

AN INTERDISCIPLINARY HEALTH DISPARITIES RESEARCH  
AND INTERVENTION STRATEGY APPLIED TO THE  
PROBLEM OF PEDIATRIC ASTHMA  
IN KANSAS CITY

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AN INTERDISCIPLINARY HEALTH DISPARITIES RESEARCH  
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PROBLEM OF PEDIATRIC ASTHMA  
IN KANSAS CITY

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University of Missouri-Kansas City, 2020

ABSTRACT

This dissertation presents a multilevel health disparities research strategy using pediatric asthma in Kansas City as a case study. The first chapter introduces the problem of pediatric asthma in Kansas City and the foundational theory, methods, and concepts used to develop the structure of the dissertation and specific research questions. This is followed by an overview of the research and findings from subsequent chapters, which include both population- and patient-level analyses. The first chapter is then concluded with a brief policy note framing future research to connect health disparities interventions with economic policy.

In the second chapter, the distribution of pediatric asthma throughout the region is explored using address-level electronic health records (EHR) for asthma-related encounters occurring between 2000 and 2012. Spatial indicators of the burden in pediatric asthma were developed from the 2012 sample including census tract incidence and prevalence rate estimates. The third chapter develops census tract Environmental Justice Screening Method (EJSM) indicators, which are used in a scanning exercise, descriptive analysis, and a Bayesian Profile Regression (BPR) cluster analysis to explore complex patterns in both the population health risks and vulnerabilities that may be contributing to the burden in pediatric asthma. Moving from the population to the patient level, the fourth chapter uses pediatric asthma encounter data geocoded to the residential parcel geography in a BPR cluster analysis to investigate the relationship between a patient's asthma severity, personal

characteristics, their record of housing instability, and environmental exposure both in and around the home.

The analyses presented in Chapters 2-4 help to characterize the disparity in pediatric asthma between socially disadvantaged and advantaged Kansas City communities and patients, providing insight into targets for population health research, intervention, and policy development strategies. The results of each chapter make it clear that social disadvantage and determinants like access to healthy and stable housing play a central role in driving the disparity in pediatric asthma between Kansas City children and communities. The findings support a combination of community-based and patient-centered interventions framed in terms of health equity to alleviate the burden of pediatric asthma and reduce the disparity over time.



## APPROVAL PAGE

The faculty listed below, appointed by the Dean of the School of Graduate Studies, have examined a dissertation titled “An Interdisciplinary Health Disparities Research and Intervention Strategy Applied to the Problem of Pediatric Asthma in Kansas City,” presented by Natalie J. Kane, candidate for the Doctor of Philosophy degree, and certify that in their opinion it is worthy of acceptance.

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## CHAPTER 1

### 1. RESEARCH STRATEGY, FINDINGS, & IMPLICATIONS

#### **Introduction**

Racial-ethnic minority and low-income children experience disproportionately high rates of pediatric asthma, with a growing disparity in disease prevalence and severity between socially disadvantaged and advantaged communities. In the case of pediatric asthma and many other chronic diseases, patient health is influenced by a wide range of place- and person-specific risk factors including environmental exposure in and around the home, genetic predisposition, chronic stress, and relative access to – and ability to effectively use – healthcare resources and services. Standard methods in health disparities research and public health reporting, however, do not capture local variation in health outcomes, vulnerability, or exposure to contributing risk factors, and rarely incorporate patient-level spatial data into their analyses. This impacts the efficacy of both public health interventions and patient treatment strategies, failing to alleviate the burden of otherwise manageable diseases like pediatric asthma in the most vulnerable communities and patients.

This dissertation presents a preliminary, comprehensive health disparities research strategy using the problem of pediatric asthma in Kansas City as a case study. This multilevel, interdisciplinary, and exploratory methodology is structured around the concept of health equity, recognizing that different populations require different interventions designed to fit their unique context and individual needs. In each chapter, the problem is investigated in the appropriate social and spatial context to identify overburdened communities, high-risk patients, and the combination of risks and vulnerabilities that may be contributing to the burden of pediatric asthma at each level.

One of the key contributions of this dissertation is the novel use of address-level electronic health records (EHR) for both patient- and population-level exploratory analyses. Address-level EHR is rarely available, and when it is available, it is typically limited in detail or application. Limited access to high-resolution health data also affects the quality of public health indicators important to

identifying health disparities and contributing risk factors, which often vary significantly within and between affected communities. In contrast, this dissertation works from the patient's residential address to different spatial aggregations of the encounter and patient samples, which allows for a flexible approach to exploratory data analysis essential to understanding and alleviating the disparity in pediatric asthma between communities and patients (Samuels-Kalow and Camargo 2019). The results provide insight into the nature of the problem in Kansas City, offering a blueprint for designing sustainable and context-specific solutions.

This first chapter introduces the problem of pediatric asthma in Kansas City and the foundational theory, methods, and concepts used to develop the structure of the dissertation and specific research questions. This is followed by an overview of the research and findings from Chapters 2-4, which are written to model a journal article format and include an additional literature review specific to each analysis. Chapter 1 is concluded with a brief policy note framing future research to connect health disparities interventions with economic policy.

## **Background**

### **Pediatric Asthma in Kansas City**

Pediatric asthma is often a focus of environmental justice and health disparities research because of the increasing prevalence of the disease in Western nations, and because of its complex relationship to environmental, socioeconomic and demographic factors (Ford & Mannino, 2010). While there is evidence suggesting the overall prevalence of pediatric asthma is plateauing in the United States, rates continue to climb for low-income and racial-ethnic minority populations (Akinbami, Simon, & Rossen, 2016). The behavior of the disease in Kansas City is consistent with national trends. Per the Missouri Department of Health and Senior Services, the prevalence of childhood asthma in the Kansas City region has increased from 9.8% in 2003, to 10.5% in 2008. This poses obvious healthcare costs to the affected communities, health institutions, and to local and state governments, with charges for asthma-related hospitalizations in the region rising from \$14.1 million



in 2003 to \$21.1 million in 2008. Furthermore, the demographic distribution of pediatric asthma incidence rates indicates a severe racial-ethnic health disparity in the region. Though African Americans made up only 14.9% of the region's population, they accounted for 47.4% of all asthma-related emergency department (ED) visits in 2008, suggesting that the social welfare and healthcare costs of pediatric asthma disproportionately impact Kansas City's racial-ethnic minority communities (Missouri Department of Health and Senior Services (DHSS) 2004; Missouri Department of Health and Senior Services (DHSS) 2009).

### **The Home of Racial Residential Segregation**

Development patterns play a key role in explaining the distribution of health risk, vulnerability, and exposure to environmental hazards, all of which are important to understanding and treating health disparities (Vlahov et al. 2007). In Kansas City, these patterns were determined in large part by racial residential segregation and extensive discriminatory economic development practices. Racial residential segregation was codified through 'redlining', a process whereby neighborhoods in major metropolitan areas were subdivided and given a grade based on the U.S. Federal Housing Administration's minimum requirements for insurance and lending. Grades were determined in large part by the proportion of racial-ethnic minority and low-income households, as well as other subjective and discriminatory perceptions of the neighborhoods. Together with existing predatory lending and development practices, redlining encouraged a bias in local planning and zoning toward suburban development, and consequently, urban disinvestment. Incentivized by federal housing policy, real estate developers exploited deep-seated discrimination against Black people to encourage a mass movement of upwardly mobile White families from the urban core to the new suburbs, which contributed to extensive suburban sprawl given Kansas City's unbounded geography (Gotham 2014, 60).

Kansas City's uneven development has implications for research and intervention strategies designed to reduce high rates of pediatric asthma in specific communities and to alleviate severe,

uncontrolled symptoms in patients.<sup>1</sup> The “white flight” from the urban core left behind significant costs in the form of an aging housing stock and crumbling infrastructure, which were compounded by active disinvestment policies that stripped the remaining Black and other underrepresented communities of the resources needed to maintain them.<sup>2</sup> Redlining also shaped the distribution of hazardous land use, concentrating industrial development in neighborhoods with low grades. Consequently, largely wealthy and White communities in the newer suburbs of the region are less exposed to the costs of historic development now borne by Kansas City’s racial-ethnic minority and low-income populations. The impact of these development patterns on health are exemplified by a recent Robert Wood Johnson Foundation study, which identified a dramatic disparity in life expectancy for children born only a few miles apart in segregated Kansas City neighborhoods (RJWF 2013).

Given what is known about the behavior of pediatric asthma and the context of Kansas City’s uneven development, the disparity between socially disadvantaged and advantaged communities is likely to depend on a complex mixture of place- and person-specific risks and vulnerabilities. The following section outlines the theory, methods, and key concepts informing a *translational* health disparities research strategy; an iterative research strategy designed to identify what might be driving the disparity between communities and patients, and to guide sustainable and ethical interventions.<sup>3</sup>

### **Theory & Methods**

The original proposal for this dissertation was primarily informed by systems theory, adaptive management, cumulative risk assessment, and alternative economic policy. These concepts supported

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<sup>1</sup> Uneven development: “the fact that inner cities lose population, wealth, and jobs while suburban areas experience economic development or population growth” (Gotham, 2014, p. 4).

<sup>2</sup> “As the racial transition of this southeast area occurred, physical deterioration and housing decay increased markedly as financial institutions and government agencies ceased making loans and city services available for residents” (Gotham 2014, 97)

<sup>3</sup> “Translational research fosters the multidirectional integration of basic research, patient-oriented research, and population-based research, with the long-term aim of improving the health of the public” (Rubio et al. 2010, 4).

a pragmatic and flexible research strategy prioritizing equity-focused and evidence-based methods from a wide range of disciplines. Consequently, the dissertation as a whole relies heavily on concepts and methods in the health disparities research literature and relevant examples of tested interventions. The first part of this section provides an overview of essential concepts in the health disparities literature that informed the analyses and language presented in Chapters 2-4. This is followed by a discussion of the original theory and methods employed in designing the dissertation research strategy.

## **Key Concepts in Health Disparities Research**

### ***Health Disparities***

The phenomenon of health disparities or inequities - differences in health and determinants of health between socially disadvantaged and advantaged populations – is well-documented in the public health, environmental, and epidemiological literature and is a nationally recognized health objective (Braveman 2006).<sup>4</sup> These disparities are typically characterized by higher rates of preventable and treatable diseases in vulnerable populations that degrade social wellbeing, contribute to damaging inefficiencies in the healthcare system, and impose extensive economic and social costs on the communities that bear the burden of this inequity (Healthy People 2010).

Social disadvantage – including that based on race, ethnicity, class, and gender – plays a key role in health disparities by determining the degree to which vulnerable people are exposed to risks and able to manage their symptoms, shaping what constitutes effective research and intervention strategies (Braveman 2006).<sup>5</sup> While there are nuances in how health disparities present themselves, racial health disparities are the most dramatic and highlight egregious problems with the healthcare

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<sup>4</sup> “Health disparities/inequalities are potentially avoidable differences in health (or in health risks that policy can influence) between groups of people who are more and less advantaged socially; these differences systematically place socially disadvantaged groups at further disadvantage on health” (Braveman 2006, 180).

<sup>5</sup> “Social advantage means one’s relative position in a hierarchy determined by wealth, power, and/or prestige” (Braveman 2006, 180).

system in the United States related to institutionalized racism (Williams and Mohammed 2009). Furthermore, a growing body of research highlights racism as a fundamental cause of racial health disparities, where comprehensive and persistent racial discrimination affects the health and wellbeing of Black Americans independently of socioeconomic status and material deprivation (Phelan and Link 2015). This is particularly troubling in the case of pediatric asthma, where Black children are subject to significantly higher rates of severe pediatric asthma compared with their White (non-Latinx) peers despite widespread efforts to improve the quality of healthcare services and interventions found to successfully control symptoms in at-risk children (Hughes et al. 2017).

Racial health disparities are a focus of this dissertation not only because of the clear burden of pediatric asthma among Black children in Kansas City, but also because of the importance of institutionalized racism and implicit bias in shaping the structure and efficacy of the healthcare system in general (H. Lee and Hicken 2018).<sup>6</sup> Furthermore, using institutionalized racism as a framework for understanding and treating health disparities supports the development of research and intervention strategies catered to the needs of communities facing different types of social disadvantage and health risk in general (Hicken et al. 2018; Bailey et al. 2017).

### ***Social Determinants of Health (SDOH)***

The social determinants of health (SDOH) is a framework for understanding how social disadvantage drives health disparities. The SDOH encompasses a wide range of social, environmental, economic and demographic factors, all of which determine an individual's cumulative health outcomes and opportunities to live well (Marmot et al. 2008).<sup>7</sup> The World Health Organization (WHO) initially defined the SDOH as the unequal access to health care resources. The definition has since been expanded to include all facets of an individual's life within their community; the

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<sup>6</sup> "Implicit biases involve associations outside conscious awareness that lead to a negative evaluation of a person on the basis of irrelevant characteristics such as race or gender" (Fitzgerald and Hurst 2017, 1).

<sup>7</sup> "Determinant: a construct or factor thought to play a causal role in explaining a health behavior or outcome" (Richard, Gauvin, and Raine 2011, 308).

conditions of the places in which a person works, lives, plays and prays, the people with which they interact, their behaviors, and the neighborhood and economic resources to which they have access (Healthy People 2010).

Ongoing research on health disparities has broadened the idea of SDOH to include structural conditions: institutionalized discrimination based on race, class, gender, and other forms of social disadvantage that determine the distribution of the SDOH and their effect on health risk (Kruize et al. 2014). For example, the WHO cites “poor and unequal living conditions” as SDOH resulting from deep-seated structural inequalities in the access to economic opportunities (CSDH 2008, 28). Structural conditions are referred to throughout this dissertation to distinguish between the SDOH generally and the underlying system of inequalities that drive health risk and exposure.<sup>8</sup>

### ***Modifiable Risks***

Health disparities research and intervention is typically focused on modifiable exposures or risk factors; elements of the patient’s condition or context that can be changed, such as dietary habits or housing conditions (Arrandale et al. 2011). Interventions targeting exposure to immediate, modifiable risk factors are important for reducing suffering and sustaining symptom control in vulnerable asthma patients. For example, pediatric asthma exacerbation can be managed or prevented by interventions that reduce exposure to environmental triggers in the home (Gruber et al. 2016). Only targeting modifiable risk factors, however, is not sufficient to reduce the disparity in pediatric asthma rates between socially disadvantaged and privileged groups, and existing evidence suggests that this strategy may cause the disparity to increase (Hicken 2015). This is particularly relevant in the case of racial health disparities given evidence that discrimination leads to chronic inflammation in racial-ethnic minorities, with cumulative impacts on health that are not explained by single risk factors or SDOH alone (Simons et al. 2018). Furthermore, many questions remain regarding the

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<sup>8</sup> Structural conditions can also be described as ‘upstream’ SDOH, in contrast to the the ‘downstream’ SDOH that are typically a target of public health research and policy (Braveman, Egerter, and Williams 2011).

degree to which known risk factors impact a racial disparity and how cumulative exposures to multiple risk factors may alter health outcomes in different places and people (Hicken, Gragg, and Hu 2011). The research strategy and analyses presented in Chapters 2-4 are designed to help identify what combination of modifiable risk factors might be contributing to the problem of pediatric asthma, taking into account their relationship with context-specific social disadvantage and vulnerability.

### ***Spatial Scale***

The spatial scale of data is of central importance to health disparities research, especially in the context of environmental and socioeconomic inequality. In public health, epidemiology, and the social sciences generally, disease is typically studied at the county or zip code level. This is either because of the difficulty of obtaining more detailed medical records, or because of the complexity and cost of geocoding these records to lower levels of geography (Juarez et al. 2014). Aggregating health data to geographies like zip codes, however, is likely to obscure variation in population health outcomes and contributing risk factors at the local level (Krieger et al. 2002). For example, the recent blood lead poisoning crisis in Flint, Michigan was missed by public health departments early on because the state of Michigan originally mapped the incidence of lead poisoning at the zip code geography. Zip codes do not line up with the city's boundaries or its water supply, so the zip code estimates failed to capture the severe disparity in blood lead poisoning between Flint residents and their neighbors outside of city limits (Sadler 2016). The dramatic increase of blood lead poisoning rates in socially disadvantaged neighborhoods within Flint city limits was only revealed when geographers mapped the incidence of blood lead poisoning at the neighborhood geography, triggering the now well-known Flint water crisis and subsequent state of emergency (Hanna-Attisha et al. 2016).

Difficulty capturing accurate spatial indicators of population health attributes relates to both the Modifiable Areal Unit Problem (MAUP) and the Unspecified Geographic Context Problem (UGCoP). The MAUP is the more commonly discussed problem where relevant spatial variation in an attribute occurs within a specific geographic unit, which is what occurred in the case of the Flint

water crisis. The UGCoP refers to the problem of uncertainty in the actual geographic context of the attribute of interest; uncertainty in how to define geographic boundaries (Kwan 2012). Beyond the risk of missing important patterns in population health outcomes, standard geographies of inference do not capture the spatial distribution of many important local and individual risk factors associated with chronic diseases, which can lead to a significant loss of information about the problem and the introduction of error into multi-level statistical models (Pickle, Waller, and Lawson 2005). This is tied to the problem of the ecological fallacy, where error arises from inference about the individual based on population characteristics.<sup>9</sup>

The problems related to spatial scale in health research are particularly important when designing a health disparities model in Kansas City, where population health and local risk factors vary at a specific spatial and social scale. The data for the analyses in this dissertation is derived from individual-level electronic health records (EHR) geocoded to the patient's residential address to help facilitate statistical modeling that maintains, to whatever degree possible, the spatial and biological complexities associated with the health outcome. Furthermore, this high-resolution health data allows for exploratory analyses of population health indicators at different spatial aggregations, which improves on common indicators published by federal, state, and local public health agencies (D. C. Lee et al. 2017).

### **Systems Theory, Cumulative Risk Assessment, & Adaptive Management**

Systems theory offered a starting point for designing a translational health disparities research strategy to understand the problem of pediatric asthma in the appropriate social and spatial context, and to develop questions that would help to inform sustainable interventions. Systems theory originated in ecology as a comprehensive, pragmatic analytical framework in which all the components of a phenomenon are conceptualized as interrelated parts of a larger system. Leverage

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<sup>9</sup> “Thus, although ecologic correlations can be a useful tool for hypothesis generation, epidemiologists generally feel that only studies of individual exposure-response relationships, appropriately controlled for both individual- and group-level confounders, can provide a secure basis for causal inference” (Thomas 2009, 203).

points are the places to intervene in a system, and their effectiveness depends on system dynamics, including feedbacks. If the goal is to change the structure of the system to generate an outcome – in this case eliminating the disparity in pediatric asthma rates between socially disadvantaged and advantaged children – each possible leverage point should be considered in the context of its production, related feedbacks, and rates of change through time and in space. While one leverage point may seem like the best place for intervention – either because of limited information or convention – it may have no impact or be counterproductive if it is dominated by other system dynamics that are not taken into consideration (Meadows 2008).

Following this methodological approach, the first step is to define the problem that needs to be solved. In the case of pediatric asthma, that means understanding who is being impacted, where they live, and what combination of risk factors may be contributing to the problem. The Cumulative Risk Assessment (CRA) framework is an interdisciplinary approach to researching the health effects of cumulative exposures to multiple chemical and nonchemical stressors, which provided a foundation for developing a research strategy to answer these questions (Sexton and Linder 2011). Specifically, the Vulnerability-Based CRA analysis is a solutions-oriented methodology combining both stressor- and effects-based approaches that integrates all relevant qualitative and quantitative information to identify at-risk groups and what might be contributing to health risk, depending on the context.

The Vulnerability-Based CRA provides several benefits over typical risk assessment, especially given the complex nature of pediatric asthma and the inconsistencies in the quality and availability of health and exposure data (Tomasallo et al. 2014; Milligan, Matsui, and Sharma 2016). It provides a practical guide to exploratory data analysis aimed at the identification of relevant risk factors given the context of the problem; it facilitates ease of communication with stakeholders via exposure and vulnerability analyses performed using geospatial tools; and the comprehensive investigative process results in the collection of the data and information required to investigate



health disparities (Sexton, 2015, p. 941). Furthermore, the Vulnerability-Based CRA is consistent with the Public Health Exposome and Human Envirome frameworks, and is designed to provide a practical basis for developing policy in the context of systemic social, racial, and economic inequalities.<sup>10</sup> This approach informed the exploratory scanning exercises in both the population and patient analyses in Chapters 2-3, which are discussed in the following section.

Adaptive management is an experimental approach to solving problems based on the assumption that the best solution is not always apparent, which supports policy designed to allow for change as trial and error improves knowledge over time (Norton 2005, xii). Adaptive management is consistent with approaches to developing public health policy in environmental epidemiology. In particular, it supports research strategies that focus on evaluation and evidence-based practices given known limitations to causal inference in data analysis. While environmental epidemiological modeling may identify an association between certain variables it does not guarantee a causal relationship, thus an effective policy approach must rely on an investigation of all types of information available beyond that provided by data alone (Thomas 2009, 339). The data analysis strategies employed throughout this dissertation were informed by this adaptive and pragmatic approach, prioritizing interdisciplinary and exploratory methods designed for reproducible and replicable research.

For adaptive management to be effective, explicit ethical positions should be stated at each phase of research, which is particularly important for this dissertation given the role of institutionalized discrimination and implicit bias in creating health disparities. While the scientific process is often considered independent of ethics, the adaptive, systems framework employed here

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<sup>10</sup> A recent transdisciplinary movement supports researching health disparities within the Public Health Exposome: a multilevel framework for tracking exposure affecting personal and population health outcomes that are simultaneously determined by biological, environmental, socioeconomic, and community context (Juarez et al. 2014). The Human Envirome is a framework that expands the concept of the exposome to include the complex interactions between the natural, social, and personal environments that impact health (Riggs, Yeager, and Bhatnagar 2018).

accepts that all research is performed based on existing knowledge produced through a social process, and so all hypotheses involve the act of valuing; every position is an ethical position even if it is intended to be neutral, with potential consequences to the health, wellbeing and livelihood of others. This is particularly important in the application of economic methods and in designing economic policy to solve public health problems. In the case of health research in economics, underlying assumptions about human behavior can affect the research questions being asked such that the results do not apply to real world subjects, with serious implications for the actual population being investigated (McMaster 2013).

Researcher bias against a certain community, whether or not it is a conscious bias, can further misalign research with the outcome it is designed to treat. This is a problem in asthma research today – an historic racial bias in sampling procedures has resulted in a dearth of knowledge regarding biological responses to asthma treatments in different racial and ethnic communities (White et al. 2016). These negative consequences can be mitigated by recognizing the role of ethics in research, connecting scientific modeling with the discussion of policy, and building evaluation into health disparities research agendas (Norton 2005, 26; Lion and Raphael 2015)

In the adaptive management framework, discourse ethics is an integral component of effective and sustainable policy development. The goal of discourse ethics is to continually engage local stakeholders in conversations to establish how the community's resources will be used and saved for the future. The population affected by health disparities, however, is by default disenfranchised and largely excluded from the decision-making process. It is for this reason that each chapter is designed to provide a transparent and accessible base investigation into the problem given all available information, which can be used to engage local stakeholders in both the research process itself and in the development of community-based interventions. This is also consistent with recent research in the quality improvement (QI) literature highlighting the importance of community-based program design and culturally competent communication in effectively reducing health disparities

(Wilkinson et al. 2017).

Drawing on alternative economic theory and policy, it is possible that elements of social disadvantage can be brought into the realm of healthcare as modifiable risk factors. Specifically, Modern Monetary Theory (MMT) and the related concept of a job guarantee program provide an informative, pragmatic backdrop for equity-focused and sustainable health disparities research and intervention strategies (Forstater 2006). MMT has emerged from a growing body of economic research that situates economic problems and policy design in the context of real-world financial systems, which reveals that there is no financial constraint on the federal government's ability to deficit spend given a sovereign, fiat currency (Connors and Mitchell 2017). While coined a theory, MMT is based on a descriptive historical account of how federal fiscal and monetary policy can and has been used to reshape and sustain economic activity; that there is massive leeway in the federal government's ability spend *without* having to tax (Hockett 2018).

MMT is an economic policy framework and can encompass a wide range of programs and interventions sustained through federal funding. These are generally referred to as 'MMT programs' throughout this chapter to maintain consistent language. Whether these programs are effective at alleviating socioeconomic, public health, and racial-ethnic inequalities depends on their design and management. Specifically, there is potential to reduce health disparities through equity-focused, community-based MMT programs designed and implemented locally. Though MMT may seem like an afterthought throughout most of the dissertation, it played an important role in both designing the research questions and interpreting the results. A brief policy note is provided at the end of this chapter to frame future research on these policy possibilities in relation to healthcare reform.

### **Research Strategy**

This dissertation employs a translational research strategy situated in an ethical framework that recognizes health disparities as evidence of institutionalized economic, social, and racial inequality; that the populations burdened by higher rates of preventable and treatable diseases are

necessarily characterized by a lack of choice and are unwillingly exposed to greater health risk; that vulnerable communities are limited in terms of political power and voice in deciding how to use society's resources. Chapters 2-4 include population- and patient-level exploratory analyses designed to provide an accessible and reproducible base investigation into the problem given available information, which can be used to engage local stakeholders in both the research process itself and in designing interventions. The methods and results of this dissertation are intended to contribute to ongoing, translational research on health disparities; the goal is not just to understand the phenomenon of health disparities, but to inform action in terms of population health interventions and patient-centered care.

### **Chapter Overviews**

The following discussion provides an overview of the analysis and findings presented in Chapters 2-4, which can be used as a guide for navigating the dissertation as a whole.

#### **Chapter 2: An Exploratory Analysis of Pediatric Asthma in Kansas City**

Chapter 2 explores the distribution of the burden in pediatric asthma within and between different communities throughout the region. This allows us to see where overburdened communities are *and* where low-risk communities are, which is essential for learning what combination of factors may contribute to population health and that characterize patient context. The data for this analysis includes address-level pediatric asthma patient electronic health records (EHR) provided by Children's Mercy Kansas City hospitals and clinics (CMH) for encounters occurring between 2000 and 2012.

#### ***Objective 1: Explore Asthma Data to Determine Possible Use***

Health disparities research should be iterative, community-based, and multidisciplinary, which means that the analyses should be developed using reproducible methods to the best degree possible. This is particularly important for health analyses that employ raw electronic health records (EHR), which are an artifact of billing and compliance rather than an explicit record of patient health

outcomes. In addition to descriptive analyses of patient and encounter samples, this chapter outlines the specific data processing steps used to classify event and patient severity, and to derive patient history and housing instability measures from the retrospective, address-level EHR.

***Objective 2: Develop Spatial and Temporal Indicators of Population Asthma Risk to Characterize the Disparity among Patients and in the General Population***

It is integral to develop indicators that are comparable to standard measures both to inform targeted population health initiatives and to track changes in the problem over time. Key indicators developed in Chapter 2 include census tract incidence rates and high-risk asthma prevalence estimates, which are high-resolution indicators rarely available for population health disparities research (D. C. Lee et al. 2017). These indicators are based on encounter and patient samples selected according to asthma severity and patient history of care, which also provide the data for a patient-level analyses in Chapter 4.

***Objective 3: Scan to Identify Over-Burdened Communities***

The foundational sample summaries and census tract indicators are used in a scanning exercise to identify patterns in the relative burden of pediatric asthma within and between different groups of patients and communities. To support this exercise, additional exploratory spatial and spatiotemporal analyses of asthma encounters are developed to identify hot spots and their change over time and in space.

