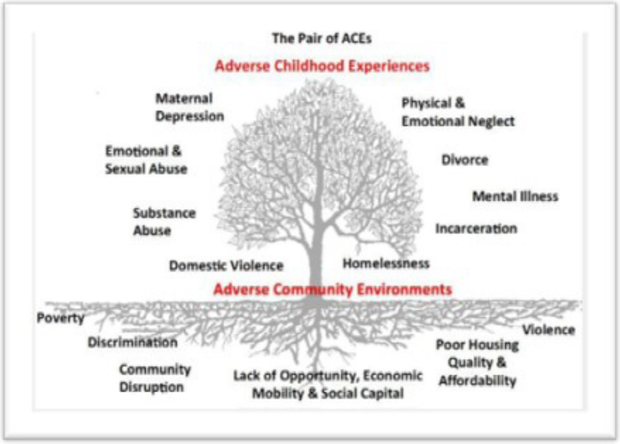

Figure 1. Pair of ACE's Framework (Ellis and Dietz 2017; Sumner M. Redstone Global Center for Prevention and Wellness 2017)

2

If you had the time, I'd also love to hear more about how your project with the CDC has moved forward.

Thank you for your incredible work with communities, Dr. Ellis!

Warmly,

Holly J. White-Wolfe, MBA

PhD Candidate

Justice and Social Inquiry

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602.935.7495

School of Social Transformation
Arizona State University

From: Ellis, Wendy <wendye@email.gwu.edu>
Sent: Friday, February 14, 2020 1:12 PM
To: Holly White-Wolfe (Student) <hwhitewo@asu.edu>
Subject: Re: Pair of ACEs Paper?

Holly

On our website we have a fuller description of the tree. We also have a set of measures for Adverse Community Environments that we are now testing in a project with CDC-- unfortunately I cannot share them as of yet. The tree was originally part of the paper but the editors dropped the graphic from the published version.

The link to the Pair of ACEs tree and description is here.

While I can't discuss our precise measures yet, I would be happy to help you think through ones that you are proposing for your study. Let me know if you would like to chat at some point.