*Summary of Findings*

Regardless of the measure or analysis, there is a clear inequity in the distribution of pediatric asthma risk by race, ethnicity, and socioeconomic status. The spatial analyses confirm that the burden of pediatric asthma is concentrated in socially disadvantaged communities and is consistent with historic racial residential segregation. The distinct pattern in asthma risk provides insight into the highly localized nature of the problem, and consequently, the need for both a community-based and patient-centered approach to research and intervention. Additionally, the indicators of health risk and

social disadvantage derived from the EHR – in particular, a housing instability measure based on records indicating a change of address – emphasize both the potential use of EHR to identify the most vulnerable patients and to provide feasible targets for translational research.

### **Chapter 3: Racial Residential Segregation, Environmental Exposure, & The Burden of Pediatric Asthma**

The third chapter uses the Environmental Justice Screening Method (EJSM) to explore patterns in both the population health risks and vulnerabilities that may be contributing to the burden in pediatric asthma in different Kansas City communities. Following methods in the health disparities literature and the Vulnerability-Based CRA framework, the goal of this exercise is to identify not just the immediate exposures contributing to pediatric asthma exacerbation, but also the communities that are most vulnerable and in need of intervention due to social disadvantage and environmental injustice. This serves as the analytical piece of what should be an iterative, community-based process to build a store of knowledge about the environmental and social risks to health throughout Kansas City.

#### ***Objective 1: Develop Environmental Justice Screening Method (EJSM) Indicators***

The EJSM is a simple index built from multiple indicators of health risk, environmental exposure, and social disadvantage, which can help to define both neighborhood and patient context. The EJSM methodology was originally developed for community-based participatory research (CBPR) and is intended to be reviewed and updated by local advocates and stakeholders. As in Chapter 2, the data processing steps used to develop the census tract EJSM indicators were documented to support reproducibility.

#### ***Objective 2: Explore the Distribution of EJSM Indicators through Scanning Exercise and Descriptive Analysis***

The different EJSM indicators were mapped at the census tract geography and explored in a scanning exercise and descriptive analysis to learn more about the combination of factors that might be contributing to the population health risk of severe pediatric asthma in different Kansas City

communities.

### ***Objective 3: Bayesian Profile Regression (BPR) Cluster Analysis***

The Bayesian Profile Regression (BPR) is a type of cluster analysis capable of teasing out patterns within a sample with multicollinearity and spatial correlation. The BPR was developed in this chapter to systematically explore the complex relationships between the census tract EJSM indicators and pediatric asthma incidence rates, helping to identify population characteristics and risk factors associated with both high and low rates of pediatric asthma throughout the region.

### ***Summary of Findings***

The scanning exercise and descriptive analysis revealed complex patterns in the combination of contextual factors that may contribute to population health risk within and between different communities. The results of the BPR analysis validated findings from Chapter 2 and the EJSM scanning exercise, suggesting that different forms of social disadvantage are driving high rates of pediatric asthma and are closely tied to historic development patterns and racial residential segregation.

These findings support research and intervention strategies designed to leverage local knowledge and resources through community-based practices, and to treat observed modifiable risks in the context of place- and person-specific social disadvantage. Additionally, the data collection and processing steps in Chapter 3 suggest significant limitations to the data available for characterizing patient and neighborhood health risk and exposure, highlighting the need for collaborative, multidisciplinary research and data collection strategies in future initiatives.

## **Chapter 4: A Patient Level Analysis of Pediatric Asthma, Housing Conditions, & Housing Instability**

While population health outcomes and related risks are essential components of health disparities research and intervention, much of what contributes to a patient's asthma control is determined by individual risk factors such as personal social disadvantage and housing conditions.

Moving from the population to the patient level, Chapter 4 uses pediatric asthma encounter data geocoded to the residential parcel geography to investigate the relationship between a patient's history of asthma acute care visits and hospitalizations (ACVs) and a covariate profile of indicators representing personal characteristics, housing instability, and environmental exposure both in and around the home.

***Objective 1: Collect and Process Data Representing Patient Characteristics, History of Care, and Exposure to Environmental Triggers of Asthma***

The data for this chapter includes retrospective pediatric asthma patient records matched with parcel housing conditions surveys conducted between 2001 and 2008. Following the methods introduced in Chapter 2, patient electronic health records (EHR) were used to develop measures of asthma severity based on the child's frequency of ACVs, their count of unique addresses – a measure of housing instability – and indicators of social disadvantage measured by patient demographics and medical coverage type. In addition to housing conditions, the parcel-geocoded asthma data was used to collect indicators of exposure to environmental pollution from traffic and industry near the patient's home address.

***Objective 2: Develop a Bayesian Profile Regression (BPR) Model to Characterize Patient Risk***

The BPR methodology was again used to explore the complex relationships between a covariate profile of risk factors and asthma severity, this time using the patient-level data. The model was tested with and without the patient housing instability indicator given the exploratory nature of the variable and, consequently, the increased risk of introducing additional bias into the model. Furthermore, housing instability was expected to act as a measure of the relative duration of patient exposure to both environmental risk factors and housing conditions.

***Summary of Findings***

The first model trial *excluding* the housing instability variable indicates that the risk of asthma-related ACVs is associated with the quality of housing conditions among both privileged and



socially disadvantaged children. Furthermore, the distinct set of risks and vulnerabilities that may be affecting health risk is tied to where children live and can vary substantially within and between seemingly homogenous groups of patients. The results of the second model trial *including* the housing instability variable show that the highest-risk patient clusters were distinguished by the greatest housing instability. Patterns in the second model trial otherwise mirror the results of the first, indicating that housing conditions are associated with the risk of ACVs but only among children *without* a record housing instability, which is consistent with expectations given differences in the duration of exposure.

The Chapter 4 results provide insight into the distinct combination of patient and contextual risks and vulnerabilities that may impact health and inform research and intervention strategies. These results also illustrate the potential to use EHR to identify high-risk patients based on their medical history and record of housing instability. Furthermore, this methodological approach demonstrates how local datasets can be combined to further our understanding of modifiable risk factors like housing conditions and local environmental exposure, and how they may interact with social disadvantage and neighborhood context to impact health.

### **Conclusion**

The results of this dissertation make it clear that social disadvantage and specific social determinants of health (SDOH) like access to healthy and stable housing play a central role in driving the disparity in pediatric asthma between Kansas City children and communities. To alleviate the burden of pediatric asthma and reduce the disparity in general will require a combination of community-based and patient-centered interventions framed in terms of health equity. Specifically, these equity-focused interventions should be designed to account for the distinct needs and resources of vulnerable patients and communities, simultaneously increasing symptom control, improving patient healthcare experience, and mitigating the impact of social disadvantage on health.

The findings from each chapter provide insight into vulnerable communities and feasible

targets for public health interventions and patient treatment strategies. The next step is to map out the process for applying this research in policy and practice. The following discussion provides an overview of disparities-focused quality improvement (QI) as a framework and platform for designing and implementing local Modern Monetary Theory (MMT) programs, which can sustain translational research capable of reducing health disparities over time.<sup>11</sup>

### **Connecting Economic Policy with Disparities-Focused Quality Improvement to Promote Health Equity**

The research and findings throughout this dissertation highlight the need for community-based and equity-focused health disparities interventions that reduce exposure to modifiable risk factors and mitigate the impact of social disadvantage on health. There are a number of barriers to designing and implementing these interventions. First, the social determinants of health (SDOH), while now seen as an essential component of health disparities, are not considered feasible targets of healthcare interventions themselves. Second, an effective and sustainable health disparities intervention program would depend on transparency, iterative design, and continual evaluation to ensure that outcomes are improved, and methods modified if they fail to solve the problem or appear to make things worse.

This policy note proposes an adaptive health disparities intervention strategy combining disparities-focused quality improvement (QI) and Modern Monetary Theory (MMT) programs to leverage existing resources and methods toward equitable and sustainable solutions. Disparities-focused QI can provide the methods and the platform required to design and manage community-based interventions, which can be sustained and expanded through MMT programs to draw SDOH into the realm of modifiable risk factors in healthcare. Together, MMT and disparities-focused QI can act as complimentary elements of a translational research strategy to sustainably reduce health

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<sup>11</sup> Translational research was defined earlier in this chapter as “the multidirectional integration of basic research, patient-oriented research, and population-based research, with the long-term aim of improving the health of the public” (Rubio et al. 2010, 4).

disparities and the social inequalities that drive them through time.

Quality Improvement (QI) “consists of systematic, data-guided, and continuous actions that aim to measurably improve health care services and the health status of targeted groups by improving uptake of best practices into clinical care” (Lion and Raphael 2015, 355). Equity is central to the design of effective QI interventions, where uniform healthcare interventions and reform have often failed to reduce disparities given the highly-localized nature of the problem and the specific needs of socially disadvantaged communities (Poynter et al. 2017).<sup>12</sup> The disparities-focused QI framed in terms of equity demonstrates the potential to reduce health disparities by designing interventions that are adapted to the specific context and needs of vulnerable target populations and patients. This approach depends on adaptive information management and reporting, drawing on QI science to measure the disparity and the impact of interventions, which can guide changes in methods to improve outcomes over time (Chen 2018).

Recent publications on disparities-focused QI interventions highlight the potential benefit to researching and treating health disparities at both population and patient levels. For example, the Community Asthma Initiative (CAI) in Boston successfully reduced pediatric asthma readmission for Emergency Department (ED) visits and hospitalizations among vulnerable patients through a multi-year QI intervention. The intervention identified a sample of at-risk patients living in the same area characterized by high utilization rates and social disadvantage. The patient-centered and community-based program design connected families with nurse home visits, case management services including culturally competent communication practices, and provided home environmental remediation services that were tailored to the needs of the family (e.g. extermination, mold remediation, mattress covers, etc.). The impact of the CAI program was measured in terms of the cost of asthma-related ED visits and hospitalizations, and in terms of quality of life (QOL) measures such as missed days of

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<sup>12</sup> “We know populations are not homogenous in their composition and needs, therefore uniform approaches often fail to deliver to those in most need. For a QI initiative to be successful, it must be adaptable to local needs.” (Poynter et al. 2017, 6)

work or school. The results of the trial were controlled for by selecting patients from similar census tracts with a comparable patient profile and history of asthma-related care.

The impact of the CAI was overwhelmingly positive. In addition to the reduction in readmission rates among participants, there was an increase in prescription adherence and an improvement in the QOL measures. A conservative cost estimate based solely on the price of ED visits and hospitalizations found the program not only paid for itself, it resulted in savings; for every dollar spent on the intervention, \$1.46 was saved. Furthermore, the highly detailed and ongoing case management recorded a sustained reduction in readmission rates (Woods et al. 2016). Beyond providing a basis for multilevel, translational research, the CAI demonstrates the capacity to connect sustained health disparities interventions with the infrastructure and methods to measure their direct costs and impact in meaningful terms.

Disparities-focused QI programs like the CAI lend weight to the argument that community-based practices and an iterative evaluation of both the problem and the impact of interventions are vital to the successful reduction in health disparities (Woods et al. 2012). Despite the shift toward a more holistic and pragmatic approach to researching and treating health disparities, however, the structural conditions and social disadvantage at the root of the problem are widely considered ‘non-modifiable’ risk factors. For example, the results of a practitioner and administrator survey published in the 2016 Community Health Needs Assessment (CHNA) for Children’s Mercy Kansas City (CMH) cites problems like poverty, homelessness, and parental underemployment as some of the most important factors contributing to high healthcare utilization rates and poor health outcomes among Kansas City children. The same survey found these risk factors as the least likely to be affected by CMH policy and intervention (Children’s Mercy Kansas City 2016).

This perspective on the limited capacity to deal with the SDOH through healthcare is mirrored in the QI literature as well. The majority of the discussion is focused on how to successfully implement QI to affect modifiable risk factors in the healthcare system, given resource limitations for

both QI interventions – especially at institutions primarily serving socially disadvantaged communities – and larger investments in the SDOH (Lion and Raphael 2015). For example, a recent publication on disparities-focused QI cites evidence that a single-payer, Medicare-for-All system would reduce costs and increase the quality of care, which the authors argue could free up resources for social investments. They note the political implausibility of this strategy, however, and focus instead on how savings generated from disparities-focused QI could be redirected toward mitigating the SDOH (Wilkinson et al. 2017).

That many SDOH fundamentally important to health disparities are not perceived as modifiable is a major barrier to effective research, intervention, and policy. Modern Monetary Theory (MMT) presents a solution to this problem through sustained federal fiscal policy supporting employment, housing, and wellness programs. These federally funded programs – generally referred to here as ‘MMT programs’ – could be designed and implemented locally as a part of national healthcare reform, bringing problems like housing instability and unemployment into the realm of modifiable risk factors. Specifically, MMT programs like a job guarantee can employ people at a living wage with childcare and medical benefits to do things that need to be done in their communities; to stabilize financially insecure families and empower the socially disadvantaged (Wisman and Pacitti 2014). Furthermore, evidence suggests that job guarantee programs can impact recipients in a multitude of ways that connect with other SDOH and health. For example, a jobs program in Argentina was designed to employ people in their communities with flexibility in terms of scheduling and activity and provided access to supplemental healthcare and childcare programs. A survey of the participants found that, while the sustained income from the employment was of course important to them, it was the sense of fulfillment and contribution to their community that had the greatest impact (Tcherneva 2012).

Integrating disparities-focused QI methods and the fiscal policy possibilities of MMT programs could improve the efficacy of translational health disparities research in general. Instead of

taking SDOH important to struggling communities and families as fixed and exogenous, they can be targeted directly through the expansion of patient-centered and culturally competent care. For example, recent reporting on the opioid crisis in rural America highlights the role of employment and access in susceptibility to drug addiction (Sable-Smith 2019). More employment opportunities in rural America involve manual labor, which can result in physical injury and exposures that lead to chronic pain, but the geography and development patterns limit access to alternative, affordable pain therapy or more physically manageable employment options. From the start, there are MMT program options targeting the rural healthcare system itself. One possibility is to employ at-risk patients in need of stable work in rural transportation services. These services can include transporting rural patients to and from the doctor, other specialized care, and their jobs. Similarly, these transportation services could act as distribution services as well, making things like fresh groceries more available to the rural poor in general.

People not eligible for this type of labor either due to frequent relapse or other disabilities could still benefit from the transport services as a part of a more comprehensive healthcare-based employment program. They could, for example, use the service to reach more appropriate types of jobs, or to simply have consistent access to the services and support groups required to work towards – and hopefully maintain – sobriety. Furthermore, these treatment plans could be designed as a form of employment with a living wage and benefits, supporting recovery and making a contribution to the community in general. There are, of course, existing services that could be used as a platform or expanded through this type of healthcare-based MMT program to prioritize local needs and leverage local resources.

In addition to increasing the political feasibility of a sustained and adaptive approach to health disparities interventions, administering MMT programs through disparities-focused QI would provide a means of tracking their impact, which would also contribute to a store of knowledge on the best program design depending on the context. Application through the healthcare system would

provide the information management infrastructure and multilevel network of providers required to communicate the benefits of MMT programs to those who need it most, and to track the success, failure, and costs locally. Furthermore, MMT programs could support and sustain disparities-focused QI in underserved networks, where resource constraints currently limit effective data collection and QI program management in the communities most impacted by health inequities (Raphael, Faro, and Oyeku 2018).

While there is obvious potential for MMT programs to improve public health, it is essential that they are designed to account for the extensive, institutionalized discrimination that has contributed to social disadvantage and health inequities in the first place. There is nothing to say that the economic activity and development spurred by MMT programs will not maintain or exacerbate existing inequalities, which is especially important given the role of place and community context in the production of public health disparities. This is clear in the case of pediatric asthma in Kansas City, where the racial disparity observed today is closely connected with historic economic development that occurred during periods of stimulus.<sup>13</sup> Through iterative review and improvement, the disparities-focused QI methodology framed in terms of equity may serve as a pragmatic and sustainable approach to community-based MMT program design and implementation.

Disparities-focused QI provides an evidenced-based approach to designing equitable, community-based MMT programs that can reduce costs, alleviate the burden of environmental and social inequalities, and stabilize economic activity. Where MMT programs provide the foundational resources required to affect SDOH through healthcare, disparities-focused QI provides a means of measuring the problem, designing context-specific solutions, assessing the impact of interventions, and using this information to modify and continually improve processes over time. Future research should define the infrastructure required to support ongoing, locally designed and implemented

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<sup>13</sup> This relates to the post-war suburban development in Kansas City discussed at the beginning of this chapter. Also see the Chapter 3 for a discussion of the planning and construction of 71 Highway through historically segregated Black Kansas City neighborhoods.

disparities-focused QI interventions sustained by MMT programs. Specifically, the information management system and standards for documentation would need to be designed to support continual program evaluation and improvement. Additionally, a legal framework would need to be developed to link adaptive federal fiscal policy management with its local design and implementation through healthcare institutions and affiliated community-based organizations.



## CHAPTER 2

### 2. AN EXPLORATORY SPATIAL ANALYSIS OF PEDIATRIC ASTHMA IN KANSAS CITY

#### **Introduction**

Public health studies and state reporting consistently identify a severe disparity in pediatric asthma incidence rates and prevalence for socially disadvantaged children relative to their peers (Kopel, Phipatanakul, and Gaffin 2014). Evidence suggests that the modifiable risk factors and structural conditions driving the disparity are specific to individual and neighborhood context (Brewer et al. 2017).<sup>14</sup> Indicators of the burden in pediatric asthma, however, are often estimated using national or state samples and are rarely reported below the county level, which can obscure disparities between socially disadvantaged and privileged communities (Garbutt et al. 2017). The following analysis uses address-level electronic health records (EHR) for asthma-related encounters from 2000-2012 provided by Children’s Mercy Kansas City hospitals and clinics (CMH) to explore the spatial distribution of pediatric asthma within and between different communities in the Kansas City region. The results of this analysis illustrate the uneven distribution of the burden in pediatric asthma and are used in subsequent analyses to identify place-specific risk factors that may be contributing to high disease rates.

Descriptive and spatial indicators are derived from samples of encounters and patients geocoded to the street centerline geography using the patient’s home address. A discussion of data collection and processing precedes a descriptive analysis of pediatric asthma encounters and patient characteristics, including their history of care, demographics, and measures related to socioeconomic status and housing instability. The centerline-geocoded encounter data is then used to develop point density and emerging hot spot analyses to explore the spatial and temporal distribution of encounters

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<sup>14</sup> Modifiable risk factors are things that can be affected through intervention and policy, for example housing conditions, while structural conditions like racism and poverty define the social context and distribution of health risk and exposure (Hicken 2015; Hicken et al. 2018; CSDH 2008). Refer to Chapter 1 for additional discussion of these concepts.

by severity, and to estimate both disease incidence rates and prevalence for census tracts throughout the Kansas City metropolitan core. These descriptive results provide insight into the complexity and severity of the burden of pediatric asthma in socially disadvantaged communities, informing further exploratory data analysis important to the design of sustainable interventions and policy.

## **Materials & Methods**

### **Sample Overview**

The data for this analysis is drawn from retrospective pediatric asthma encounters in the Children’s Mercy Kansas City hospital network (CMH).<sup>15</sup> The encounter data was geocoded to the street centerline geography using the patient’s home address (B. Wilson, Wilson, and Martin 2019). A preliminary review of the CMH asthma data compared with Environmental Public Health Tracking (EPHT) system estimates for Kansas City counties highlighted the strengths of the CMH dataset. Not only is it likely to capture approximately 70% of the state-recorded emergency department (ED) visits for pediatric asthma, it includes sufficient information to capture out-of-state treatment within the CMH network. Furthermore, it can be used to identify distinct patients and to develop indicators at a much finer spatial scale than what is published by the states.<sup>16</sup>

The centerline-geocoded asthma encounter data is available for the years 2000-2012. The focus of this investigation will be the most recent year of data - 2012 - but the full dataset is explored spatially and temporally to assess the evolution of the CMH network coverage area and to inform and validate indicators of asthma incidence and prevalence rates. The datasets provided by CMH were queried by category and shared in annual batches. An overview of the original data format is provided in table 2.1. A unique account number is recorded for each asthma-related encounter in the diagnosis

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<sup>15</sup> The Children’s Mercy Kansas City Section of Toxicology and Environmental Health (CMH-STEHE) provided retrospective health records to the University of Missouri-Kansas City Center for Economic Information (UMKC-CEI) for a Healthy Homes Technical Grant (#MOHUU0016-13) funded by the Department of Housing and Urban Development (HUD). The joint research project is referred to as the KC Home Environmental Assessment Research Taskforce (KC-HEART).

<sup>16</sup> See appendix tables A.2.3-A.2.5 for details.

and visit characteristics data. A unique medical record number (MRN) is assigned to each patient. The MRN is the key for matching patient encounter data - the diagnosis and visit characteristics - with patient demographics.

Table 2.1. Asthma Data Structure

Category	Key Data Attribution
Diagnosis	Date of Admission ICD-9 Diagnosis Code Event Account Number Patient Medical Record Number Patient Residential Address
Demographics	Birthdate Sex Race Ethnicity
Visit Characteristics	Payment Type Patient Class (Location of Visit)

The study area includes 4 counties within the Kansas City Metropolitan Area (KCMA): Wyandotte and Johnson counties in Kansas, and Jackson and Clay counties in Missouri. The spatial analysis and discussion will also reference the community district geography in the urban core of Wyandotte County, KS (WYCO) and Kansas City, MO (KCMO).<sup>17</sup> Community districts are groupings of neighborhoods with similar socioeconomic and demographic characteristics, which generally align with the social and political geographies of interest and offer relevant spatial reference for the census tract indicators (Bowles 2011).<sup>18</sup> Troost Ave. is symbolized on all maps as a marker of the extreme inequity in the Social Determinants of Health (SDOH) associated with historic racial residential segregation in KCMO (Gotham 2014). The communities east of Troost Ave. are largely

<sup>17</sup> See the study area base maps A.2.1 and A.2.2 in the Chapter 2 appendix.

<sup>18</sup> The community district geography was provided by Dr. Doug Bowles at the UMKC-CEI. Dr. Bowles developed the community district geography through years of work with local stakeholders and neighborhood leaders on numerous urban economic development projects throughout the Kansas City region.

racial-ethnic minority, low-income, renter-occupied, and are characterized by dramatic disparities in life expectancy and other key measures of health in contrast to the communities immediately west of Troost Ave., which are some of the healthiest, wealthiest, and whitest in Kansas City (RJWF 2013).<sup>19</sup>

### **Tools & Software**

The majority of the data processing was done using R/RStudio and Esri's ArcGIS Pro. RStudio (v. 1.1.447) was the primary tool for data munging and analysis. Data processing methods were structured around the principles of 'tidy' data for reproducible research and relied heavily on the Tidyverse packages (v. 1.2.1) (Wickham and RStudio 2014). ArcGIS Pro (v. 2.2.1) was used for spatial data collection, spatial analysis, and to map the results of data processing performed in RStudio.

### **Data Collection & Processing**

#### ***Encounter Severity***

Defining the type and severity of an asthma encounter is necessary to identify patients suffering from poorly controlled or severe asthma symptoms, for processing electronic health records (EHR) to create distinct encounter and patient samples, and for developing indicators of pediatric asthma incidence and prevalence rates.<sup>20</sup> The CMH asthma sample is a record of all asthma-related patient encounters. Each encounter is associated with a standard asthma diagnosis code and the patient class, which is a record of the encounter type. Both variables provide information about the relative severity of an encounter. The asthma diagnosis codes are based on the International Classification of Diseases, 9<sup>th</sup> revision (ICD-9), which are the standard means of identifying asthma-related encounters and can provide insight into different asthma phenotypes. Disease classification by

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<sup>19</sup> Kansas City's history of historic racial residential segregation and the relationship with health disparities is covered in the Background section of Chapter 1.

<sup>20</sup> An incidence rate is "a measure of the frequency with which new cases of illness, injury, or other health condition occur, expressed explicitly per a time frame" (Centers for Disease Control and Prevention (CDC) 2012, 499). A prevalence rate measures "the proportion of a population that has a particular disease, injury, or other health condition, or attribute at a specified point in time (point prevalence) or during a specified period (period prevalence)" (Centers for Disease Control and Prevention (CDC) 2012, 504).

ICD-9 code alone, however, is subject to error and may not capture important variation in symptoms and severity between different patients (Nissen et al. 2017). The patient class records the location and type of treatment a patient received (e.g. emergency department, inpatient, outpatient, etc.), which provides a relatively consistent indicator of the general severity of an asthma-related encounter and can be used to validate or modify the severity recorded by ICD-9 codes.

Three asthma encounter severity levels were identified using the EHR for diagnosis codes and patient class: (1) controlled, (2) acute care, and (3) hospitalization.<sup>21</sup>

1. A controlled asthma encounter is a non-severe patient visit at a CMH hospital or clinic for asthma-related care. Controlled encounters would include, for example, an appointment with a primary care physician to discuss an asthma action plan with the patient. These are asthma-related encounters that can be used to identify the general asthma patient population within the CMH network but do not necessarily represent an asthma attack or other presentation of symptoms at the time of the visit.
2. An acute care encounter is recorded for patients who received treatment for an asthma attack. Acute care visits (ACVs) include treatment for immediate asthma symptoms at urgent care centers (same day clinics) and emergency departments (ED).
3. Hospitalization is the most severe type of asthma encounter. These are recorded for patients presenting persistent, acute asthma symptoms requiring observation stays or relatively aggressive inpatient treatment.<sup>22</sup>

Appendix tables A.2.6 and A.2.7 show how the ICD-9 code and patient class values were sorted into the three asthma severity categories. The highest of the two values was used as the final

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<sup>21</sup> The asthma encounter severity levels were constructed with input from CMH pediatric asthma specialists involved in the KC HEART research project.

<sup>22</sup> Though severity levels 2 and 3 represent distinct types of asthma encounters, they both indicate that a patient exhibited acute or severe symptoms. Indicators presented later in the chapter group these together and refer to them both as 'ACVs'.

asthma severity indicator for each encounter, which is consistent with methods reported elsewhere (Engelkes et al. 2016). For example, an encounter may be assigned an ICD-9 code of 493.00 indicating that it is a controlled visit, or severity level 1, while the patient class may indicate that it was an ED visit, or severity level 2. In this case the encounter severity level would be based on the patient class record and assigned a 2, indicating that it was an ACV.

### ***Encounter Sample Selection***

Significant data processing was required to transform the raw EHR for asthma encounter data into something useful for an investigation into patient and population health outcomes. The original asthma dataset was produced by querying CMH's databases for all encounters with an asthma diagnosis based on the ICD-9 codes associated with an encounter.<sup>23</sup> This general query resulted in duplicate records and included observations for patients below the standard age of diagnosis at the time of the encounter.

Duplication is a problem often encountered with EHR, though it is not well documented, and its form depends on the data collection and storage processes of the originating institution (Belgrave et al. 2017). Observations were flagged as duplicates if more than one asthma-related encounter was recorded in a single day for the same patient. This duplication was typically associated with a change in the recorded asthma diagnosis code or patient class. Discussion with CMH staff indicates that this is likely due to separate billing for each hospital unit or for specific interventions. For example, a patient may have been taken to the ED for an asthma attack, then admitted to the hospital for an inpatient procedure if their condition worsened. Consequently, what was actually a single asthma event for the purpose of this analysis was recorded in the EHR twice.

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<sup>23</sup> The record for single encounter can include multiple ICD-9 codes if the patient was treated for more than one condition at the time of the visit. Patient records for asthma encounters, however, are typically queried based on the primary diagnosis, or the first ICD-9 code recorded for an encounter, which can exclude a significant number of valid observations (Missouri Department of Health and Senior Services (DHSS) 2014). In contrast, the CMH asthma dataset includes any asthma-related encounters regardless of the sequence of the ICD-9 code in the EHR.

The full encounter dataset was subset to exclude duplicates based on the patient’s medical record number (MRN) and the date of admission, which is consistent with guidelines published by the Environmental Public Health Tracking (EPHT) system (Missouri Department of Health and Senior Services (DHSS) 2014). If there was a difference in the severity level recorded for a set of duplicate encounters, the encounter data with the highest severity rating was retained to ensure that the sample represented only unique patient encounters.

It is difficult to diagnose asthma in children under the age of 2, even if the patient is presenting what appear to be asthma or asthma-related symptoms (Kaplan and Vandewalker 2018). Including all encounters for patients under the age of 2 may misrepresent both incidence rates and prevalence among the general population. To account for potential misdiagnosis associated with age, the sample was subset to only include observations for patients between the ages of 2 and 18 at the time of the encounter.<sup>24</sup>

### ***Patient Variables***

Table 2.2 lists the patient variables and values assigned to each encounter. Demographic data was recorded for patients annually and included conflicting records for some of the patients observed in more than one year. The majority of conflicting records occurred if information was available for a patient in one year but missing in another. These records were consolidated to obtain a unique patient demographic profile per MRN that included all available information.<sup>25</sup>

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<sup>24</sup> Removing encounter records for patients under the age of 2 was also advised by CMH asthma specialists and is consistent with the age ranges employed in similar studies of pediatric asthma following National Asthma Education and Prevention Program (NAEPP) guidelines (Capo-Ramos et al. 2014, 620).

<sup>25</sup> In rare cases patients had contradictory records. For example, if a patient’s race was recorded as Black in one year and White in another. In these cases, conflicting entries were flattened to a string and separated by a comma to consolidate the remaining patient records. The corresponding patient variable was recorded as ‘unknown’ or ‘NA’ in order to keep the consistent demographic records without introducing additional error to the patient and encounter samples.

Table 2.2. Pediatric Asthma Patient Variables

Variable	Values
Age (in years)	Min: 2 years Max: Under 19 years
Sex	1 - Female 0 - Male
Race and Ethnicity	1 - White (non-Latinx) 2 - Latinx (any race) 3 - Black (non-Latinx) 4 - Multi-Racial, Asian, or Native American Indian (non-Latinx) 5 - Unknown
Medical Coverage Type	1 - Medicaid or Other State Coverage 2 - Private Insurance 3 - Self-Pay
Patient Count Variables - Previous 365 Days	Acute Care Visits (max count per patient) Unique Residential Addresses

Additional data processing was required to create consistent classifications of patient characteristics for each variable. A medical coverage type variable was specified to indicate whether a patient was covered by Medicaid or another government program pay source, or by commercial insurance at the time of the encounter. If the patient was not covered by either major pay source, or if they paid out of pocket for the cost of the encounter, it is recorded as ‘self-pay’ in the EHR.<sup>26</sup> Age at the time of the encounter was based on the number of days between a patient’s birthdate and the date of admission, which was divided by 365 to get a continuous estimate of age in years. The dummy variable for sex assigned to each patient encounter was derived directly from the EHR and did not require additional data processing. The single indicator of race and ethnicity was based on the patient’s race and modified by their recorded ethnicity, if any. A patient was assigned to the Latinx category regardless of their race if they had a record of Latinx ethnicity, otherwise they were assigned to a category based on race alone.<sup>27</sup>

<sup>26</sup> The classification of asthma encounters by medical coverage type was recommended by CMH staff and is consistent with methods used in recent publications (Urman et al. 2018).

<sup>27</sup> The race and ethnicity patient variables were originally recorded in separate fields. The string values were



A rolling count of ACVs - acute care encounters or hospitalizations - in the previous 365 days was estimated for each patient encounter. This variable represents patient health care utilization and acts as an indicator of both patient asthma severity and their level of symptom control.<sup>28</sup> A rolling count of unique addresses in the previous 365 days was also estimated for each patient encounter to capture how frequently a child may have moved as a proxy for housing instability.<sup>29</sup> While this measure may be biased – it is more likely to observe a change in address if a patient has a higher number of encounters – it offers insight into patient social determinants of health (SDOH) and the association with pediatric asthma health outcomes.<sup>30</sup>

### ***Patient Sample Selection***

Unique patient samples need to be identified to learn more about the distribution of pediatric asthma among children within the CMH network and to investigate the general disparity in pediatric asthma prevalence in Kansas City. Two patient samples were selected from a single year of encounter data – 2012 – for consistent comparison of annual indicators and population estimates: (1) all asthma patients, and (2) high-risk asthma patients. The full sample of pediatric asthma patients will help to characterize the inequity for children within the CMH network. The sample of all asthma patients was selected by identifying unique patient MRNs for encounters recorded in 2012. For children with more than one encounter in 2012, the data for the patient encounter associated with the maximum count of previous ACVs in a 365-day period – the health care utilization measure - was retained.

The CMH network, while serving children from all core counties within the KCMA, is not likely to capture the full pediatric asthma population. Acute or other severe asthma encounters,

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cleaned and standardized to create consistent race and ethnicity categories within each field.

<sup>28</sup> The frequency of previous emergency department (ED) visits are found to be predictive of future patient ED visits (Hanson et al. 2016).

<sup>29</sup> The count of unique addresses was estimated using all available patient records, regardless of encounter severity.

<sup>30</sup> Refer to Chapter 1 for an overview of SDOH and other key concepts in health disparities research.

however, are likely to be represented by the data because of CMH's specialized services and agreements with other institutions. CMH hospitals are considered 'hub hospitals', and as the only locations specializing in pediatric emergency care in the region, they are not a part of any specific catchment area (Mid-America Regional Council Emergency Rescue Committee 2016). Because of their unique role in the region's health care system, pediatric emergency patients are typically diverted or transferred to CMH from other local hospitals and clinics. The 'high-risk' patient subsample was created by selecting only those unique patients with 2 or more ACVs in a 365-day period, measured by the health care utilization variable, which can be used to estimate the prevalence of high-risk asthma in the general population. This indicator captures children subject to above-average asthma severity and health care utilization rates, both of which are important elements of the spatial and temporal behavior of the burden in childhood asthma.

The following section covers the results of the exploratory data analysis of both annual indicators and change over time in pediatric asthma among Kansas City children. The 2012 pediatric asthma encounter and patient samples were used to develop sample descriptive statistics, encounter point density per square mile, and census tract incidence and prevalence rate estimates. The results for the annual indicators are followed by an Emerging Hot Spot Analysis (EHSA) of pediatric asthma encounters occurring between 2000 and 2012 to investigate temporal trends in asthma encounters by location within the region.

## **Data Analysis Results**

### **Asthma Encounters**

#### ***All Encounters***

Table 2.3 shows sample characteristics for all asthma patient encounters in 2012, and for encounters grouped by severity level.

Table 2.3. Pediatric Asthma Encounters by Severity Level, 2012

	All Encounters	Severity Level: (1) Controlled	Severity Level: (2) Acute Care	Severity Level: (3) Hospitalization
<b>Sample Size</b>				
N (%)	17721 (100%)	8335 (47%)	7667 (43.3%)	1719 (9.7%)
<b>Sex</b>				
Female	7,244 (40.9%)	3,414 (41.0%)	3,104 (40.5%)	726 (42.2%)
Male	10,477 (59.1%)	4,921 (59.0%)	4,563 (59.5%)	993 (57.8%)
<b>Age</b>				
2 - 6	7,579 (42.8%)	3,044 (36.5%)	3,722 (48.5%)	813 (47.3%)
7 - 10	4,777 (27.0%)	2,274 (27.3%)	2,059 (26.9%)	444 (25.8%)
11 - 14	3,590 (20.3%)	1,974 (23.7%)	1,313 (17.1%)	303 (17.6%)
15 - 18	1,775 (10.0%)	1,043 (12.5%)	573 (7.5%)	159 (9.2%)
<b>Race and Ethnicity</b>				
White (Non-Latinx)	5,113 (28.9%)	2,338 (28.1%)	2,254 (29.4%)	521 (30.3%)
Latinx (Any Race)	2,938 (16.6%)	1,528 (18.3%)	1,182 (15.4%)	228 (13.3%)
Black (Non-Latinx)	8,496 (47.9%)	3,971 (47.6%)	3,688 (48.1%)	837 (48.7%)
Other or Multiracial (Non-Latinx)	1,092 (6.2%)	468 (5.6%)	504 (6.6%)	120 (7.0%)
Unknown	82 (0.5%)	30 (0.4%)	39 (0.5%)	13 (0.8%)
<b>Medical Coverage Type</b>				
Medicaid	11,492 (64.8%)	5,578 (66.9%)	4,893 (63.8%)	1,021 (59.4%)
Commercial Insurance	5,076 (28.6%)	2,383 (28.6%)	2,114 (27.6%)	579 (33.7%)
Self Pay	1,153 (6.5%)	374 (4.5%)	660 (8.6%)	119 (6.9%)

The disproportionate presence of minority patient encounters is immediately apparent.<sup>31</sup> According to the 2010 Decennial Census population estimates, Black (non-Latinx) children age 2-18 make up only 17% of the total population in the study area counties (U.S. Census Bureau 2017). The asthma patient encounters for Black (non-Latinx) children, however, constitute 48-49% of the sample in each category of severity.<sup>32</sup>

The distribution of encounters by ethnicity also indicates an inequity in uncontrolled pediatric asthma among Latinx children. Latinx children make up 13.8% of the total population in the study area and represent 15% of acute care visits and 13% of all hospitalizations in the 2012 CMH sample.

<sup>31</sup> The term ‘minority’ is used throughout this chapter to refer to non-White or Latinx children; racial-ethnic minority children.

<sup>32</sup> The CMH sample estimates for asthma-related ACVs for Black (non-Latinx) children in the study area are consistent with the rates reported by the Missouri Department of Health and Senior Services for the Kansas City region (Missouri Department of Health and Senior Services (DHSS) 2004; Missouri Department of Health and Senior Services (DHSS) 2009).

In contrast, 61.4% of the total child population in the study area is White (non-Latinx), while less than 30% of asthma encounters - overall or by severity level - are for White (non-Latinx) patients. Additionally, the medical coverage type variable illustrates that patients relying on Medicaid – a proxy for relatively low socioeconomic status – constitute the majority of asthma patient encounters at CMH regardless of event severity.

The distribution of encounters by sex and age is consistent with findings that younger children – especially boys – are at a higher risk of severe asthma (National Asthma Education and Prevention Program (NAEPP) 2007; Largent et al. 2012; Dharmage, Perret, and Custovic 2019). The proportion of controlled visits by age exhibits a modest decline as age increases relative to the other encounter severity categories. These sample characteristics demonstrate an inequity in pediatric asthma health outcomes for minority and low-income children compared with the rest of the sample, and are consistent with reported variation in the presentation and severity of asthma symptoms by sex and age (Chung, Hathaway, and Lew 2015).

The distribution of controlled encounters might indicate that the over-representation of low-income and minority children in the CMH EHR is, at least in part, a consequence of the service area and in-network patient population; that minority and low-income children are more likely to show up in the sample regardless of asthma severity or prevalence in the general population. Potential sample selection bias due to the location and patient population of the primary CMH service area, however, does not explain the extreme disparity in acute and severe asthma rates, which are not dependent on - or solely representative of – in-network asthma patient encounters.

### ***Point Density of ACVs***

The point density of ACVs per square mile was estimated for the encounter data geocoded to the street centerline geography in 2012 using the Point Density tool in ArcGIS Pro.<sup>33</sup> This is an

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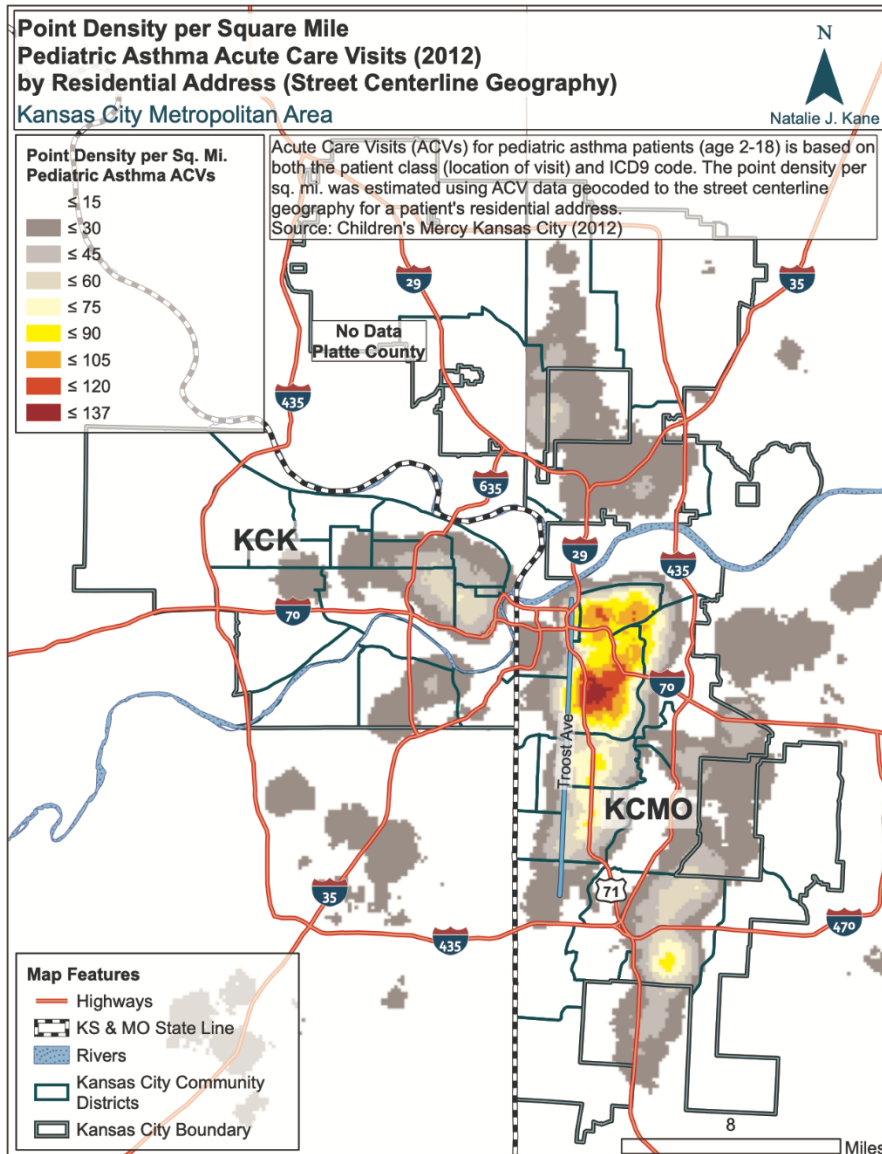
<sup>33</sup> The point feature class selection of 2012 asthma ACVs was used as the input feature class. The output raster cell size was set to 400 map units and the neighborhood circle was given a radius of 5000 map units. The area units parameter - the unit of measurement for the resulting raster output - was set to square miles.

important first step in exploring pediatric asthma in Kansas City because it shows the relative distribution of ACVs by residential address across the full study area without having to aggregate the data to a higher geography, which can obscure relevant clustering.<sup>34</sup> Map 2.1 shows the point density per square mile of pediatric asthma ACVs by patient address in 2012.

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<sup>34</sup> This relates to both the Modifiable Areal Unit Problem (MAUP) and the Unspecified Geographic Context Problem (UGCoP) introduced in Chapter 1.

Map 2.1. Point Density of Pediatric Asthma Acute Care Visits, 2012



The distribution of ACVs demonstrates clear clustering in predominantly Black census tracts east of Troost Avenue - the historic boundary between racially segregated residential neighborhoods in KCMO. Clustering also appears in a number of historically segregated and industrialized neighborhoods with large Latinx populations in Wyandotte County, Kansas (WYCO). In addition to social disadvantage, the clustering in WYCO may be associated with both environmental exposure from industry and housing inequality (D. Norris and Baek 2016; Global Community Monitor 2015).

There is also a noticeable clustering of ACVs by patient address along the I-35 corridor in Johnson County, KS (JOCO). This clustering may be related to a number of factors including development practices that concentrate rental and low-income housing near major highways and other sources of environmental pollution, supporting a relatively high density of socially disadvantaged communities susceptible to an inequity in pediatric asthma (Kopel, Phipatanakul, and Gaffin 2014).

### ***ACVs per Capita***

The rate of pediatric asthma ACVs per capita was estimated for census tracts in the study area through a combination of spatial data collection in ArcGIS Pro and data processing using the suite of Tidyverse packages in RStudio. The Spatial Join tool in ArcGIS Pro was used to assign a unique census tract geographic identifier (geoid) to the asthma encounters based on the patient's home address to estimate the count of asthma encounters by census tract.<sup>35</sup> The census tract pediatric asthma ACVs per capita was then estimated by dividing the total number of ACVs in 2012 by the 2010 decennial census population estimates for children age 2-18 (U.S. Census Bureau 2010).<sup>36</sup>

Variation in population density between different parts of the Kansas City region may obscure important patterns in asthma-related health care utilization. Patterns in the census tract rate of pediatric asthma ACVs per capita in map 2.2, however, confirms that the observed clustering in map 2.1 is not solely a consequence of population density. The distribution of ACVs per capita is generally consistent with the point density estimate in map 2.1, though map 2.2 reveals a more

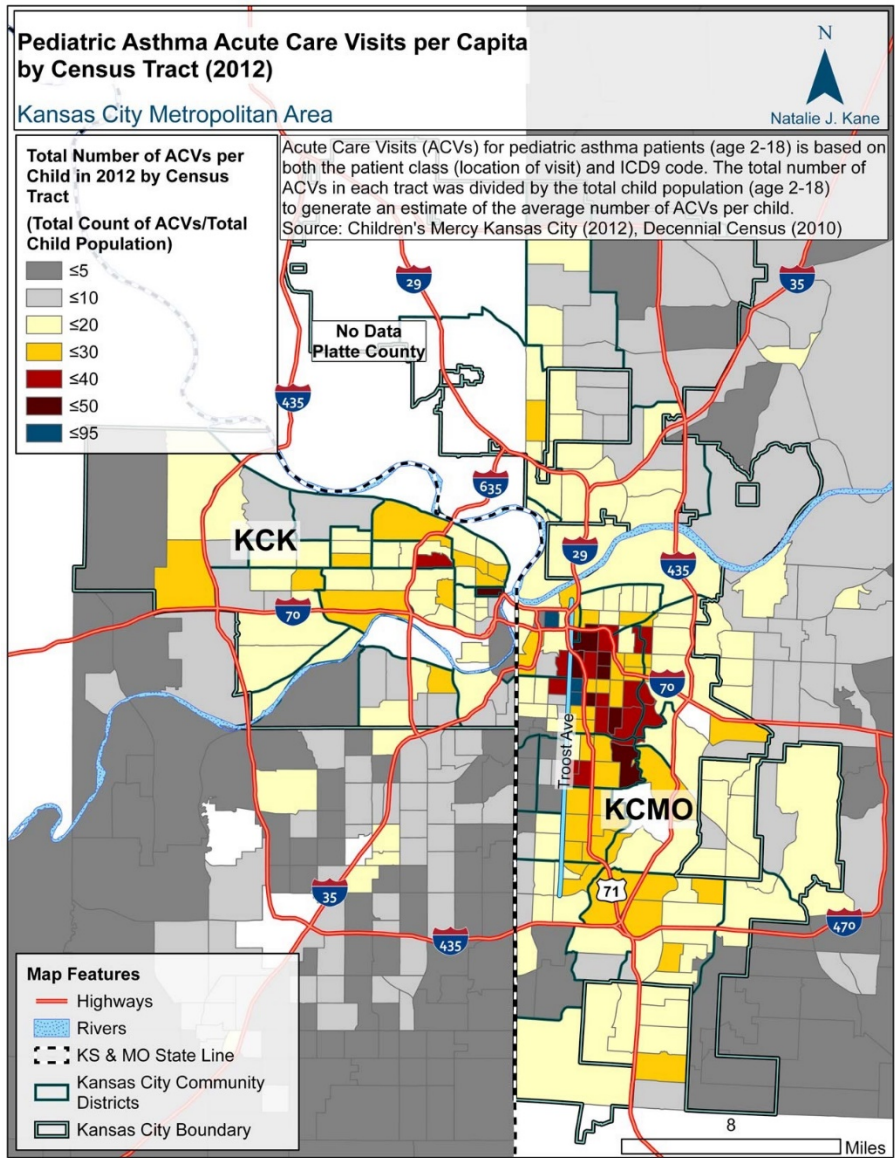
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<sup>35</sup> The pediatric asthma encounters geocoded to the street centerline geography - a point feature class layer - were selected as the target features; the join features were the US Census Bureau 2010 TIGER census tracts. A one-to-one join operation matched the inputs if the target features had their center in the join feature. The output feature class was exported to a table using the Copy Rows tool to complete the remaining data processing in RStudio. A census tract reference file consisting of all the tract geoids in the study area ( $N = 466$ ) was also exported to build a final indicator file that could be joined back to the original layer in ArcGIS Pro to map the results. In RStudio, the Tidyverse dplyr package was used to filter the 2012 encounter data by severity levels 2 and 3, which are generally referred to as ACVs to indicate that a child experienced some kind of acute or severe asthma symptoms. The encounter subset was then grouped by geoid and summarized to produce a count of ACVs per census tract. The new variable was joined by geoid with the census tract reference file. Any tracts without a count - tracts that did not have children living there with a record of at least one ACV in 2012 - were assigned a count of 0.

<sup>36</sup> 'Per capita' in this context refers to the total child population age 2-18.

complex pattern of the burden of pediatric asthma within socially disadvantaged communities.

Map 2.2. Pediatric Asthma Acute Care Visits per Capita by Census Tract, 2012



## Patients & Prevalence

### *All Patients*

Table 2.4 provides the descriptive statistics for all asthma patients identified in the 2012 CMH encounter sample. Patients were grouped by their maximum count of ACVs recorded in a year



period.

Table 2.4. All Pediatric Asthma Patients by History of Acute Care, 2012

	All Patients	ACV Count: 0	ACV Count: 1	ACV Count: 2+
<b>Sample Size</b>				
N (%)	9788 (100%)	2852 (29.1%)	4428 (45.2%)	2508 (25.6%)
<b>Sex</b>				
Female	3,994 (40.8%)	1,197 (42.0%)	1,799 (40.6%)	998 (39.8%)
Male	5,794 (59.2%)	1,655 (58.0%)	2,629 (59.4%)	1,510 (60.2%)
<b>Age</b>				
2 - 6	4,204 (43.0%)	984 (34.5%)	1,997 (45.1%)	1,223 (48.8%)
7 - 10	2,647 (27.0%)	799 (28.0%)	1,160 (26.2%)	688 (27.4%)
11 - 14	1,970 (20.1%)	691 (24.2%)	864 (19.5%)	415 (16.5%)
15 - 18	967 (9.9%)	378 (13.3%)	407 (9.2%)	182 (7.3%)
<b>Race and Ethnicity</b>				
White (Non-Latinx)	3,130 (32.0%)	924 (32.4%)	1,591 (35.9%)	615 (24.5%)
Latinx (Any Race)	1,519 (15.5%)	465 (16.3%)	659 (14.9%)	395 (15.7%)
Black (Non-Latinx)	4,446 (45.4%)	1,293 (45.3%)	1,837 (41.5%)	1,316 (52.5%)
Other or Multiracial (Non-Latinx)	628 (6.4%)	153 (5.4%)	302 (6.8%)	173 (6.9%)
Unknown	65 (0.7%)	17 (0.6%)	39 (0.9%)	9 (0.4%)
<b>Medical Coverage Type</b>				
Medicaid	6,019 (61.5%)	1,777 (62.3%)	2,520 (56.9%)	1,722 (68.7%)
Commercial Insurance	3,078 (31.4%)	930 (32.6%)	1,554 (35.1%)	594 (23.7%)
Self Pay	691 (7.1%)	145 (5.1%)	354 (8.0%)	192 (7.7%)

The results of the descriptive analysis for all CMH asthma patients in 2012 are generally consistent with the findings for the full encounter sample in table 2.3. Taking into consideration demographic estimates for the general population, these results illustrate the clear disparity in pediatric asthma prevalence among socially disadvantaged children compared with the rest of the CMH patient population. Both Latinx and Black (non-Latinx) patients are over-represented in the sample, with noticeable differences between Black (non-Latinx) children compared with White (non-Latinx) children based on their record of ACVs. 41% of patients in 2012 with only 1 ACV were Black (non-Latinx); 36% were White (non-Latinx). In contrast, over 52% of patients with 2 or more ACVs were Black (non-Latinx); 25% were White (non-Latinx).

A similar pattern is observed with the distribution of the patients by health care utilization

and medical coverage type; 57% of the patient population with only 1 ACV were covered by Medicaid, compared with 69% of the patient population with a record of 2 or more ACVs. In contrast, 35% of patients with commercial insurance coverage had a record of 1 ACV; 24% had 2 or more ACVs. This is consistent with findings that the pediatric asthma population covered by Medicaid exhibits higher utilization rates, lower adherence to prescribed preventative treatments, and further inequities in health outcomes by race and ethnicity, all of which are related to various aspects of social disadvantage (Capo-Ramos et al. 2014).

### ***High-Risk Patients***

Table 2.5 provides the descriptive statistics for the high-risk patient sample - patients in 2012 with a record of 2 or more ACVs in a year period. The high-risk patient sample is grouped by the count of unique addresses recorded during the same period that a child experienced their maximum count of previous ACVs. The difference between the proportion of Black (non-Latinx) and White (non-Latinx) asthma patients becomes more pronounced with the increase in unique addresses. Of the children who have no record of moving during the period in which they experienced 2 or more ACVs - only 1 unique address is recorded for the patient - 25% were White (non-Latinx); 48% were Black (non-Latinx). In contrast, 17% of children with 2 unique addresses were White (non-Latinx); 62% were Black (non-Latinx). Of the children with 3 or more unique addresses - suggesting that they moved 2 or more times in a year period according to CMH records - 15% were White (non-Latinx); 71% were Black (non-Latinx).

The proportion of children covered by Medicaid also increases substantially with the count of unique addresses. 69% of all high-risk patients are covered by Medicaid. Of the children covered by Medicaid, 65% have 1 unique address; 75% have 2 unique addresses; 85% have 3 or more unique addresses. These results suggest that housing instability is associated with increased risk of severe asthma encounters and high healthcare utilization rates among socially disadvantaged children in

Kansas City, which is consistent with findings in the literature (Rosenbaum 2008).<sup>37</sup>

Table 2.5. All High-Risk Pediatric Asthma Patients by the Count of Previous Addresses, 2012

	High-Risk Patients	Address Count: 1	Address Count: 2	Address Count: 3+
<b>Sample Size</b>				
N (%)	2508 (100%)	1776 (70.8%)	615 (24.5%)	117 (4.7%)
<b>Sex</b>				
Female	998 (39.8%)	727 (40.9%)	222 (36.1%)	49 (41.9%)
Male	1,510 (60.2%)	1,049 (59.1%)	393 (63.9%)	68 (58.1%)
<b>Age</b>				
2 - 6	1,223 (48.8%)	838 (47.2%)	321 (52.2%)	64 (54.7%)
7 - 10	688 (27.4%)	490 (27.6%)	168 (27.3%)	30 (25.6%)
11 - 14	415 (16.5%)	313 (17.6%)	89 (14.5%)	13 (11.1%)
15 - 18	182 (7.3%)	135 (7.6%)	37 (6.0%)	10 (8.5%)
<b>Race and Ethnicity</b>				
White (Non-Latinx)	615 (24.5%)	493 (27.8%)	104 (16.9%)	18 (15.4%)
Latinx (Any Race)	395 (15.7%)	304 (17.1%)	78 (12.7%)	13 (11.1%)
Black (Non-Latinx)	1,316 (52.5%)	849 (47.8%)	384 (62.4%)	83 (70.9%)
Other or Multiracial (Non-Latinx)	173 (6.9%)	123 (6.9%)	47 (7.6%)	3 (2.6%)
Unknown	9 (0.4%)	7 (0.4%)	2 (0.3%)	0 (0.0%)
<b>Medical Coverage Type</b>				
Medicaid	1,722 (68.7%)	1,160 (65.3%)	463 (75.3%)	99 (84.6%)
Commercial Insurance	594 (23.7%)	475 (26.7%)	108 (17.6%)	11 (9.4%)
Self Pay	192 (7.7%)	141 (7.9%)	44 (7.2%)	7 (6.0%)

### ***High-Risk Asthma Prevalence***

Exploring the spatial distribution of encounters is an important step to identify communities subject to relatively high risk of severe asthma and health care utilization rates. These disparity indicators relate to inequities in other SDOH, such as access to the basic care required to manage symptoms, and elevated exposure to risk factors including unhealthy housing conditions and environmental pollution (Gold and Wright 2005; Samuels-Kalow and Camargo 2019). Health care utilization rates as a measure of pediatric asthma inequity, however, do not provide direct information

<sup>37</sup> Refer to Chapter 1 for an overview of the role of modifiable risk factors and structural conditions in health disparities.

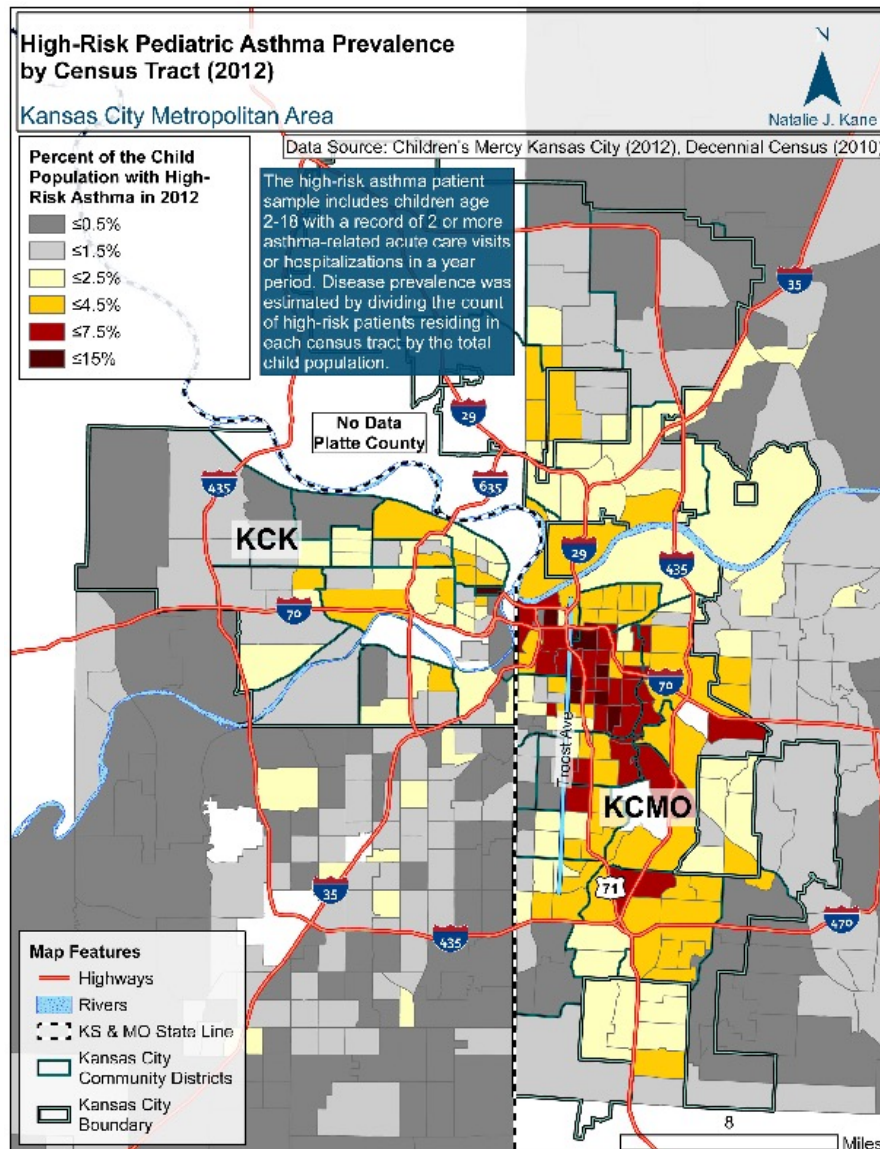
about the rate of the disease in the general population. A trial indicator of pediatric asthma prevalence was estimated using the high-risk patient sample, which provides a relatively reliable and representative asthma patient sample given the unique role of CMH hospitals and clinics in the Kansas City region. The geocoded encounter dataset with census tract identifiers was subset to include only high-risk patients in 2012; patients with 2 or more ACVs in a year period. The count of high-risk asthma patients was summarized by census tract geoid, then normalized by the 2010 child population estimates.

The census tract indicator for high-risk asthma prevalence symbolized in map 2.3 demonstrates consistent clustering of high-risk asthma patients in socially disadvantaged communities, validating the patterns observed in the population-level health care utilization indicators in maps 2.1 and 2.2. The patterns in map 2.3 also suggest that there is significant variation in the rate of high-risk asthma within and between different communities. For example, while the clustering identified in the Northeast community district of WYCO is visible in all indicator maps, map 2.3 suggests that specific areas within the Northeast may be more impacted by the inequity in pediatric asthma than others.<sup>38</sup> These findings also highlight the significant variation in the risk factors and SDOH that may be contributing to high rates of severe pediatric asthma in each place.

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<sup>38</sup> See appendix map A.2.2 for reference. Note that the Northeast is a community district in WYCO, while the Old Northeast and Northeast Industrial community districts are located in KCMO.

Map 2.3. High-Risk Pediatric Asthma Prevalence by Census Tract (2012)



## Change Over Time

### *Trends in Daily Observations*

Determining whether the CMH sample can be used to represent the general pediatric asthma population is important for defining the spatial behavior of the disparity in childhood asthma. The comparison of the CMH and state asthma ED incidence rates suggests that the CMH data provides a

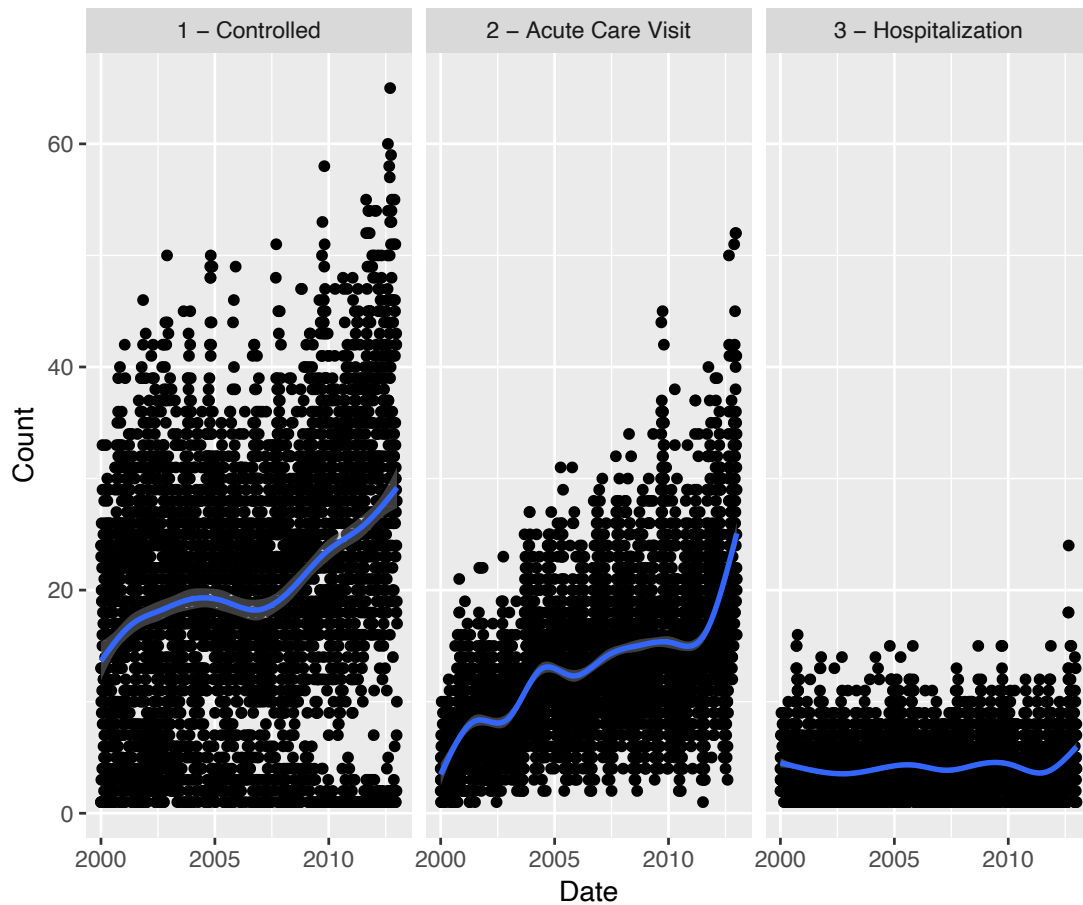
robust and representative sample of pediatric asthma-related encounters in the Kansas City region.<sup>39</sup> They do not, however, provide sufficient information about the consistency of sampling throughout the study area. Whether or not pediatric asthma – or a specific indicator such as asthma ED visits – is represented more fully in one community compared with another in the study area has implications for the quality and accuracy of incidence and prevalence rate estimates in the general population. Furthermore, the ability to measure how these indicators change over time is important for setting public health priorities.

Figure 2.1 shows the daily count of asthma encounters by severity from 2000-2012, which illustrates a general upward trend in the frequency of both controlled encounters and ACVs. The increase in daily controlled visits may indicate an increase in the number of in-network patients. The increase in ACVs, however, may not be explained entirely by changes in access to CMH services given the regional ambulance diversion policy and specialized pediatric care. These observed trends have significant implications for an analysis of asthma prevalence by residential address if the distribution of patients in the CMH network is uneven and changing over time.

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<sup>39</sup> See the Sample Overview section of this chapter for a discussion of the CMH asthma sample representativeness compared with state-published disease incidence rates.

Figure 2.1. Frequency of Asthma Encounters by Severity – Daily Observations, 2000-2012



### *Emerging Hot Spot Analysis (EHSA)*

The full sample of asthma encounters from 2000-2012 were used in an Emerging Hot Spot Analysis (EHSA) to assess changes in regional health care utilization for pediatric asthma. The ArcGIS Pro EHSA tool is one of a series of space-time pattern mining tools used to simultaneously analyze both spatial clustering and temporal trends to capture complex patterns in dynamic systems (Harris et al. 2017). This methodology has been used across disciplines to better understand how a spatial problem is evolving, which can help to target resources for intervention (Wang, Varady, and Wang 2008; Golbon et al. 2019; Cheng, Zu, and Lu 2019; Raina MacIntyre et al. 2018).

The EHSA was developed for two CMH asthma encounter subsamples: (1) controlled

encounters, and (2) acute care encounters and hospitalizations (ACVs). A record of controlled encounters suggests that a child is an in-network CMH patient and, for example, visits a primary care physician at one of the CMH locations. The ACV sample is expected to capture asthmatic children both within and outside of the regular CMH patient population and primary service area. The EHSA for controlled encounters alone may provide insight into changes in the CMH network coverage over time; the EHSA for ACVs may help to identify communities with a growing burden in pediatric asthma indicative of an inequity.<sup>40</sup> The output of the EHSA is a polygon feature class with a hexagon grid geometry containing information about the hot spot or cold spot pattern, if any, at each location during the study period from 2000-2012.<sup>41</sup>

The EHSA captures both the density of encounters by location and their change over time, helping to characterize the nature of asthma encounter frequency throughout the study area. While this analysis does not account for population density, it provides insight into the CMH network service area and potential emerging hot spots in pediatric asthma. Map 2.4 shows the EHSA results for controlled encounters from 2000-2012, which indicate a change in the CMH patient population in different parts of the region.

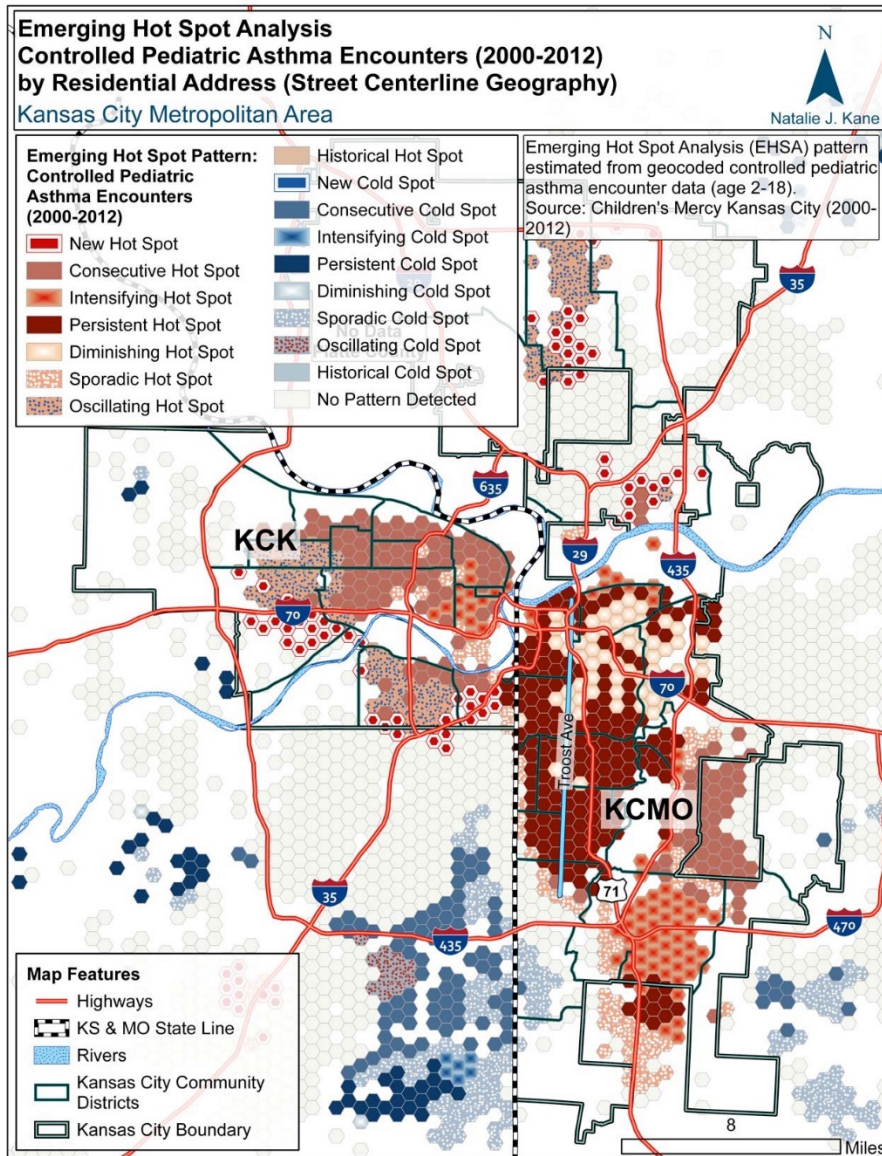
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<sup>40</sup> The EHSA for each sample was estimated using a series of tools in ArcGIS Pro. First, the geocoded asthma encounter data was cleaned using the Repair Geometry tool. This tool removed features with a null geometry, for example, rows that were not matched with a street centerline address in the geocoding process. The Create Space Time Cube by Aggregating Points tool aggregates a point layer into space-time bins to measure their spatial distribution over a series of time intervals. This tool was applied to each sample, where the input was the repaired and filtered encounter point feature class; the date of admission was selected as the time field; the time step interval was set to 1 year(s); the time step alignment was set to 'end time'; the aggregation shape type was set to 'hexagon grid'. The results of the space time cube tool include a record of the default distance interval, the number of points, the number of hexagon grid locations, and the dimensions of the output. It also includes a record of the number of time step intervals and summarizes trends according to the specified time step alignment method. In this case, the space time cube results indicate change from the start of the period to the end of the period, which includes 13 time step intervals; one time step per year from the beginning of 2000 through the end of 2012. The space time cube results for both the controlled and ACV point encounter samples suggest a statistically significant increase in points over time. The space time cube output for each sample - a netCDF - was selected as the input for the EHSA tool. The analysis variable for the EHSA was set to 'count' to identify patterns in the occurrence of encounters by patient address in each time step interval.

<sup>41</sup> See the Chapter 2 appendix tables A.2.8 and A.2.9 for hot spot and cold spot pattern definitions.



Map 2.4. Emerging Hot Spot Analysis – Controlled Pediatric Asthma Encounters, 2000-2012

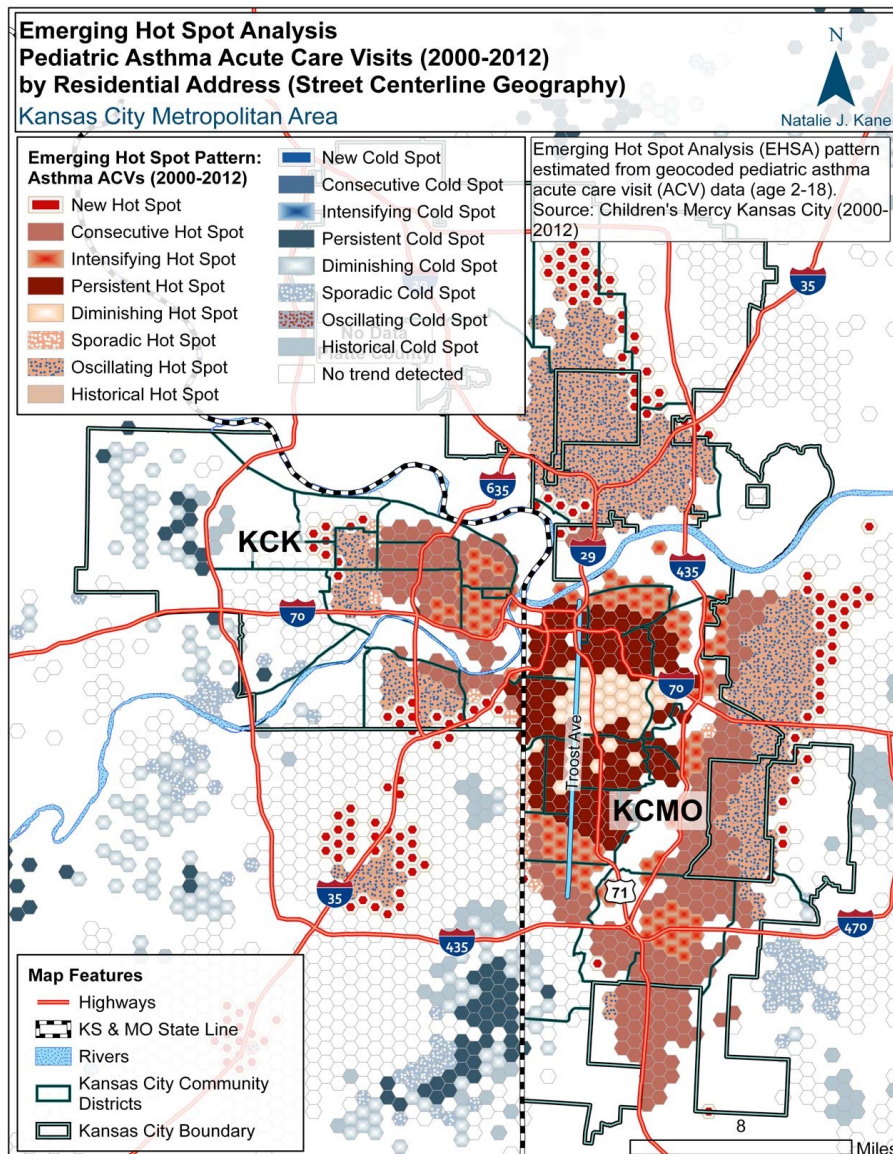


The pattern in EHSA hot and cold spots - both of which indicate a concentration of controlled encounters at some point during the study period - are not restricted to the areas with noticeable clustering in pediatric asthma identified in maps 2.1-2.3. An increase in controlled patient encounters during the 2000-2012 period may relate to a change in the total child population, a change in the availability of CMH services for new patient populations, or an increase in asthma utilization or

prevalence by location.<sup>42</sup>

Map 2.5 shows the EHSA results for the ACV sample. The hot spot patterns generally reflect the clustering of ACVs shown in maps 2.1-2.3.

Map 2.5. Emerging Hot Spot Analysis –Pediatric Asthma Acute Care Visits, 2000-2012



<sup>42</sup> Unexplained variation in the EHR frequency and distribution may also relate to inconsistencies and changes over time in the collection and management of EHR within and between different CMH locations. This is a problem with EHR in general and should be reviewed and discussed further with CMH staff in future analyses (Glynn and Hoffman 2019).

Similar to the findings from map 2.4, the EHSA patterns in map 2.5 suggest that the overall increase in ACVs from 2000-2012 was unevenly distributed between different Kansas City communities. Map 2.5, however, indicates that the increase in ACVs may have been more restricted to socially disadvantaged communities burdened by high rates of pediatric asthma compared with the increase in controlled encounters.

#### *Comparing the EHSA Results*

Differences in the EHSA maps may help to identify communities experiencing an increase in pediatric asthma in terms of utilization or prevalence, and to provide insight into how the disparity between different communities is changing over time. For example, neighborhoods in the Old Northeast community district of KCMO are characterized by hot spots in both maps, though the pattern is inconsistent. In map 2.4, the Old Northeast neighborhoods have a significant concentration of diminishing hot spots compared with map 2.5. The same area in map 2.5 has only intensifying or persistent hot spots. Though encounters of each type are generally increasing over time in the Old Northeast neighborhoods, the rate of ACVs is increasing consistently while the number of controlled encounters is leveling out. The relative increase in ACVs compared with controlled encounters for children living in the Old Northeast suggests that the burden of pediatric asthma - as indicated by health care utilization rates - may be getting worse.

The area south of Kansas City in JOCO near the location of the CMH South hospital exhibits similar variation but in terms of cold spots. Map 2.4 shows a much larger area subject to cold spots, while map 2.5 shows a relatively isolated cluster of cold spots. The cold spot patterns suggest that, while there was a concentration of encounters at some point during the study period – an indication of growth in the CMH patient population or general asthma population - the trend is decreasing over time.

The clustering in ACVs along the I-35 corridor north of I-435 is captured by map 2.5 as a mix of intensifying and oscillating hot spots. In contrast, map 2.4 shows no hot or cold spots for controlled

encounters in that area. This suggests that the apparent clustering along the I-35 corridor in JOCO is not entirely a consequence of the increased network coverage of CMH services. Instead, it may represent a relatively recent concentration of severe pediatric asthma compared with other parts of JOCO. It also suggests that the ACV encounter data samples the pediatric asthma population more consistently throughout the study area than the controlled encounter data. These findings support the specification of asthma prevalence based on patients with a history of ACVs.

The EHSA results generally reinforce the temporal trends identified in figure 2.1 and provide insight into the pattern of these trends in space. While figure 2.1 indicates that the frequency of CMH asthma encounters of all types are increasing for the Kansas City region, the EHSA results demonstrate that this increase is not evenly distributed between different communities, nor is it temporally consistent. This supports recent findings that asthma prevalence and severity is increasing for vulnerable communities despite generally leveling off in the population overall (Akinbami, Simon, and Rossen 2016).<sup>43</sup>

## **Discussion**

### **Summary of Findings**

The results of this analysis demonstrate the dramatic inequity in pediatric asthma between socially advantaged and disadvantaged communities in the Kansas City region. This inequity is apparent in terms of the relative severity of pediatric asthma symptoms, health care utilization rates,

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<sup>43</sup> The change in the distribution and frequency of encounters - both controlled and ACVs - may be associated with changes in underlying population density, SDOH, or pediatric asthma prevalence. The change in two basic indicators were mapped for comparison and are included in the appendix to this chapter. Map A.2.10 shows the change in the percent of the population living below 200% of the federal poverty line - the change in the low-income population - for the study area census tracts. Map A.2.11 shows the change in the percent of the population under age 18 between 2000 and 2010 during the same period. Comparing these maps with the EHSA results suggests that the observed increase in encounters may be associated with changes in population, socioeconomic status - a general indicator of changes in related SDOH - or a combination, depending on location. These trends are cited in the 2016 CMH Community Health Needs Assessment (CHNA) and highlight the complicated nature of the burden of pediatric asthma in socially disadvantaged communities (Children's Mercy Kansas City 2016). Further research is required to validate whether the EHSA results are representative of the general child asthma population, and to what degree they are a consequence of changes in underlying population characteristics.

and disease prevalence. These patterns are consistent with historic racial residential segregation, suggesting that structural conditions – specifically racism and economic inequality – may be driving the health disparity. Possible emerging hot spots identified through the spatial and temporal analyses are indicative of a growing burden in pediatric asthma, with some hot spots appearing in areas traditionally characterized by social and economic prosperity. The count of addresses also highlights opportunities to mine EHR to identify patients struggling with housing instability, which might offer a target for research and intervention strategies.

### **Limitations & Opportunities for Improvement**

The use of EHR to identify at-risk patients is important to improving interventions and treatment plans (Castillo, Peters, and Busse 2017). The methods and results of this study, however, highlight some of the limitations of using EHR in this context. Given that EHR are not recorded for the purpose of this type of analysis, and furthermore are entered in a wide range of circumstances by many different individuals, the detail of certain attributes are limited and there is significant room for error (Al Sallakh et al. 2017). This is particularly true for attributes such as race and ethnicity (Bauer 2014). While demographic indicators can offer insight into variation in health outcomes for vulnerable populations, future research should investigate the intersection of each element of identity - and their representation in EHR - in greater depth (Green, Evans, and Subramanian 2017).

This preliminary analysis of the spatial patterns in pediatric asthma used patient data geocoded to the street centerline geography to develop census tract asthma disparity indicators. These methods revealed significant variation in the distribution of pediatric asthma within and between socially disadvantaged communities, which has important implications for future research and intervention strategies. However, geocoding encounters to the street centerline introduces error in the estimated spatial location of the patient's home address and could affect the accuracy of census tract indicators (Edwards, Strauss, and Miranda 2014). Future research should validate the accuracy of the street centerline geocoding method and the degree of error in aggregated census tract estimates, and

alternative, consistently reproducible geocoding methodologies should be considered as well.

### **Implications for Research and Policy**

The variation in the burden of pediatric asthma within and between communities highlights the need for community-based participatory research (CBPR) methods. Involving socially disadvantaged communities affected by high rates of pediatric asthma in the research and policy process would help to define the specific circumstances, population vulnerabilities, and risk factors that may be contributing to the inequity. Furthermore, a place-based approach to designing interventions is better suited to the sustainable use of local resources, leveraging the unique features within a community that may provide a means of offsetting the deleterious effects of social disadvantage on health.

Further research should be done to better understand the trends in encounters and patients in the CMH network over time, and to incorporate other data sources to improve representation of the general pediatric asthma population. For example, future iterations of the EHSA can include a review of different distance interval options, which can affect the resolution of the hot spot analysis results (Gates 2017). This preliminary, exploratory analysis, however, has helped define the spatial behavior of the disparity in pediatric asthma and how it varies between distinct communities within the region. In the following chapter, the Environmental Justice Screening Method (EJSM) will be developed to scan for patterns in vulnerabilities and modifiable risk factors possibly contributing to the disparity in each place, and to inform subsequent exploratory regression analyses.

## CHAPTER 3

### 3. RACIAL RESIDENTIAL SEGREGATION, ENVIRONMENTAL EXPOSURE, & THE BURDEN OF PEDIATRIC ASTHMA IN KANSAS CITY

#### **Introduction**

The high-resolution pediatric asthma indicators developed in Chapter 2 illustrate significant variation in the incidence and prevalence of pediatric asthma within and between different Kansas City communities. The way in which different combinations of modifiable exposures and structural conditions vary in relation to population health risk for pediatric asthma may provide insight into their cumulative effect on health, helping to identify targets for research and intervention strategies that meet the place-specific needs of over-burdened communities (DePriest and Butz 2017).<sup>44</sup> In the first part of this chapter, the Environmental Justice Screening Method (EJSM) is developed for census tracts in the Kansas City metropolitan core to capture both population health risk and vulnerability. These trial EJSM indicators are explored in a scanning exercise and descriptive analysis to preliminarily identify patterns in contextual factors that may be contributing to the rate of pediatric asthma acute care visits (ACVs) per capita (J. L. Sadd et al. 2011). In the second part of this chapter, the results of the scanning exercise and descriptive analysis are tested using a Bayesian Profile Regression (BPR) cluster analysis; a method for analyzing complex patterns in health risk from cumulative and combined exposure to multiple, correlated risk factors (Coker et al. 2016).

Pediatric asthma exacerbation has been linked to a wide range of social determinants of health (SDOH) and environmental risk factors, which are often correlated with one another (Salam, Islam, and Gilliland 2008; Ding, Ji, and Bao 2015). Evidence also suggests that social disadvantage may modify the effect of environmental exposure on health, making it difficult to identify the

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<sup>44</sup> ‘Modifiable exposures’ or risk factors can be thought of as the actionable components of the problem; things that may be directly affected by policy or other interventions (Arrandale et al. 2011). Structural conditions such as racism and poverty drive health inequities and the uneven distribution of related, modifiable risk factors (CSDH 2008). Refer to Chapter 1 for additional discussion of these concepts.



cumulative and combined effects of multiple stressors (Erickson and Arbour 2014; Hicken et al. 2012). The EJSM offers a means of exploring variation in the different types of vulnerabilities and risks potentially contributing to the observed disparity in pediatric asthma between socially disadvantaged and privileged communities. Furthermore, the EJSM data collection and processing spans multiple geographies and is derived from heterogeneous datasets, informing future data collection and research strategies to better represent both the victims and their environments. This exercise acts as a demonstration of concept and supports a highly localized, reproducible, community-based research and policy development strategy (J. L. Sadd et al. 2011).

The EJSM consists of three primary domains - Health Risk and Exposure (HRE), Social and Health Vulnerability (SHV), and Sensitive Land Use and Hazard Proximity (HAZ) - derived from a series of intermediate indicators related to health inequities. The census tract scores for each domain are estimated using publicly available census tract data collected by federal agencies. The HRE serves as an indication of ambient exposure to air pollution from diesel exhaust and health risk due to carcinogenic or respiratory hazards. The SHV domain is a general index of social disadvantage; population characteristics that suggest communities may be more vulnerable to inequitable health outcomes (Barkley et al. 2013). The primary HAZ domain is based on census tract indicators of the impact of local hazards on nearby sensitive receptors, capturing the intra-urban variation in cumulative risks that may not be represented in the HRE and SHV domains.

The EJSM methodology allows for the HAZ domain indicators to be developed for land use polygons, which can provide a detailed view of the combined indicator of exposure and vulnerability in the immediate context of the built environment. While the focus of this chapter is on regional patterns, trial, high-resolution HAZ domain indicators are developed for a sample of the full study area as a demonstration of concept and a reference for the quality and limitations of the primary census tract HAZ domain indicators.<sup>45</sup> The sample of high-resolution HAZ indicators is included in

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<sup>45</sup> The high-resolution, parcel HAZ domain indicators depend on a mix of local and regional datasets that were



the scanning exercise and descriptive analysis to gain insight into the distribution of local hazards and the availability of this type of data for both population- and patient-level analyses.

The three primary EJSM domains are then combined to produce a single, aggregate measure of cumulative impact at both the census tract and parcel geographies. Each domain and the cumulative impact indicator are explored through basic geographic inference and sample summaries in relation to the rate of pediatric asthma ACVs per capita to define the context of the inequity specific to different Kansas City communities. This exercise is followed by additional descriptive analyses to scan for aggregate patterns in the relationship between individual and composite measures of health risk, vulnerability, and pediatric asthma incidence rates.

A Bayesian Profile Regression (BPR) cluster analysis is developed in the second part of this chapter to explore the complex patterns in the relationships between intermediate EJSM measures and the rate of pediatric asthma ACVs per capita, both supplementing and enhancing the findings from the scanning exercise and descriptive analysis.<sup>46</sup> The BPR provides a means of identifying latent clusters within a sample based on both a covariate profile and a disease response submodel, using the patterns inherent in the data multicollinearity to identify specific combinations of risk factors associated with low-, average-, and high-risk groups (Barrera-Gómez et al. 2017; Molitor et al. 2010).<sup>47</sup> Furthermore, the BPR model permits the inclusion of a large number of highly correlated covariates; it can be

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not available for all municipalities in the Kansas City region at the time of this study, which is discussed in greater detail in the Materials and Methods section of this chapter.

<sup>46</sup> While the aggregate EJSM domain scores developed for the scanning exercise are helpful for communication with stakeholders and exploratory geographic inference of the cumulative impact from multiple risks and vulnerabilities, they can obscure important relationships between specific risk factors and health outcomes (Liverani, Lavigne, and Blangiardo 2016).

<sup>47</sup> Limitations in the most common statistical methods and available exposure data have obstructed progress toward analysis of the simultaneous effect of multiple chemical and nonchemical stressors important to understanding and reducing the burden of pediatric asthma (Egeghy et al. 2016). While multiple logistic regression analysis alone is useful for inferring the risk to individual patients in the sample, the difficulty in identifying the relative risk between groups based on a wide range of risk factors, and to assessing cumulative or joint exposures, make standard regression methods incompatible with the goals of this type of exploratory analysis (Mattei et al. 2016).

modified to suit time series, cohort, and case-control study designs; it is capable of producing results that can be easily interpreted, communicated to a large audience, and efficiently incorporated into policy (Pirani et al. 2015; Mattei et al. 2016; Papatthomas et al. 2011). This approach to identifying patterns in risk factors throughout the region and their association with specific disease outcomes is consistent with the EJSM methodology, providing a transparent means of testing the results of the scanning exercise and descriptive analysis. The results of the BPR cluster analysis are reported in a series of tables, figures, and maps that summarize the census tract clusters by their relative risk of asthma, their covariate profile, and their location within the region.

## **Materials & Methods**

### **Tools & Software**

R/RStudio (v. 1.1.447) and the Tidyverse (v. 1.2.1) packages were used for processing and summarizing data, and the PRemiuM R package was used for the BPR analysis and reporting (Wickham and RStudio 2014; Hastie, Liverani, and Richardson 2018). Spatial data collection and analysis was performed with Esri's ArcMap (v. 10.5.1) and ArcGIS Pro (v. 2.2.1) applications. ArcMap was used for a multi-ring buffer analysis and spatial data collection for the EJSM, and ArcGIS Pro was used for mapping both the final EJSM and BPR results.

### **Data & Study Area**

The primary SHV, HRE, and HAZ domains were developed for census tracts in the full study area, which includes Johnson and Wyandotte counties in Kansas, and Jackson and Clay counties in Missouri.<sup>48</sup> While the primary EJSM domains are based on publicly available, national datasets, the high-resolution HAZ domain indicators depend on land use data that is often collected and maintained by local governments, which results in significant differences in both the attribution - the type and detail of land use codes, for example - and spatial resolution of the data, depending on the

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<sup>48</sup> Refer to the incorporated places and counties base map A.2.1 in the Chapter 2 appendix.

source (Lobdell et al. 2011). Parcel records for Kansas City, MO (KCMO) and Wyandotte county, KS (WYCO) were the only land use datasets with consistent attribution and spatial resolution readily available to the author at the time of this study. Though this restricts the high-resolution HAZ domain indicators to census tracts mostly or completely within the boundaries of WYCO and KCMO, these parcel-level indicators provide insight into local variation in hazardous land use and possibilities for future CBPR to develop high-resolution HAZ estimates for the full study area. Furthermore, the trial development of the parcel HAZ domain guided a thorough review available data, which helped to inform the environmental exposure estimates used in the patient-level analysis in Chapter 4.

The period of interest is during or near 2012 for comparison with the asthma disparity indicators developed in Chapter 2. Certain EJSI indicator datasets were unavailable during this time period or were collected over a number of years and reported only intermittently. For example, the National Emissions Inventory (NEI) regulated facilities dataset – an intermediate indicator in the high-resolution HAZ domain – is only reported every three years (U.S. Environmental Protection Agency (EPA) 2019). In these cases, the best available data – the data published closest to the period of interest or that provided the most complete information – was selected for this study.

Census tracts are used as the primary geography to summarize population-level EJSI and asthma data. The census tract geography is the lowest level at which most EJSI indicator data is available and reliable, and they provide more granularity than other common geographies in health research – for example, counties and zip codes – but are still large enough that they can be distinguished from one another when mapped at the regional scale.<sup>49</sup> Furthermore, the size of census tracts is determined in part by population, which provides a visual aid for comparing the distribution of EJSI indicators in urban, suburban, and rural communities with different population densities

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<sup>49</sup> Standard geographies used in health data analyses like counties and zip codes do not capture the spatial distribution of many important risk factors associated with childhood asthma, which can lead to a significant loss of information and the introduction of error to multi-level statistical models (Pickle, Waller, and Lawson 2005).

(U.S. Census Bureau 2012).

Census tracts with fewer than 50 people were eliminated from the sample to reduce error in relative census tract rankings based on intermediate EJSM domain indicators, particularly the SHV indicators derived from American Community Survey (ACS) 5-year estimates. Exclusion based on low-population estimates is in line with the standard EJSM methodology and similar publications (Schulz et al. 2016). Finally, the EJSM study area was restricted to exclude Platte County, MO census tracts because pediatric asthma data was unavailable for this area at the time of the study. As in Chapter 2, the spatial analysis and discussion will reference the community district and Troost Ave. geographies.<sup>50</sup>

### **Indicator Specification**

The objective of the EJSM is to create consistent indicators of risk and vulnerability. The data selected for each domain was based on the standard EJSM methodology, with modifications and substitutions where data was unavailable or to represent locally relevant indicators. Following the standard EJSM methodology, census tracts were assigned a quintile rank ( $R$ ) for the intermediate indicators,  $i$ , within each EJSM domain,  $D_x$ , which were summed to produce an *overall domain score*,  $OS_{D_x}$ :

$$OS_{D_x} = \sum_{i=1}^{n_x} R(D_{xi})$$

Census tracts were then assigned a quintile rank based on the overall score for each domain to produce the *final domain score*,  $FS_{D_x}$ . This simple scoring method indicates the degree of impact for each composite measure of risk and vulnerability, with values ranging from 1 (low impact) to 5 (high impact).

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<sup>50</sup> Refer to the community district base map A.2.2 in the Chapter 2 appendix.

### ***Pediatric Asthma Acute Care Visits (ACV) per Capita***

The census tract pediatric asthma incidence rate and prevalence estimates developed in Chapter 2 provide high-resolution indicators rarely available for population health disparities research (D. C. Lee et al. 2017). The rate of pediatric asthma ACVs per capita is used as the primary indicator for exploring the association between the EJSM domains and pediatric asthma because it is a relatively consistent and general indicator, providing a measure of population-level healthcare utilization associated with racial disparities in pediatric asthma (Keet et al. 2017). Census tracts in the EJSM study area were assigned a quintile rank for the rate of pediatric asthma ACVs per capita in 2012, which is used to group the descriptive statistics for raw, intermediate indicator values in each EJSM domain, described below.

### ***Social & Health Vulnerability (SHV) Domain***

The Social and Health Vulnerability (SHV) domain consists of 8 intermediate indicators, detailed in table 3.1. These indicators are generally consistent with the original EJSM model specification for the SHV domain, excluding voter turnout and birth outcomes data, which were not readily available at the census tract level for the full sample of census tracts at the time of this study.

Table 3.1. Social and Health Vulnerability (SHV) Domain Data<sup>51</sup>

Indicator	Apportionment Type
Percent of the Population Identified as Racial or Ethnic Minority	Population
Percent of the Population Living Below Twice the National Poverty Level	Population
Percent of the Population Living in Renter Occupied Housing Units	Population
Median Home Value	Housing Units
Percent of the Population Age 25 and Over without a High School Diploma or Equivalent	Population
Percent of the Population Age 5 and Under	Population
Percent of the Population Age 60 and Over	Population
Percent of Households with Language Isolation	Households

*Source:*

U.S. Census Bureau. 2012-2016 American Community Survey (ACS) 5-Year Estimates. ACS 5-year estimates become available in December of the year following the calendar year of the data. ACS (2012-2016) 5-year estimates were released December 7 2017. Distributed by mySidewalk, Inc. Accessed May 6, 2018. <https://www.census.gov/programs-surveys/acs/>.

***Health Risk & Exposure (HRE) Domain***

The Health Risk and Exposure (HRE) domain consists of three indicators of potential health risk from environmental pollution, summarized in table 3.2. Two of the intermediate HRE indicators are derived from the EPA’s National Air Toxics Assessment (NATA), capturing relative respiratory hazard and cancer risk for residents in the study area census tracts. The third indicator, Diesel Particulate Matter (PM) (ug/m<sup>3</sup>) was selected as a relevant pollutant measure for the Kansas City region given significant freight traffic from both railroads and highways.<sup>52</sup>

<sup>51</sup> The median home value indicator was multiplied by -1 before ranking the census tracts so that higher median home value estimates are associated with a lower impact score and vice versa.

<sup>52</sup> Kansas City is the nation’s second largest rail transportation center (Missouri Department of Transportation (MODOT) 2013).

Table 3.2. Health Risk & Exposure (HRE) Domain Data

Indicator	Apportionment and Aggregation	Source
<b>Air Quality: Respiratory Hazard Index (2011)</b>	Population-weighted block apportionment	Environmental Protection Agency. National Air Toxics Assessment: Modeled Ambient Concentrations, Exposures, and Risks. 2011. Published Dec 17, 2015. <a href="https://www.epa.gov/national-air-toxics-assessment">https://www.epa.gov/national-air-toxics-assessment</a> . Distributed by mySidewalk, Inc. Accessed May 6, 2018.
<b>Air Quality: Individual Lifetime Cancer Risk (2011)</b>	Population-weighted block apportionment	Environmental Protection Agency. National Air Toxics Assessment: Modeled Ambient Concentrations, Exposures, and Risks. 2011. Published Dec 17, 2015. <a href="https://www.epa.gov/national-air-toxics-assessment">https://www.epa.gov/national-air-toxics-assessment</a> . Distributed by mySidewalk, Inc. Accessed May 6, 2018.
<b>Diesel Particulate Matter (ug/m<sup>3</sup>) (2011)</b>	Aggregated to geography through population-weighted averaging	Environmental Protection Agency. Environmental Justice Mapping and Screening Tool. Distributed by mySidewalk, Inc. Accessed May 6, 2018.

***Sensitive Land Use & Hazard Proximity (HAZ)***

Two versions of the Sensitive Land Use and Hazard Proximity (HAZ) domain were developed for the EJSM scanning exercise and descriptive analysis: a primary HAZ domain and a high-resolution HAZ domain. The primary HAZ domain was derived from census tract datasets available for the full study area, while the high-resolution HAZ domain was developed from parcel land use and address-level environmental data to estimate the impact of local hazards on nearby sensitive receptors, in this case residential parcels. Given the limited availability of consistent, high-resolution land use data throughout the Kansas City region, the focus of this analysis is on the primary HAZ domain, which is explored in both the scanning exercise and the BPR analysis for census tracts in the full study area.<sup>53</sup> The high-resolution HAZ domain indicators were developed to

<sup>53</sup> Results from Chapter 2 suggest important patterns in pediatric asthma in Johnson County, Kansas (JOCO) and Clay County, MO, where communities burdened by high rates of pediatric asthma may face a distinct set of risks and vulnerabilities compared with urban core residents. Including data for the full study area in the EJSM scanning exercise, descriptive analysis, and BPR may improve results, providing information about the combination of structural conditions and modifiable risk factors contributing to pediatric asthma exacerbation in each place.

supplement the scanning exercise and descriptive analysis, providing insight into local variation in environmental risk not captured by the census tract data used in the primary HAZ domain.

*Primary HAZ Domain Indicators*

The primary HAZ domain is based on census tract proxies for the high-resolution HAZ indicators referenced in the original EJSM publication, which are described below (J. L. Sadd et al. 2011). Proxy indicators were used to expand the sample to include the full study area, where the high-resolution HAZ indicators were only available for KCMO and WYCO at the time of this study. Each primary HAZ domain indicator listed in table 3.3 is based on population or housing units, providing information about where people live and different types of potential exposure to point source and traffic-related land use hazards.<sup>54</sup>

Table 3.3. Primary Sensitive Land Use and Hazard Proximity (HAZ) Domain Data

Indicator	Unit of Measurement	Source
<b>Proximity to Risk Management Plan (RMP) Sites</b>	Number of Sites per Kilometer from the Average Person	Environmental Protection Agency. EJSCREEN. 2016. Distributed by mySidewalk, Inc. Accessed May 6, 2018.
<b>Proximity to Treatment Storage and Disposal (TSD) Facilities</b>	Number of Sites per Kilometer from the Average Person	Environmental Protection Agency. EJSCREEN. 2016. Distributed by mySidewalk, Inc. Accessed May 6, 2018.
<b>Traffic Proximity and Volume</b>	Annual Average Daily Traffic per Kilometer	Environmental Protection Agency. EJSCREEN. 2016. Distributed by mySidewalk, Inc. Accessed May 6, 2018.
<b>Walkability Proximity to Transit Ranking</b>	Index Range: 1-20	Environmental Protection Agency. National Walkability Index. 2010-2012. Published December 23, 2015. <a href="https://www.epa.gov/smartgrowth/smart-location-mapping">https://www.epa.gov/smartgrowth/smart-location-mapping</a> . Distributed by mySidewalk, Inc. Accessed May 6, 2018.

*Note:*  
All indicators were aggregated to the census tract geography by population-weighted averaging, according to the mySidewalk, Inc. data library.

<sup>54</sup> Note that the primary HAZ domain indicators were not pre-defined by the standard EJSM methodology and instead were selected as a demonstration of concept and exploratory exercise. Future research should review the options for primary census tract HAZ domain indicators available for the full study area, ideally consulting local advocates and stakeholders through community-based participatory research (CBPR).



### *High-Resolution HAZ Domain Indicators*

The high-resolution HAZ domain was designed to capture intra-urban variation in local hazardous land use that may pose a health risk. Multiple datasets were collected and integrated to generate a high-resolution HAZ domain score for residential parcels in KCMO and WYCO, which are outlined in table 3.4. All data processing steps were documented so they can be revised and improved by local stakeholders and advocates through community-based participatory research (CBPR) according to the EJSM methodology. The data processing steps are described in detail in the supplemental materials provided at the end of this chapter.

Table 3.4. High-resolution HAZ domain data

Indicator	Feature	Source
<b>Residential Land Use Parcels</b>	Polygon	City of Kansas City, Missouri. Parcel Land Use Data. Accessed October 7, 2017. <a href="http://maps.kcmo.org/apps/parcelviewer/">http://maps.kcmo.org/apps/parcelviewer/</a> .
	Polygon	Unified Government of Wyandotte County. Parcel Land Use Data. 2010. Distributed by the UMKC Center for Economic Information. Accessed October 7, 2017.
<b>Hazardous Land Use - General</b>	Polygon	City of Kansas City, Missouri. Parcel Land Use Data. Accessed October 7, 2017. <a href="http://maps.kcmo.org/apps/parcelviewer/">http://maps.kcmo.org/apps/parcelviewer/</a> .
	Polygon	Unified Government of Wyandotte County. Parcel Land Use Data. 2010. Distributed by the UMKC Center for Economic Information. Accessed October 7, 2017.
<b>Hazardous Land Use - Railroads</b>	Polygon	United States Bureau of Transportation Statistics. National Transportation Atlas Database: 2011. Accessed October 7, 2017. <a href="https://doi.org/10.21949/1502424">https://doi.org/10.21949/1502424</a> .
	Polygon	City of Kansas City, Missouri. Parcel Land Use Data. Accessed October 7, 2017. <a href="http://maps.kcmo.org/apps/parcelviewer/">http://maps.kcmo.org/apps/parcelviewer/</a> .
	Polygon	Unified Government of Wyandotte County. Parcel Land Use Data. 2010. Distributed by the UMKC Center for Economic Information. Accessed October 7, 2017.
<b>Regulated Facilities</b>	Point	U.S. Environmental Protection Agency. 2011 National Emissions Inventory Point Data. Accessed October 7, 2017. <a href="https://www.epa.gov/air-emissions-inventories/2011-national-emissions-inventory-nei-data">https://www.epa.gov/air-emissions-inventories/2011-national-emissions-inventory-nei-data</a> .
<b>Intermodal Terminal Facilities</b>	Point	United States Bureau of Transportation Statistics. National Transportation Atlas Database: 2011. Accessed October 7, 2017. <a href="https://doi.org/10.21949/1502424">https://doi.org/10.21949/1502424</a> .
<b>Railroad Nodes</b>	Point	United States Bureau of Transportation Statistics. National Transportation Atlas Database: 2011. Accessed October 7, 2017. <a href="https://doi.org/10.21949/1502424">https://doi.org/10.21949/1502424</a> .
<b>Railroad Lines</b>	Line	Mid-America Regional Council. Street Centerline Geography for the Kansas City Metropolitan Area. 2015. Distributed by the UMKC Center for Economic Information. Accessed October 7th, 2017.
<b>Highways &amp; Freeways (Federal Functional Classification = 1 2)</b>	Line	U.S. Department of Transportation Federal Highway Administration. 2011 Highway Performance Management System (HPMS) Data. Accessed March 15, 2018. <a href="https://www.fhwa.dot.gov/policyinformation/hpms/shapefiles.cfm">https://www.fhwa.dot.gov/policyinformation/hpms/shapefiles.cfm</a> .

The cleaned set of intermediate indicators were used in a multi-ring buffer analysis and distance weighting procedure to estimate the overall high-resolution HAZ score for residential parcels. This methodology was based on regulatory standards and designed with stakeholder input for the original EJSM publication (J. L. Sadd et al. 2011; California Air Resources Board 2005). First, three 1,000ft buffers were generated around the edge of every residential land use parcel identified in KCMO and WYCO. A distance weight was then applied to the count of hazards intersecting with each buffer: the count of hazards in the first buffer from 0-1000ft was weighted by 1; the count of

hazards in the second buffer from 1000ft-2000ft was weighted by 0.5; the count of hazards in the third buffer from 2000ft-3000ft was weighted by 0.10. The distance-weighted hazard counts for all three buffers were summed to estimate the overall HAZ score for each residential parcel in the sample.<sup>55</sup>

Block group housing occupancy data from the 2010 Decennial Census was used to weight the overall HAZ score assigned to each residential parcel to account for the variation in housing occupancy within and between different communities, incorporating an additional indicator of relative vulnerability into the high-resolution HAZ estimates. A quintile rank was then assigned to the residential parcels based on the overall occupancy- and distance-weighted high-resolution HAZ score to map the indicators for the scanning exercise.

The final step was to aggregate the parcel-level HAZ scores to the census tract geography for comparison with the primary EJSM domains and asthma incidence rates in the scanning exercise and descriptive analysis. The residential parcels were assigned a census tract geographic identifier to calculate the average overall parcel HAZ score within each census tract. This average was used to assign a quintile rank to census tracts in the KCMO and WYCO sample to estimate the final high-resolution HAZ domain score.

### ***Cumulative Impact***

A cumulative impact (CI) score was assigned to census tracts in the full study area by summing the final scores in each of the three primary EJSM domains:

$$CI = \sum_{x=1}^3 FS_{D_x}$$

Where:

$FS_{D_1}$  = *Health Risk and Exposure (HRE) Domain*

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<sup>55</sup> An illustration of the multi-ring buffer analysis and distance weighting procedure is published in figure 2 of the original EJSM publication (J. L. Sadd et al. 2011, 1448).

$FS_{D_2}$  = Social and Health Vulnerability (SHV) Domain

$FS_{D_3}$  = Sensitive Land Use and Hazard Proximity (HAZ) Domain

This produced a census tract CI indicator ranging from 1 (low cumulative impact) to 15 (high cumulative impact).

### **BPR Model Specification**

A Bayesian Profile Regression (BPR) analysis is used in this chapter to explore the complex patterns in the relationship between pediatric asthma and the EJSM measures of risk and vulnerability for census tracts throughout the full study area. The BPR model uses a non-parametric Dirichlet Process Mixture Model in a Bayesian framework, which is founded on a global perspective, “where inference is based on clusters representing covariate patterns as opposed to individual risk factors”(Molitor et al. 2010, 485). Through Markov Chain Monte Carlo (MCMC) sampling, this model approach produces a “best” partition of clusters – the most likely clustering of individuals given repeated sampling and the measured uncertainty associated with individual cluster assignment at each sweep. In contrast to traditional cluster analysis, the BPR does not require that an arbitrary number of clusters be defined in advance, instead allowing the number of clusters to vary. The posterior distributions of each cluster, or ‘risk profiles’, in the best partition can then be used to assess whether the groups are high- or low- risk relative to the average, and to identify patterns in the covariate characteristics relative to the risk of health outcomes (Molitor et al. 2010).

The following represents the likelihood for the full profile regression model, with  $f_Y$  as the response model, and  $f_X$  the covariate model:

$$p(D_i|Z_i, \Theta, \Lambda, W_i) = f_Y(y_i|\Theta_{Z_i}, \Lambda, W_i)f_X(x_i|\Theta_{Z_i}, \Lambda)$$

Where:

$D = (Y, X)$ , such that the data contain information for both a response,  $Y_i$ , and covariates  $X_i$  for each individual,  $i$

$Z_i$  is a cluster allocation variable  
 $\Theta_{Z_i}$  is a cluster specific vector of parameters  
 $\Lambda$  is a vector of global parameters  
 $W_i$  are fixed effects for each individual<sup>56</sup>

**Covariate Model,  $f_X$ :**

The covariate model,  $f_X$ , is based on the ‘discrete mixtures’ model specified by Liverani et al. (2015). The covariate profile consists of the census tract scores – or quintile rank – for the intermediate indicators in the primary EJSM domains, which are treated as categorical variables with five categories. In this case, for each individual,  $i$ ,  $D_i = X_i$  is a vector of discrete categorical random variables,  $j = 1, 2, \dots, J$ , assumed to be locally independent with  $K_j$  number of categories per covariate, and with the parameter vector rewritten as  $\Theta_c = \Phi_c = \Phi_{c,1}, \Phi_{c,2}, \dots, \Phi_{c,J}$ , and  $\Phi_{c,j} = \phi_{c,j,1}, \phi_{c,j,2}, \dots, \phi_{c,j,K_j}$ , the model can be specified:

$$p(D_i | Z_i, \Theta_{Z_i}, \Lambda) = f(D_i | \Phi_{Z_i}) = \prod_{j=1}^J \phi_{Z_i, j, X_{i,j}}^{57}$$

In the context of discrete categorical random variables,  $\Theta_0 = a = (a_1, a_2, \dots, a_J)$  where  $j = 1, 2, \dots, J$ , the parameter can be written  $a = (a_{j,1}, a_{j,2}, \dots, a_{j,K_j})$  with conjugate Dirichlet priors,  $\phi_{c,j} \sim \text{Dirichlet}(a_j)$ . The conjugate priors adopted for the discrete covariates allow the Gibbs sampler to directly update the distribution parameters associated with either active clusters ( $A$ ) or potential clusters ( $P$ ).<sup>58</sup>

**Response Model,  $f_Y$ :**

The response is the rate of pediatric asthma ACVs per capita by census tract in 2012, which is

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<sup>56</sup> No fixed effects,  $W_i$ , were included in this version of the BPR model.

<sup>57</sup> See the original PReMiuM package publication for details (Liverani, Hastie, and Richardson 2015, 12).

<sup>58</sup> Following the PReMiuM package documentation, no global parameters,  $\Lambda$ , were specified for the covariate model.

modeled as a continuous variable. The global parameter vector  $\Lambda$  contains both  $\beta$  and  $\sigma_Y^2$  to produce the Gaussian response likelihood:

$$f_Y(y_i | \Theta_{Z_i}, \Lambda, W_i) = p(Y_i | \theta_{Z_i}, \beta, \sigma_Y^2, W_i) = \frac{1}{\sqrt{2\pi\sigma_Y^2}} \exp \left\{ -\frac{1}{2\sigma_Y^2} (Y_i - \lambda_i)^2 \right\}$$

where  $\lambda_i = \theta_{Z_i} + \beta^T W_i$ . For  $\theta_c$  and  $\beta$ , the prior models are specified as t-location distributions with a default specification of 7 degrees of freedom, and  $Gamma(s_{\tau_Y}, r_{\tau_Y})$  is included as a conjugate prior on  $\tau_Y = 1/\sigma_Y^2$ .<sup>59</sup>

### ***Variable Specification***

The full BPR model consists of 16 variables, formally specified as follows:

*Dependent Variable,  $y_i$ :*

$y_i$  Pediatric acute care visits (ACVs) per capita by census tract in 2012

*Categorical Discrete Covariates,  $D_i$* <sup>60</sup>:

#### **Sensitive Land Use and Hazard Proximity (HAZ)**

$x_{i1}$  Traffic proximity and volume (annual average daily traffic per kilometer)

$x_{i2}$  Proximity to Risk Management Plan sites (number of sites per kilometer from the average person)

$x_{i3}$  Proximity to treatment, storage, and disposal facilities (number of sites per kilometer from the average person)

$x_{i4}$  Walkability Proximity to Transit Ranking (EPA Walkability Index)

#### **Health Risk and Exposure (HRE)**

$x_{i5}$  Individual Lifetime Cancer Risk

$x_{i6}$  Diesel Particulate Matter in Air ( $\mu\text{g}/\text{m}^3$ )

$x_{i7}$  Respiratory Hazard Index

<sup>59</sup>  $s_{\tau_Y}$  is the shape hyperparameter, and  $r_{\tau_Y}$  is the rate hyperparameter (Liverani, Hastie, and Richardson 2015, 12).

<sup>60</sup> See tables 3.1-3.3 in the Indicator Specification section of this chapter for the full data source information for each intermediate EJS domain indicator.

## Social and Health Vulnerability (SHV)

- $x_{i8}$  Median home value
- $x_{i9}$  Percent of the population age 24 and over without high school diploma or equivalent
- $x_{i10}$  Percent of the population living in linguistically isolated households
- $x_{i11}$  Percent of the population living at or below 200% of the federal poverty level
- $x_{i12}$  Percent of the population identified as minority
- $x_{i13}$  Percent of the population living in renter occupied housing units
- $x_{i14}$  Percent of the population age 6 and under
- $x_{i15}$  Percent of the population age 60 and over

## Results

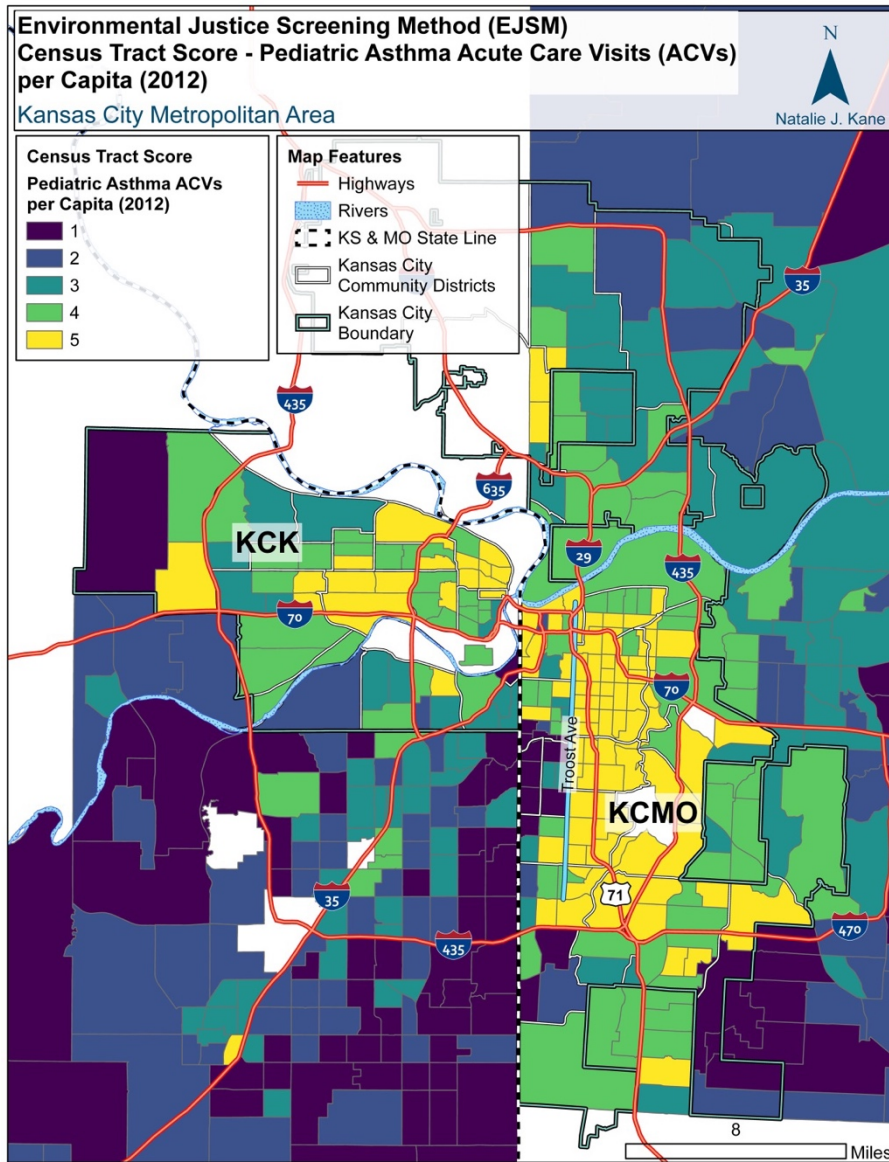
### Scanning Exercise & Descriptive Analysis

Map 3.1 shows the EJSM study area census tracts ranked from 1 to 5 by the rate of pediatric asthma ACVs per capita in 2012, which is used as a reference for exploring the association between the EJSM domains and pediatric asthma in both the scanning exercise and descriptive analysis.<sup>61</sup>

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<sup>61</sup> Map 2.2 in Chapter 2 shows the raw rate of pediatric asthma ACVs in 2012 for census tracts throughout the full study area.

Map 3.1. The Rate of Pediatric Asthma Acute Care Visits (ACVs) per Capita – Census Tract Score

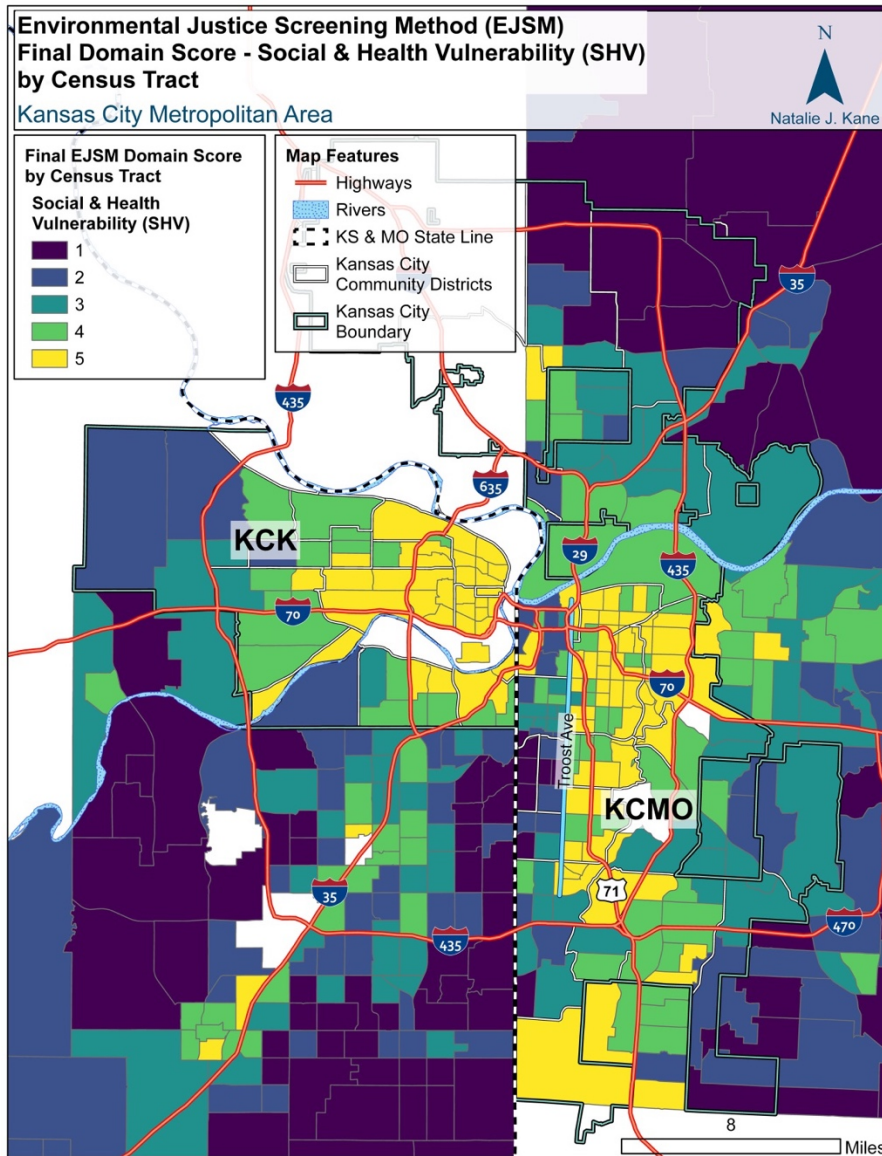


***Racial Residential Segregation and the SHV Domain***

Patterns in SHV scores symbolized in map 3.2 suggest a strong relationship between asthma and social disadvantage consistent with historic racial residential segregation. The patterns also mirror Chapter 2 findings of hot spots in pediatric asthma along the I-35 corridor in JOCO.



Map 3.2. Social & Health Vulnerability (SHV) – Census Tract Score



The summary statistics in table 3.5 validate these observations, particularly with respect to the intermediate SHV indicators including the percent minority, the percent without a high school diploma or equivalent degree, the percent below 200% poverty, median home value, and the percent of the population in renter occupied households. The SHV results also support the findings from Chapter 2 and recent literature that both housing quality and stability may be relevant and modifiable risk factors in historically segregated Kansas City neighborhoods burdened by high rates of severe

pediatric asthma (Hughes et al. 2017).<sup>62</sup>

Table 3.5. SHV Indicators Summarized by the Census Tract Score for the Rate of Pediatric ACVs per Capita

	All Tracts	1	2	3	4	5
<b>Population Age Under 5 (%)</b>						
mean (sd)	6.92 (3.08)	5.93 (2.89)	6.71 (2.59)	6.60 (2.14)	7.78 (3.53)	7.57 (3.69)
min	0.0	0.0	0.0	1.4	0.6	0.0
max	22.0	22.0	14.8	10.4	19.2	20.3
<b>Population Age 60+ (%)</b>						
mean (sd)	18.81 (7.00)	21.27 (8.73)	18.56 (6.77)	19.36 (7.35)	17.11 (5.55)	17.75 (5.47)
min	3.2	5.1	5.9	7.2	6.2	3.2
max	48.3	48.3	36.0	46.0	35.2	29.1
<b>Minority Population (%)</b>						
mean (sd)	36.32 (27.74)	14.32 (8.88)	18.35 (9.20)	25.71 (14.85)	48.53 (22.05)	75.15 (20.53)
min	0.0	0.0	2.1	3.7	10.0	20.6
max	99.4	57.6	45.4	88.2	98.0	99.4
<b>Population Age 25+ Without HS Diploma or Equivalent (%)</b>						
mean (sd)	11.05 (10.50)	3.69 (5.20)	6.04 (4.82)	9.38 (7.90)	17.29 (12.88)	18.92 (9.68)
min	0.0	0.0	0.7	0.6	0.4	1.1
max	55.5	43.1	28.1	54.3	55.5	42.6
<b>Household Language Isolation (%)</b>						
mean (sd)	3.14 (5.21)	0.86 (1.19)	1.81 (2.69)	2.54 (3.40)	6.77 (8.71)	3.71 (4.46)
min	0.0	0.0	0.0	0.0	0.0	0.0
max	33.5	6.5	11.3	19.4	33.5	16.8
<b>Ratio of Income to Poverty Level: 200% and Under (Low Income) (%)</b>						
mean (sd)	33.94 (21.46)	13.98 (10.30)	21.31 (12.72)	30.95 (15.26)	46.24 (17.11)	57.50 (15.73)
min	1.4	1.4	2.5	5.4	12.8	15.2
max	89.8	67.8	55.2	73.7	82.6	89.8
<b>Population in Renter-Occupied Housing Units (%)</b>						
mean (sd)	37.09 (21.46)	19.69 (15.75)	27.18 (18.99)	37.14 (18.24)	45.91 (17.04)	55.76 (16.03)
min	0.0	0.0	1.9	1.3	8.5	5.3
max	94.2	78.0	89.8	88.3	89.2	94.2
<b>Median Home Value (USD)</b>						
mean	157,968	266,042	192,894	146,508	103,191	80,300
min	9,999	75,000	66,300	47,200	9,999	19,300
max	870,200	870,200	523,100	295,900	246,100	228,900

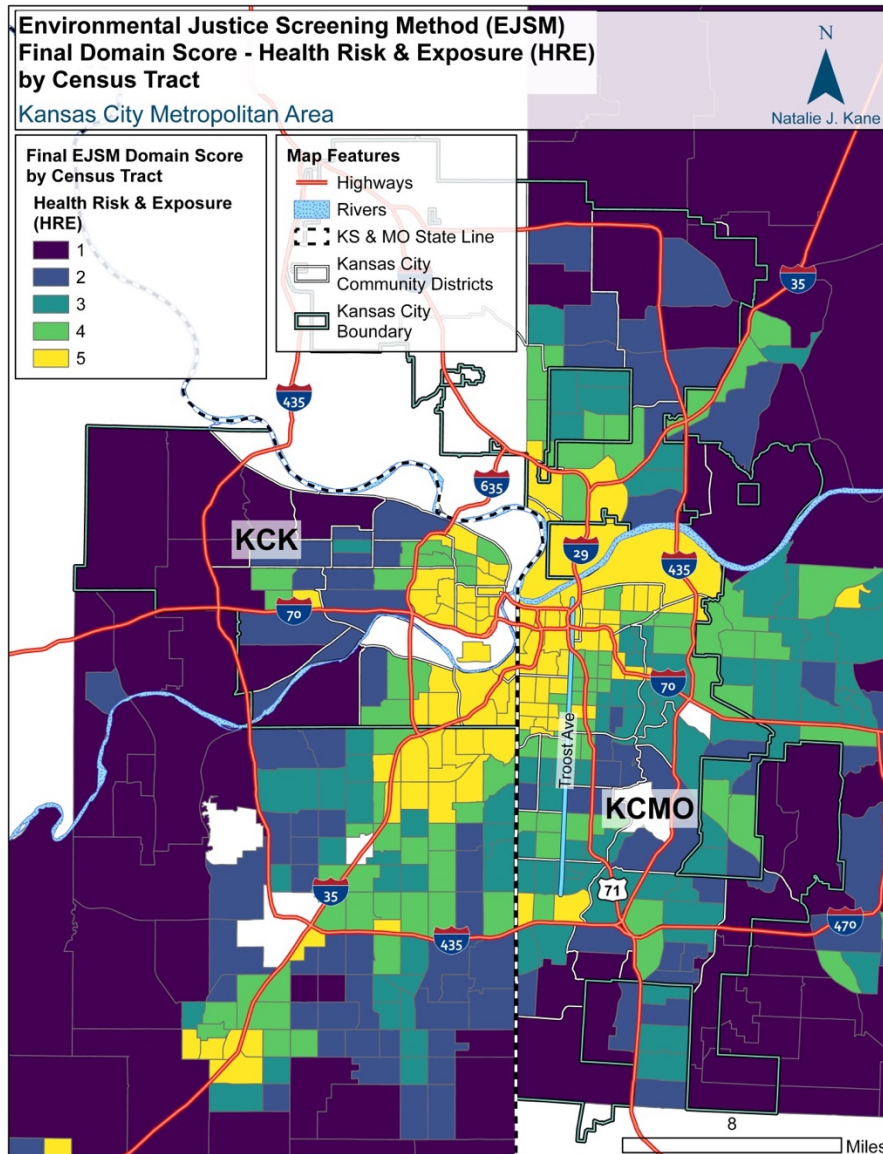
### *Historic Industrial Development and the HRE Domain*

Patterns in the HRE domain scores symbolized in map 3.3 suggest elevated exposure to ambient environmental pollution and health risk in neighborhoods with a concentration of industrial

<sup>62</sup> The relationship between pediatric asthma, housing quality, and housing stability will be explored in greater detail in the patient-level analysis, reported in Chapter 4.

and transportation infrastructure, some of which also exhibit elements of social disadvantage and relatively high rates of pediatric asthma ACVs per capita.<sup>63</sup>

Map 3.3. Health Risk & Exposure (HRE) – Census Tract Score



<sup>63</sup> The Chapter 3 appendix maps A.3.1-A.3.3 provide examples of the spatial distribution of industry and transportation infrastructure throughout the full study area.

In KCMO, the impact of HRE factors is largely concentrated in the Old Northeast, Northeast Industrial, Greater Downtown, and Midtown community districts. Similarly, all of the community districts east of or bordering I-635 in WYCO exhibit concentrations of relatively high HRE scores, as do different places in northeast JOCO, particularly along the I-35 corridor. Other census tracts with elevated scores for the HRE domain suggest that the type of risk and source of pollutant exposure is dependent on place-specific industry. While there is some overlap, there is no consistent relationship between the distribution of HRE scores and historic racial residential segregation in map 3.3. The aggregate descriptive statistics in table 3.6, however, do suggest a general increase in the mean levels for cancer risk and diesel particulate matter (PM) as the risk of asthma increases.

Table 3.6. HRE Indicators Summarized by the Census Tract Score for the Rate of Pediatric ACVs per Capita

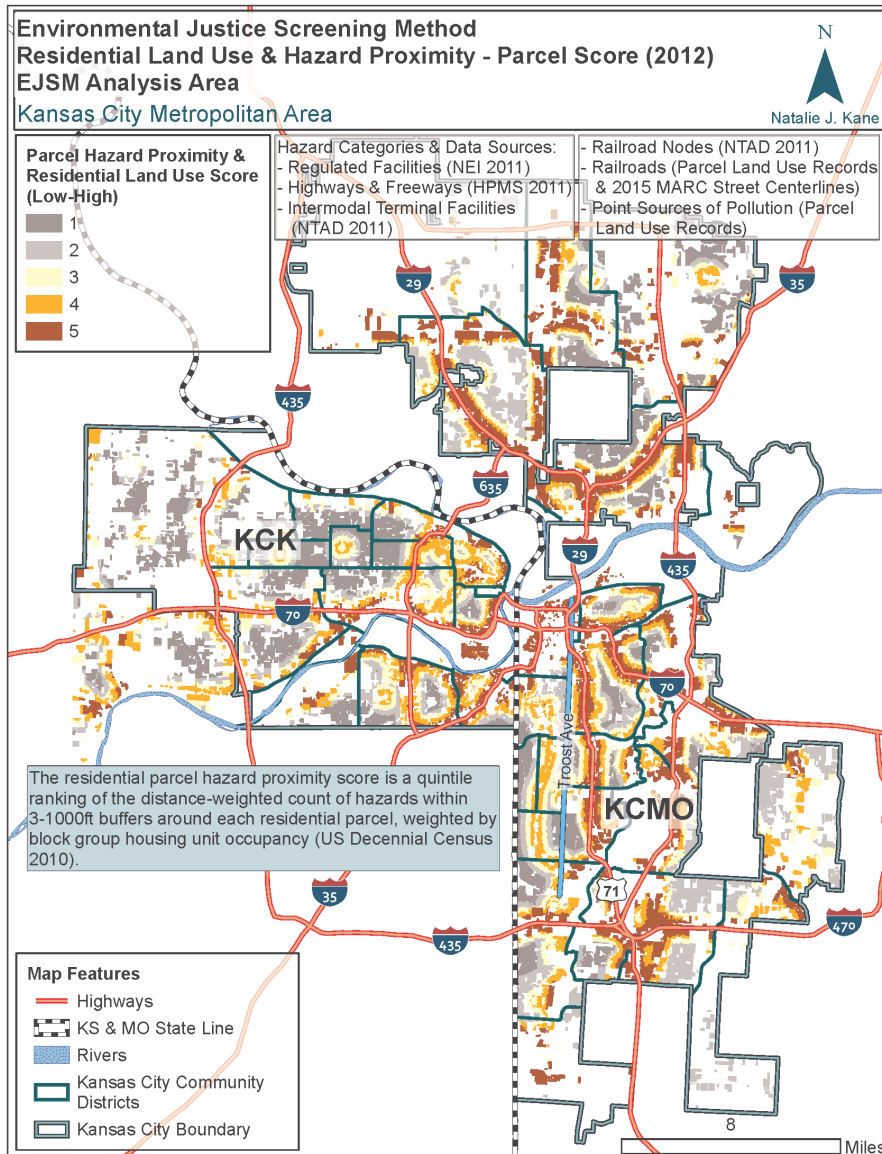
	All Tracts	1	2	3	4	5
<b>Air Quality: Individual Lifetime Cancer Risk</b>						
mean (sd)	45.1 (5.2)	42.8 (5.4)	42.9 (4.5)	46.0 (5.7)	46.7 (4.1)	47.2 (4.5)
min	34.1	35.1	34.1	35.9	37.1	37.4
max	72.3	68.6	57.2	72.3	61.5	66.8
<b>Air Quality: Respiratory Hazard Index</b>						
mean (sd)	2.0 (0.5)	1.9 (0.7)	1.9 (0.3)	2.1 (0.5)	2.1 (0.3)	2.1 (0.3)
min	1.2	1.3	1.2	1.3	1.4	1.4
max	7.9	7.9	3.0	4.3	3.6	3.5
<b>Diesel Particulate Matter Level in Air (ug/m<sup>3</sup>)</b>						
mean (sd)	1.2 (0.5)	0.9 (0.4)	1.0 (0.4)	1.2 (0.5)	1.3 (0.5)	1.4 (0.6)
min	0.4	0.4	0.6	0.5	0.6	0.6
max	4.7	2.9	3.7	4.2	3.5	4.7

### ***Local Environmental Hazards and Transportation Infrastructure in the HAZ Domain***

#### *High-Resolution HAZ Domain Indicators*

The high-resolution HAZ scores for residential parcels in map 3.4 suggest that transportation may be the dominant source of local exposure to environmental hazards in KCMO and WYCO.

Map 3.4. High-Resolution HAZ Domain – Census Tract Score



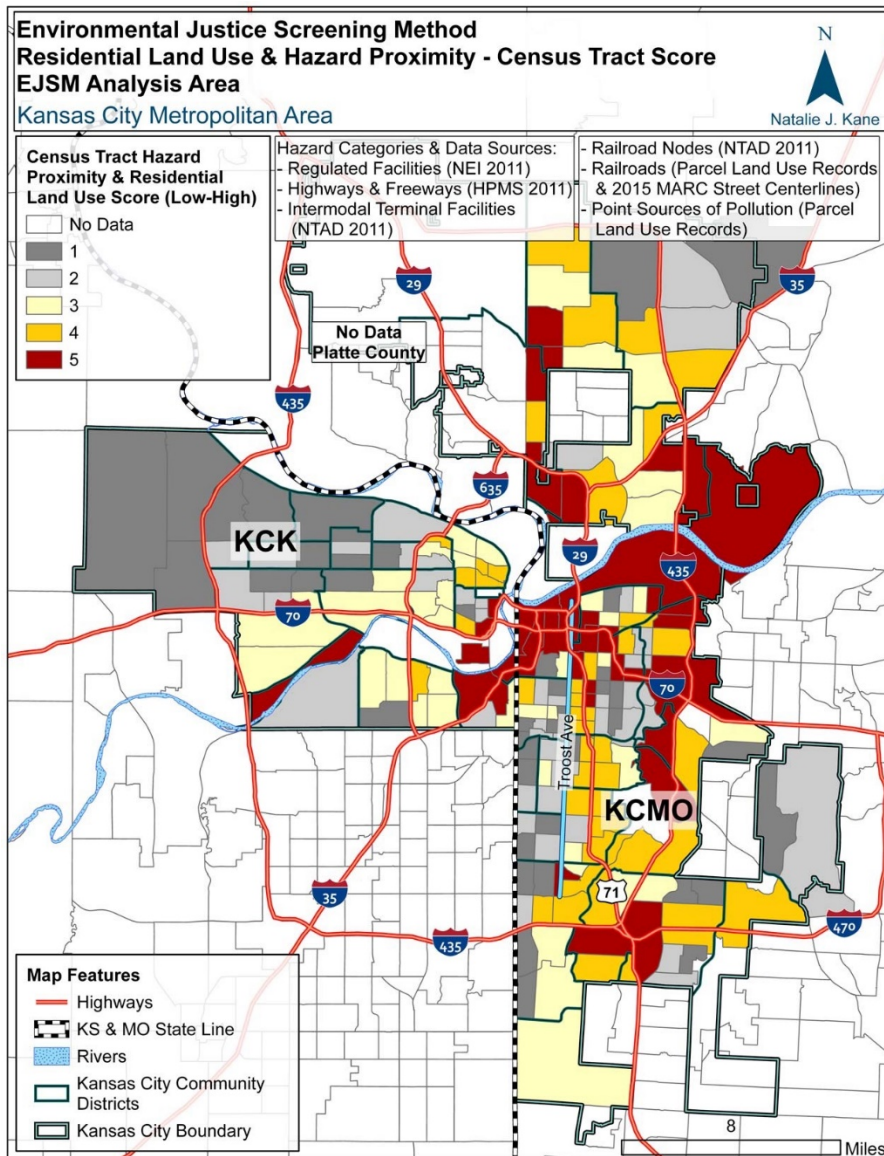
There is also significant variation in the type and degree of exposure for residents in many socially disadvantaged neighborhoods that is not captured by the HRE domain. For example, point sources of pollution may be prominent in certain communities like the Bethel community district of WYCO, while transportation features may act as the primary source of residential exposure to hazards in community districts such as Brookside and Brush Creek South in KCMO. Other community districts are characterized by patterns of exposure to both transportation and point source hazards,



most notably the Shawnee Heights and Northeast community districts in WYCO, which is generally consistent with the distribution of HRE scores for these areas in map 3.3.

The parcel high-resolution HAZ scores aggregated to the census tract geography are symbolized in map 3.5. Like the parcel HAZ domain map, patterns in map 3.5 indicate that transportation is a dominant hazardous land use feature throughout the EJSM study area, particularly in areas like the community districts east of Troost Ave. in KCMO, which are divided by 71 Highway.

Map 3.5. High-Resolution HAZ Domain – Census Tract Score



Distinct patterns also emerge in the Old Northeast community district in KCMO, where there appear to be concentrations of both high HAZ scores and a high rate of pediatric asthma ACVs per capita around the edges of the community district, with heavier concentrations of exposure and inequity in the northeast corner. These spatial patterns in the high-resolution HAZ domain indicators and asthma, however, are not reflected in the table 3.7 summary statistics for census tracts in the KCMO and WYCO sample.

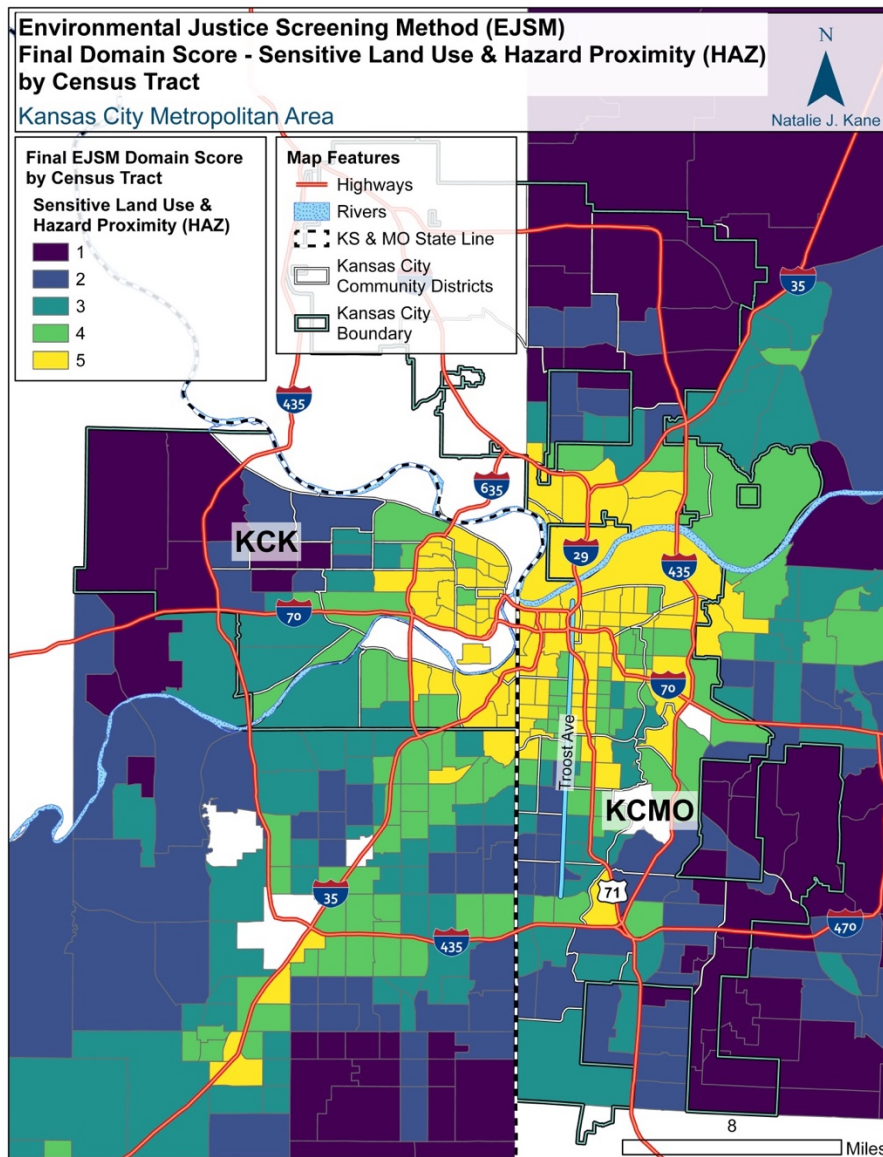
Table 3.7. Census Tract High-Resolution HAZ Domain Indicators Summarized by the Census Tract Score for the Rate of Pediatric ACVs per Capita

	All Tracts	1	2	3	4	5
<b>Overall</b>						
mean (sd)	2.5 (3.3)	1.8 (3.5)	2.4 (2.1)	2.4 (3.4)	3.4 (4.5)	2.6 (2.8)
min	0.0	0.0	0.0	0.0	0.0	0.0
max	20.6	20.6	9.6	18.2	19.9	15.1
<b>Land Use</b>						
mean (sd)	0.4 (0.8)	0.2 (0.4)	0.7 (1.4)	0.3 (0.5)	0.5 (0.8)	0.2 (0.3)
min	0.0	0.0	0.0	0.0	0.0	0.0
max	7.4	1.7	7.4	2.2	4.2	1.6
<b>Traffic</b>						
mean (sd)	1.5 (2.5)	0.9 (2.4)	1.2 (1.4)	1.4 (3.0)	1.9 (2.8)	1.9 (2.3)
min	0.0	0.0	0.0	0.0	0.0	0.0
max	17.5	14.4	4.6	17.5	12.7	10.6
<b>Railroad</b>						
mean (sd)	0.4 (0.6)	0.4 (0.5)	0.3 (0.4)	0.5 (0.6)	0.6 (0.9)	0.3 (0.4)
min	0.0	0.0	0.0	0.0	0.0	0.0
max	3.3	1.8	1.7	2.5	3.3	1.8
<b>Rail Node</b>						
mean (sd)	0.1 (0.4)	0.2 (0.5)	0.1 (0.2)	0.1 (0.2)	0.2 (0.5)	0.1 (0.2)
min	0.0	0.0	0.0	0.0	0.0	0.0
max	2.5	2.4	0.6	0.8	2.5	0.9
<b>NEI</b>						
mean (sd)	0.1 (0.1)	0.0 (0.1)	0.1 (0.2)	0.1 (0.1)	0.1 (0.2)	0.1 (0.2)
min	0.0	0.0	0.0	0.0	0.0	0.0
max	1.1	0.4	0.8	0.5	1.1	0.6
<b>Intermodal Terminal Facility</b>						
mean (sd)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.0)	0.0 (0.1)	0.0 (0.1)
min	0.0	0.0	0.0	0.0	0.0	0.0
max	0.8	0.7	0.2	0.2	0.5	0.8

*Primary HAZ Domain Indicators*

Map 3.6 shows the primary HAZ domain score for census tracts throughout the full study area. While the high-resolution HAZ indicators contribute to both the scanning exercise and planning for future data collection and research, the primary HAZ domain broadens the view of how these types of risks and vulnerabilities relate to pediatric asthma regionally.

Map 3.6. Primary HAZ Domain - Census Tract Score





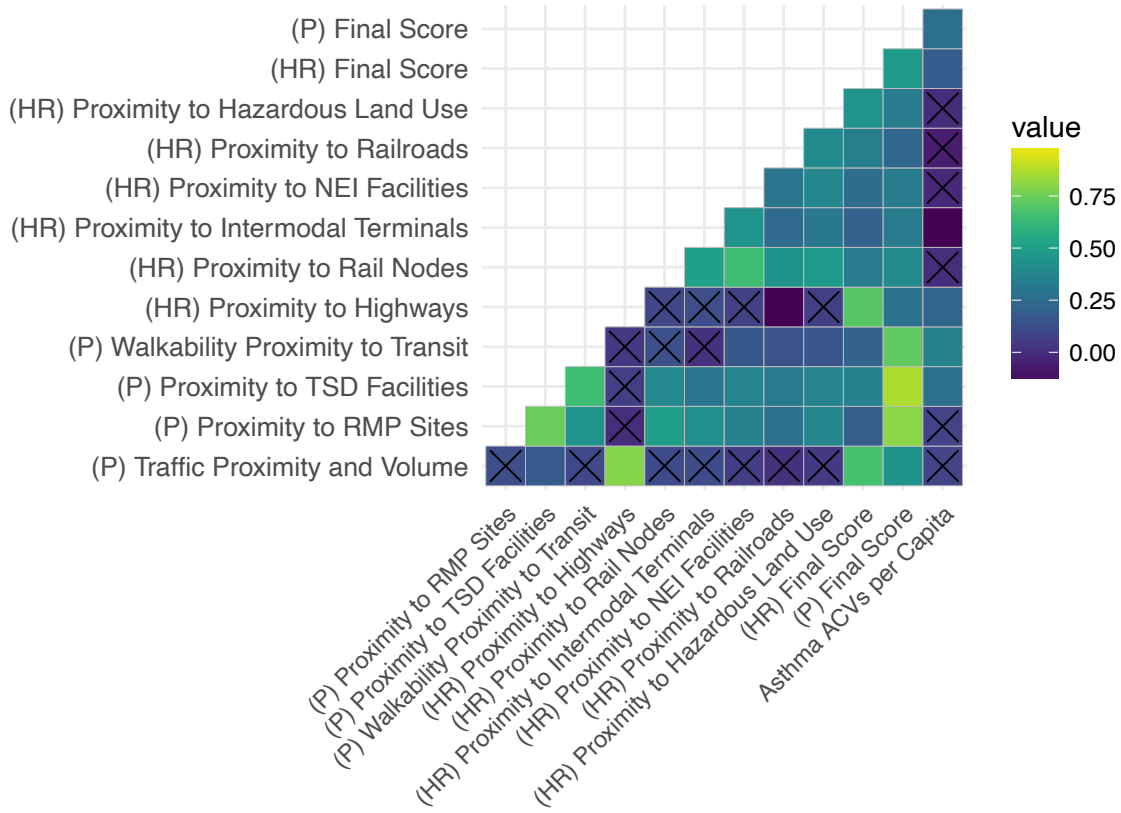
The distribution of the primary HAZ domain scores in map 3.6 mirror the distribution of the high-resolution HAZ indicators in KCMO and WYCO, showing distinct patterns of elevated scores along transportation lines like 71 Highway, which is not captured by the HRE domain. Furthermore, the primary HAZ domain provides additional context for areas with elevated rates of pediatric asthma ACVs per capita in JOCO and Clay County, MO, which appear to strengthen observed relationships between pediatric asthma and environmental exposure throughout the region. This is illustrated by the patterns in table 3.8, which indicates that the mean levels for each of the four intermediate indicators in the primary HAZ domain generally increase with the census tract score for the rate of pediatric asthma ACVs per capita.

Table 3.8. Primary HAZ Domain Indicators Summarized by the Census Tract Score for Pediatric Asthma ACVs per Capita

	All Tracts	1	2	3	4	5
<b>Traffic Proximity and Volume</b>						
mean (sd)	379.0 (629.8)	188.8 (438.4)	251.4 (405.0)	404.1 (563.9)	424.5 (694.1)	629.3 (855.4)
min	0.0	0.0	0.4	0.0	0.1	2.5
max	5,050.6	3,846.1	2,879.7	3,861.6	5,050.6	4,316.0
<b>Walkability Proximity to Transit Ranking</b>						
mean (sd)	8.7 (7.3)	4.3 (5.5)	4.0 (4.8)	8.0 (6.7)	11.8 (6.5)	15.8 (4.8)
min	1	1	1	1	1	1
max	20	19	20	18	20	20
<b>Proximity to Risk Management Plan Sites</b>						
mean (sd)	0.9 (1.1)	0.6 (0.7)	0.6 (0.8)	0.9 (1.1)	1.1 (1.2)	1.2 (1.5)
min	0.0	0.0	0.0	0.0	0.1	0.0
max	8.7	3.7	4.5	4.2	4.5	8.7
<b>Proximity to Treatment Storage and Disposal Facilities</b>						
mean (sd)	1.8 (2.1)	0.8 (1.0)	1.0 (1.2)	1.5 (1.5)	2.6 (2.5)	3.3 (2.5)
min	0.0	0.0	0.0	0.0	0.1	0.1
max	10.7	4.2	8.3	7.4	10.4	10.7

Figure 3.1 shows the correlation matrix comparing the high-resolution and primary HAZ domains – both intermediate indicator scores and the final domain scores – with the census tract score for the rate of pediatric asthma ACVs per capita in the KCMO and WYCO sample.

Figure 3.1. Spearman Correlation Matrix: Primary HAZ Domain and High-Resolution HAZ Domain<sup>64</sup>



Patterns in figure 3.1 indicate that the HAZ domains are fairly consistent particularly with respect to the indicators for traffic proximity and volume, which are correlated with one another and the final domain scores but are not consistently correlated with the other intermediate indicators. This supports the findings from the scanning exercise that both versions of the HAZ domain represent intra-urban variation in the impact of local hazardous land use – especially traffic-related land use – not captured by the HRE domain. Like the descriptive statistics in table 3.7, however, there is no clear

<sup>64</sup> High-resolution HAZ domain indicators are labeled (HR) and the primary HAZ domain indicators are labeled (P). Boxes marked with an 'X' are not statistically significant beyond the  $\alpha = 0.5$  level.

correlation between the high-resolution HAZ domain indicators and pediatric asthma for the sample of census tracts in KCMO and WYCO. While both versions of the HAZ domain make contributions to the scanning exercise, future research should test the association between local hazardous land use indicators and readily available population-level estimates to improve the reproducibility and accessibility of the EJSM for regions with multiple municipalities and limited availability of high-resolution data in this domain.<sup>65</sup>

### ***Cumulative Impact***

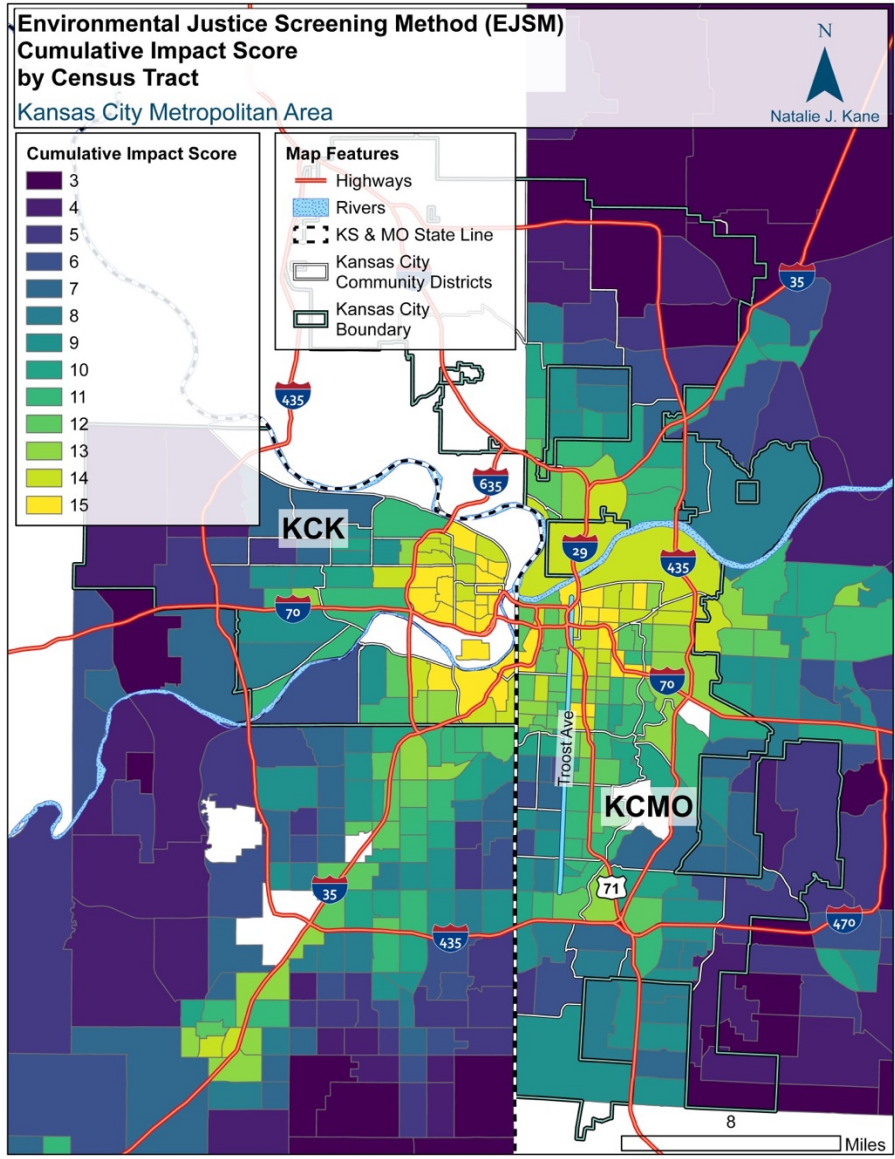
The last step in the EJSM scanning exercise is to review the cumulative impact (CI) score, which provides an indicator of the total burden of risks and vulnerability within and between different communities. The final scores for the primary HRE, SHV, and HAZ domains were summed to produce a CI score for census tracts in the full study area. The distribution of the CI scores symbolized in map 3.7 is consistent with historic racial residential segregation along Troost Ave. in KCMO, and with patterns observed throughout the scanning exercise in areas like the I-35 corridor in JOCO, and in the communities east of I-635 in WYCO. By incorporating measures of both vulnerability and environmental risk, however, the CI score may understate the severity of social disadvantage and health risk in certain neighborhoods; not all areas subject to high disease rates are characterized by high CI scores and vice versa, which is consistent with findings from similar studies (Alexeeff et al. 2012). This also supports the hypothesis that the combination of factors possibly contributing to the rate of pediatric ACVs per capita is likely to vary significantly within and between

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<sup>65</sup> The BPR model was run for census tracts in KCMO and WYCO to compare the results using intermediate indicator scores for each version of the HAZ domain. Appendix map A.3.17 shows the results of the BPR model using the intermediate indicators in high-resolution HAZ domain, which identified 6 clusters: 2 below average risk, 3 average risk, and 1 above average risk. Map A.3.18 shows the model results using the intermediate indicators for the primary HAZ domain, which identified 5 distinct clusters: 1 below-average risk, 3 average risk, and 1 above-average risk. That the second model symbolized in map A.3.18 resulted in 1 less cluster is expected given that the primary HAZ scores are likely to provide less information locally, though the distribution of the clusters is fairly consistent between each map. Future research should perform additional analyses to validate the census tract HAZ domain indicators derived from parcel land use data and explore the best available substitutes to improve accuracy and reproducibility.

different communities, emphasizing the importance of a place-based approach to researching health disparities and designing interventions.

Map 3.7. Cumulative Impact (Census Tract Score)

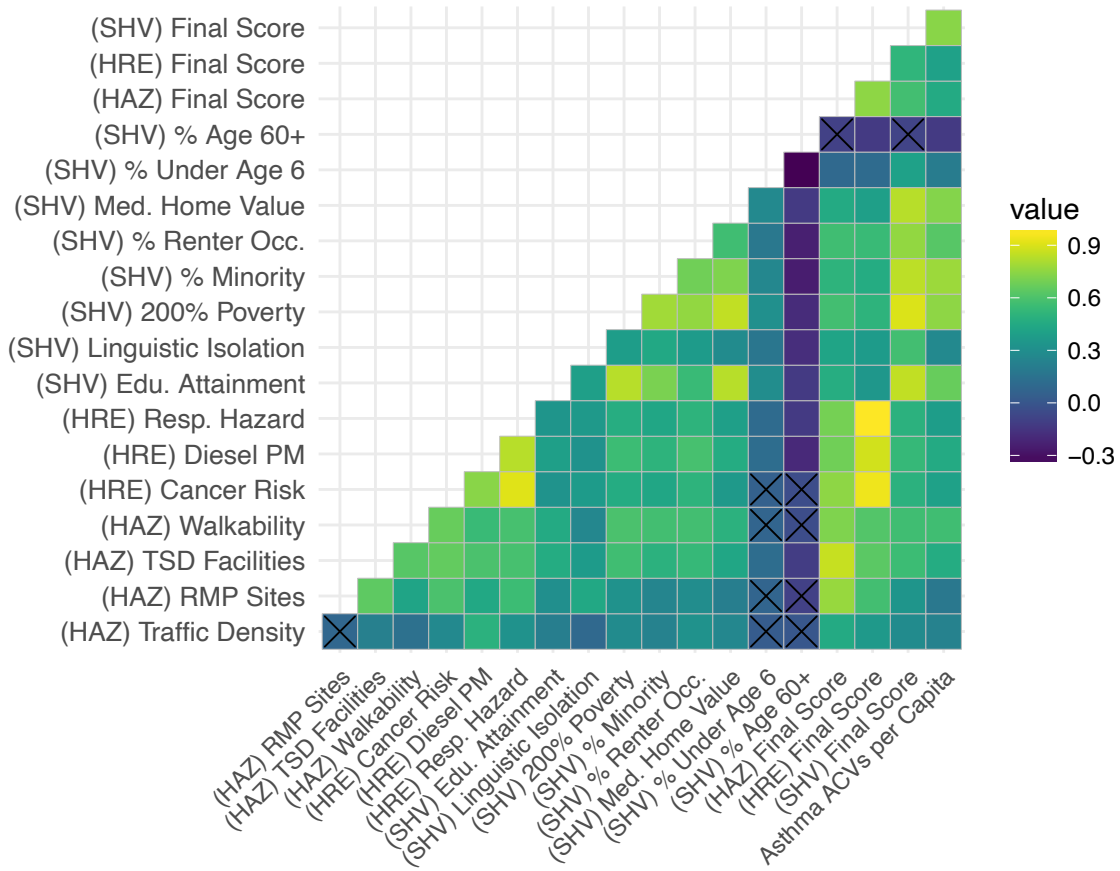


***Comparison of EJSM Domains and Pediatric Asthma***

A series of correlation matrices and density plots were developed to aid the scanning exercise and to review if there are any dominant relationships throughout the sample. Figure 3.2 shows the

Spearman correlation matrix comparing the census tract scores for pediatric asthma ACVs per capita, the intermediate indicators in each primary EJSM domain, and the final domain scores.

Figure 3.2. Spearman Correlation Matrix: EJSM & Pediatric Asthma Census Tract Scores



The rate of pediatric ACVs per capita appears to have a somewhat strong correlation with a few of the intermediate indicators in the SHV domain, which is consistent with the table 3.5 summary statistics. These include median home value, renter occupancy, the percent of the population identified as minority, and the percent of the population living below 200% of the federal poverty line. In addition to being correlated with one another, the intermediate HRE indicators appear to have a relatively strong correlation with the final score for the primary HAZ domain. This suggests that

different combinations of hazards are frequently co-located, supporting the observations from previous scanning exercises that distinct combinations of risks are likely to vary significantly over small areas.

Figures 3.3 and 3.4 show the density of census tracts by the rate of pediatric asthma ACVs per capita. Tracts are grouped by the percent of the population identified as minority in figure 3.3 and by and the percent living below 200% poverty in figure 3.4.

Figure 3.3. Density of Census Tracts by the Rate of ACVs per Capita & Demographics

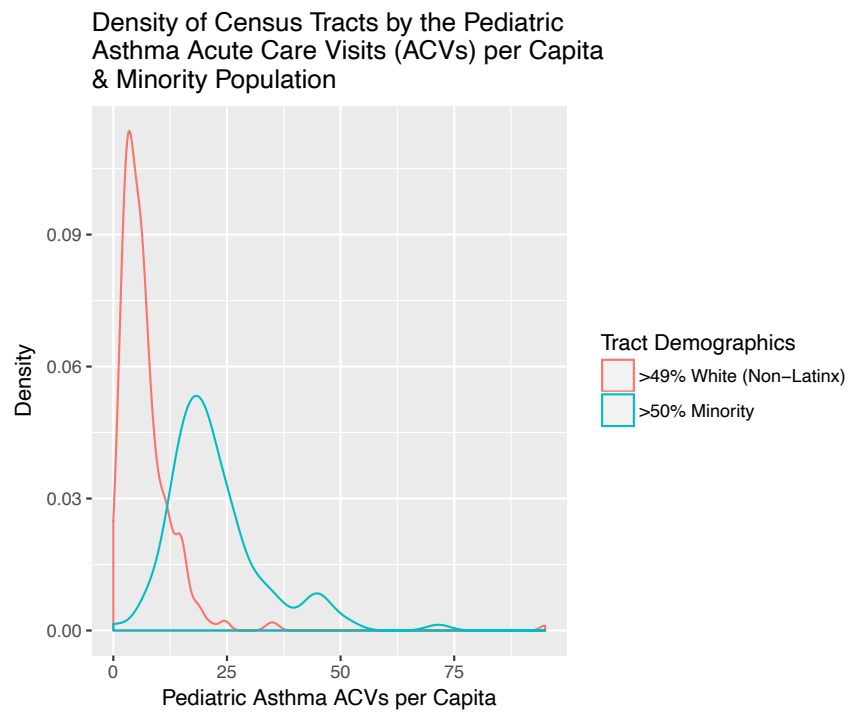
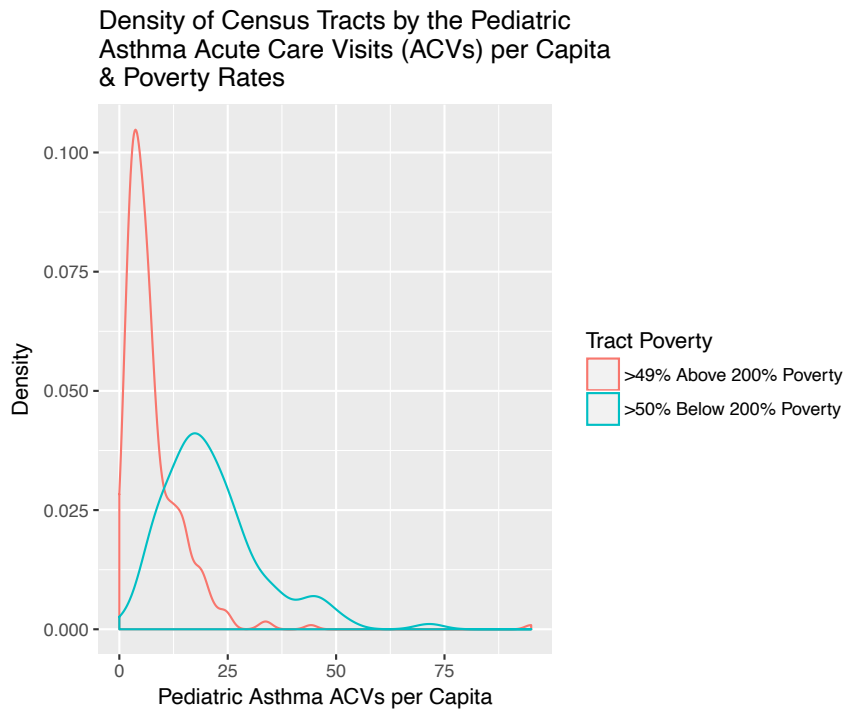


Figure 3.4. Density of Census Tracts by the Rate of ACVs per Capita & Poverty



The aggregate trends in each density plot emphasize the importance of general social disadvantage in the community-level risk of high rates of pediatric asthma ACVs throughout the study area. The density patterns also suggest, however, that there are a number of census tract outliers in the sample with very high rates of pediatric asthma ACVs per capita, but with relatively low levels of social disadvantage.

### Bayesian Profile Regression

The BPR model was run in the PReMiuM R package using a slice-dependent sampler with an initial cluster size of 20.<sup>66</sup> The initial model chain was run for 20,000 iterations after a burn-in sample

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<sup>66</sup> The slice-dependent sampler is a Gibbs sampler based on both slice and retrospective sampling procedures. The slice sampling procedure updates cluster membership jointly, allowing for sampling from the full Dirichlet Process Mixture Model (DPMM) space. The retrospective sampling is complimentary to the slice sampling procedure, but introduces a Metropolis-within-Gibbs step in a dynamic model to determine the number of mixture components, their parameters, and cluster membership, which adapts with the sampler progress (Hastie, Liverani, and Richardson 2015, 1025).

of 10,000. Trace plots for the concentration parameter for the Dirichlet distribution,  $\alpha$ , and for the number of clusters are presented in the appendix figures A.3.9 and A.3.10. While the authors of PReMiUM note the limited availability of Markov Chain Monte Carlo (MCMC) diagnostics for the BPR model, the trace plots do not provide evidence against the convergence of the chains to the posterior distribution (Liverani, Hastie, and Richardson 2015, 22).

The PReMiUM package output includes risk profile box plots, which report the posterior distribution for each cluster in terms of the response and the model covariates. These provide a detailed view of how clusters compare with one another and are provided in the appendix figures A.3.6-A.3.8.<sup>67</sup> The box plot colors indicate whether the 95% credible intervals of the posterior distributions for each cluster-specific parameter include the average (green), are fully below average (blue), or are above average (red), relative to the other clusters. These three risk groups – below-average risk, average risk, and above-average risk - are useful for distinguishing between clusters based on the relative risk of asthma. Regardless of whether a place is subject to a burden in pediatric asthma at the population level, each cluster may provide important contextual information – in terms of both risk factors *and* protective factors - for designing research, intervention, and patient-specific treatment strategies (Benka-Coker et al. 2018).

The BPR for the full study area identified 9 census tract clusters with similarities in terms of both the response and their EJSM covariate profile. To gain insight into the major patterns defining pediatric asthma risk by location in the region, the census tract clusters are reviewed overall and by risk group. Map 3.8 shows the location of all 9 clusters, ordered from low- to high-risk in terms of the mean rate of pediatric asthma ACVs per capita.

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<sup>67</sup> The risk profile box plots were included in the appendix given the relatively large image format, and because the high number of covariates and clusters makes it difficult to summarize the relationships between each cluster and the risk of asthma.



Map 3.8. Census Tract Risk Profile Clusters – Full Study Area

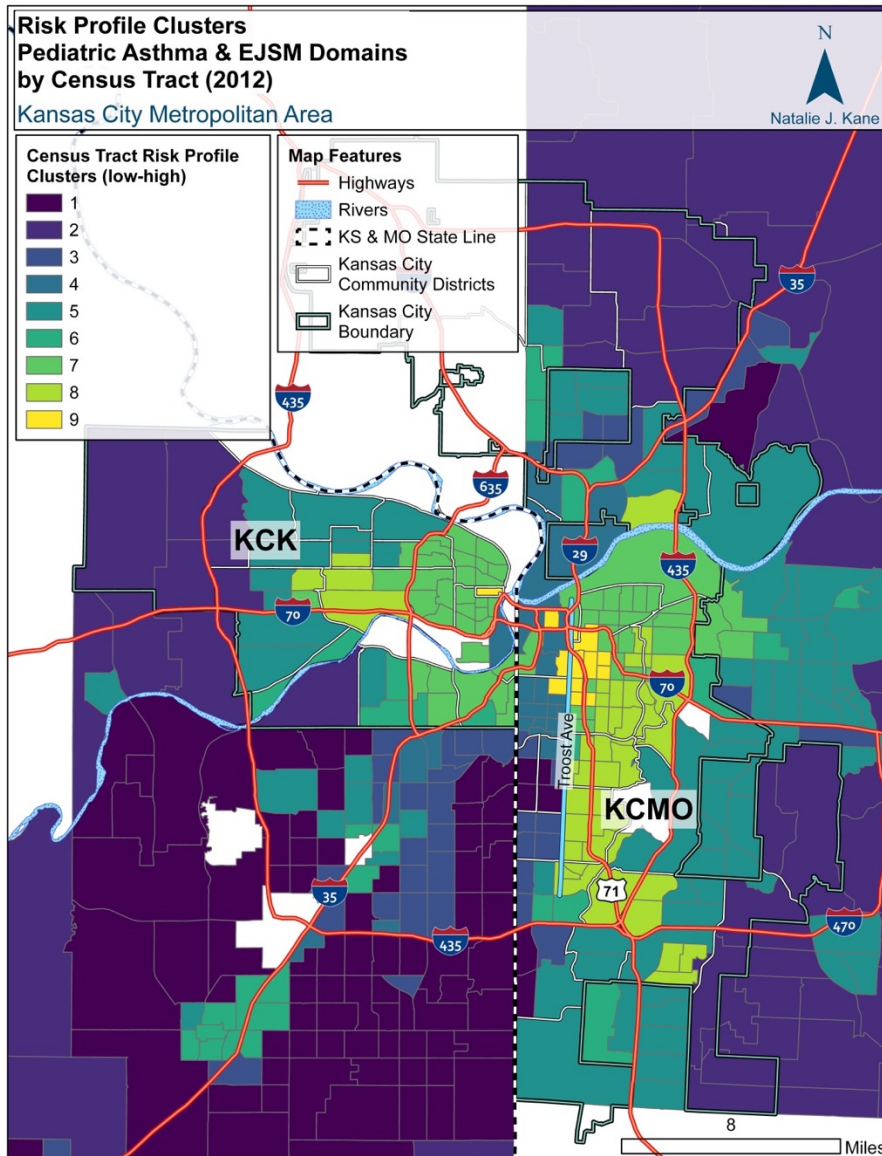


Table 3.9 consolidates the information provided in the risk profile box plots to summarize the distinguishing characteristics of each cluster. The columns represent the 9 census tract clusters identified through the BPR analysis, which are arranged from low to high by the mean rate of pediatric asthma ACVs per capita. The Viridis package was used to assign perceptually uniform

colors to the cells by value in table 3.9 to help with scanning for patterns (Garnier 2018).<sup>68</sup> Despite showing relatively simple summaries of covariate rankings by cluster, table 3.9 provides rich detail and insight into patterns in risk and vulnerability related to pediatric asthma.

Table 3.9. Mean Asthma Risk & EJSM Covariate Values by Cluster

Asthma Risk and Covariates by EJSM Domain	Relative Risk by Cluster - 90% Credible Interval								
	Below Avg.			Contains Avg.			Above Avg.		
	C1	C2	C3	C4	C5	C6	C7	C8	C9
Pediatric Asthma Acute Care Visits per Capita	3	5	7	9	11	11	17	27	49
Sample Size (Percent of Total)	19	17	9	6	18	7	13	8	3
<b>Sensitive Land Use and Hazard Proximity</b>									
Traffic Proximity and Volume	2.2	2.6	3.2	3.7	3.2	3.9	3.5	2.9	3.8
Proximity to Risk Management Plan Sites	3.1	1.7	3.2	4.3	2.2	3.7	4.6	2.4	4.5
Proximity to Treatment Storage and Disposal Facilities	2.4	1.6	2.9	4.6	2.4	3.6	4.8	3.7	4.9
Walkability Proximity to Transit Ranking	2.4	1.3	3.2	4.1	2.8	2.9	4.5	4.3	4.8
<b>Health Risk and Exposure</b>									
Individual Lifetime Cancer Risk	2.4	1.2	4.1	5	2.6	3.8	4.7	2.8	4.4
Diesel Particulate Matter Level in Air	1.9	1.6	3.7	4.8	2.8	4.1	4.5	3	4.8
Respiratory Hazard Index	2.3	1.3	4.1	4.7	2.7	4.1	4.6	2.6	4.4
<b>Social and Health Vulnerability</b>									
Percent Age 24 and Over without High School Edu.	1.4	2.3	2.2	2.3	3.5	3.9	4.9	4.4	4.2
Percent Living in Linguistically Isolated Households	2.8	1.9	2.8	3.3	2.8	4.4	4.4	2.6	3.2
Percent Living at or below 200 Percent Poverty	1.3	1.9	2.4	3.2	3.4	3.9	4.9	4.7	4.4
Percent Identified as Minority	1.7	1.8	2.3	3	3.3	3.9	4.7	4.9	4.7
Percent Living in Renter Occupied Housing Units	1.8	1.7	2.8	4.4	3.1	4.1	4.1	4.5	4.6
Median Home Value (Inverse)	1.3	2.1	2.6	2.2	3.7	3.6	4.8	4.7	3.9
Percent Age 6 and Under	2.6	2.7	2.9	1.7	3.1	3.7	4	3.5	2.5
Percent Age 60 and Over	3.3	2.9	3.8	2.6	3.4	2	2.2	2.9	3.2

Note:

Average Pediatric Asthma ACVs per Capita (all tracts) = 11.2

### All Clusters

The spatial distribution of the 9 census tract clusters in map 3.8 follow a familiar pattern consistent with the findings in Chapter 2 and the EJSM scanning exercise, where higher risk census tracts are concentrated in historically segregated and socially disadvantaged communities, while

<sup>68</sup> “Perceptually uniform means values close to each other have similar-appearing colors and values far away from each other have more different-appearing colors, consistently across the range of values” (Rudis, Ross, and Garnier 2018).

wealthier, mostly White (non-Latinx) suburban and rural census tracts are generally assigned to below-average risk clusters. This is supported by the patterns in table 3.9, which show a strong relationship between the rate of pediatric asthma ACVs per capita and the SHV domain indicators for the percent below 200% poverty, the percent minority, the percent without a high school diploma or equivalent, and renter occupancy.

While these measures of social disadvantage appear to play an important role in both cluster assignment and asthma risk, the combination of risk factors and vulnerabilities distinguishing each cluster are complex. In the following discussion, clusters are reviewed by risk group and compared with one another to examine how the indicators in each EJSM domain interact and relate to different levels of population health risk.

### ***Below-Average Risk Clusters***

Map 3.9 shows only the census tract risk profile clusters with below average risk in terms of the rate of pediatric asthma ACVs per capita, which offers a dramatic expression of the inequity in pediatric asthma rates between socially disadvantaged and privileged communities. Census tracts in c1 - the cluster with the lowest average rate of pediatric asthma ACVs per capita - are clearly concentrated in the wealthiest parts of JOCO, as well as some extremely high-income areas of KCMO including the Ward Parkway and Brookside community districts directly west of Troost Ave, which are areas with high property values and a recent history of racial restrictive covenants (Gotham 2014).

Map 3.9. Census Tract Risk Profile Clusters – Below-Average Risk Census Tracts

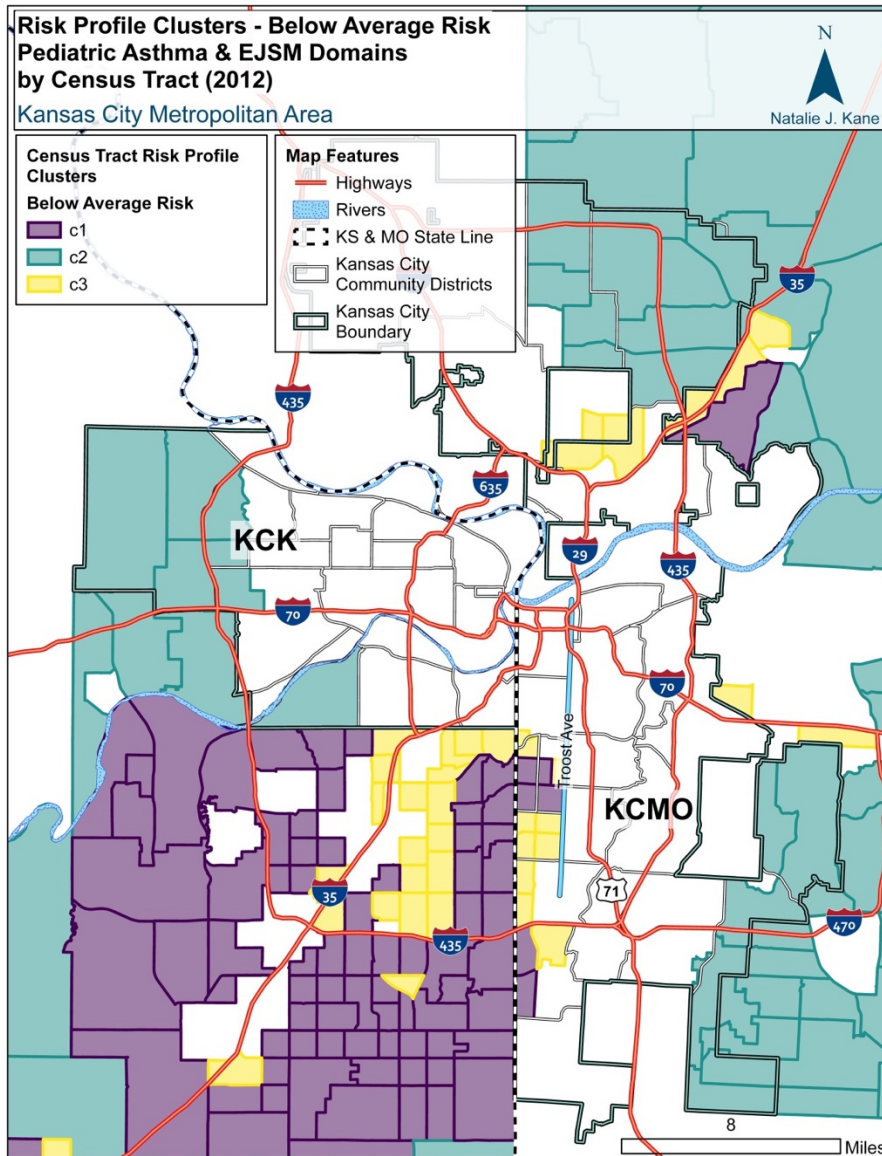


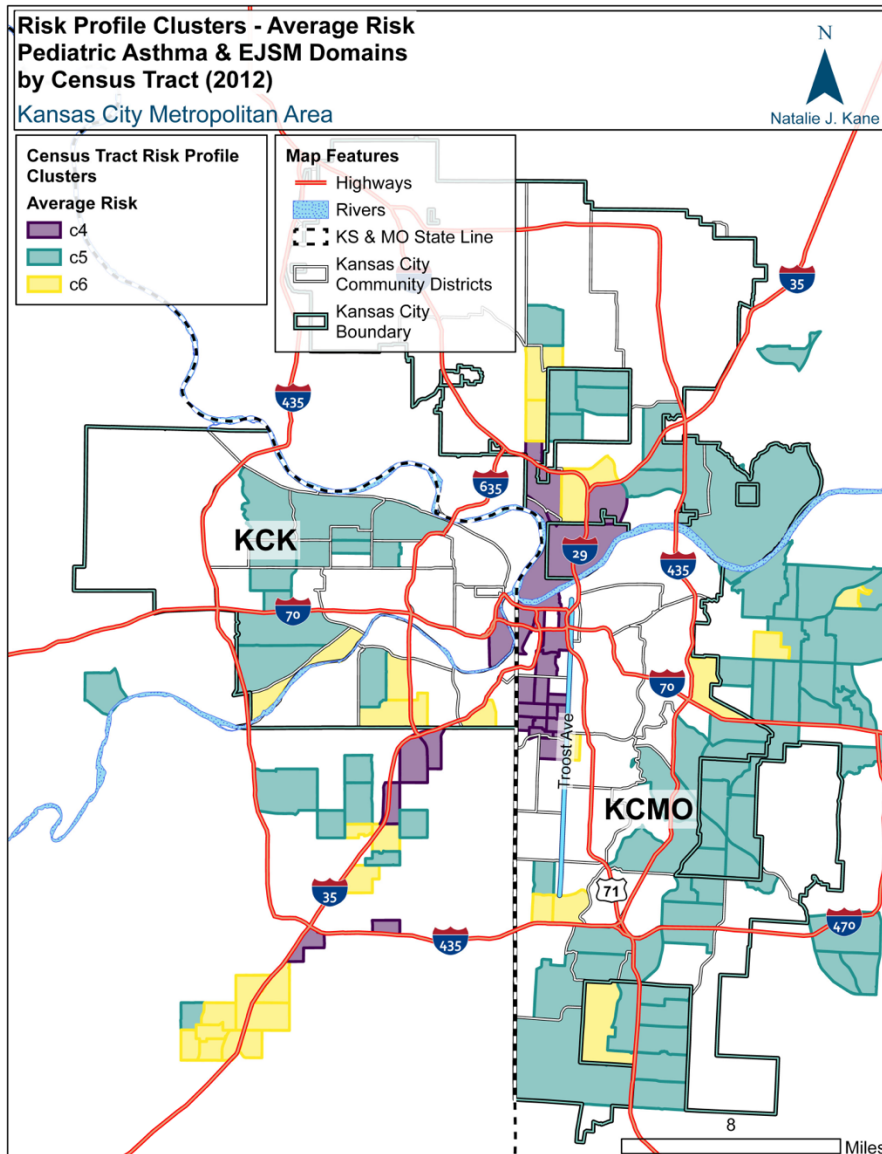
Table 3.9 indicates that c1 and c2 are relatively similar in terms of the mean rate of pediatric asthma ACVs per capita. Census tracts in c2, however, have lower average covariate levels in most EJSM categories with the exception of the HRE indicator for traffic proximity and volume, and the SHV indicators for the percent below 200% poverty, educational attainment, and median home value. Map 3.9 shows that the c2 census tracts are concentrated in relatively rural areas of the KC metro and in less wealthy suburbs, compared with the c1 census tracts in JOCO.

Table 3.9 suggests that c3 census tracts have the highest mean rate of pediatric asthma ACVs per capita, and higher mean levels of all 3 EJSM domains relative to the other below-average risk clusters. The most noticeable difference is in the percent of the population age 60 and over. Census tracts in c3 are more likely to have a larger retirement-age population, possibly with greater concentrations of townhomes, condos, and rentals. While not likely to relate to asthma risk directly, the age variables might contribute to cluster assignment by acting as a signal of development patterns regionally.

### ***Average Risk Clusters***

Map 3.10 shows the distribution of census tract clusters in the average risk group. That these clusters are “average” in terms of the mean rate of pediatric asthma ACVs per capita does not mean that they are not areas of concern or that they should not be a priority for research and intervention. For example, potential emerging hot spots of pediatric asthma were identified along the I-35 corridor in JOCO in Chapter 2. Census tracts in the I-35 hot spot southwest of I-435 are predominantly assigned to c6, while census tracts in the hot spot north of I-435 are assigned to a mix of all three average-risk clusters, c4-c6. The distinction between the average-risk clusters illustrates the degree of variation in the combination of risk factors and vulnerabilities that may be contributing to the growing burden of pediatric asthma in these communities.

Map 3.10. Census Tract Risk Profile Clusters – Average Risk Census Tracts



C4 is characterized by very high mean HAZ and HRE levels, both within the average-risk group and compared with the full sample. On average, c4 also exhibits higher levels of renter occupancy and a relatively small population under the age of 6. These patterns suggest c4 may be subject to higher concentrations of commercial and industrial land use and a lower concentration of residential housing compared with c5 and c6. This is consistent with findings from the EJSM scanning exercise, which indicate that hazardous land use features are frequently co-located and that

their distribution in space follows transportation and industrial infrastructure.

C5 is truly an “average” cluster in terms of relative EJSM levels and asthma risk. C5 census tracts are mostly located in the suburbs of Kansas City with relatively low population density compared with c4 and c6. On average, census tracts in the c5 cluster are located in areas with less consistently high property values, a larger population living below 200% poverty, and lower levels of educational attainment compared with clusters in other suburban areas like c1 or c2 in the below-average risk group. C6 has the same mean rate of pediatric asthma ACVs per capita as c5, but it has a very distinct set of risk factors and spatial distribution. C6 is characterized by high levels of traffic proximity and volume, renter occupancy, linguistic isolation, and it has the lowest mean levels for the percent of the population age 60 and over of all 9 clusters. The high levels of linguistic isolation are likely related to the immigrant populations in parts of c6. For example, there are large Latinx immigrant communities in the c6 census tracts along the I-35 corridor south of I-435 in Olathe, KS. This suggests that the pediatric asthma hot spots identified in Chapter 2 disproportionately impact vulnerable populations, indicating that there may be a growing racial-ethnic health disparity in parts of JOCO.

### ***Above-Average Risk Clusters***

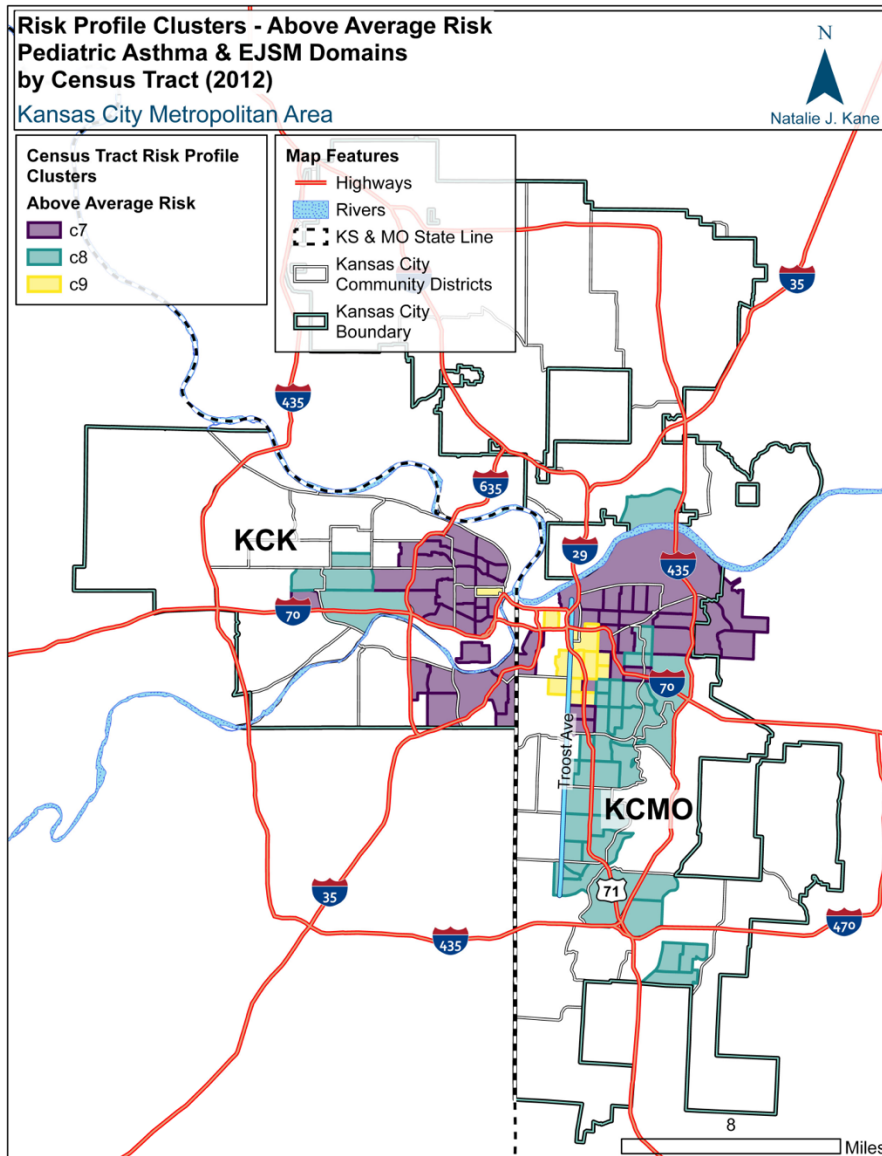
The above-average risk group clusters are symbolized in map 3.11. The rate of pediatric asthma ACVs per capita is consistently higher for c9 census tracts compared with c7 and c8, indicating that sample outliers were concentrated into c9 and that they face a distinct set of risks and vulnerabilities.<sup>69</sup>

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<sup>69</sup> See the risk profile box plots A.3.6-A.3.8 in the appendix for a comparison of the posterior distribution of each cluster in terms of the rate of pediatric asthma ACVs per capita.



Map 3.11. Census Tract Risk Profile Clusters – Above-Average Risk Census Tracts



Map 3.11 shows that c7 census tracts are predominantly located in the Old Northeast community district in KCMO, and in most of the WYCO community districts east of I-635. Both areas are characterized by a high concentration of industrial and transportation infrastructure and are home to a number of different immigrant and refugee communities. These patterns are reflected in the distribution of the c7 covariate values in table 3.9, which shows that, on average, census tracts in c7 have a relatively young population characterized by high levels of environmental exposure and social



disadvantage in general, and much higher levels of linguistic isolation compared with c8 and c9.

C8 is distinguished by high mean levels in the SHV domain indicators for educational attainment, poverty, renter occupancy and median home value, and it has highest mean levels for the percent minority of all 9 census tract clusters. C8 also exhibits relatively low mean levels among the HAZ and HRE domain scores compared with the other above-average risk clusters, c7 and c9. In map 3.11, c8 census tracts are clearly concentrated in the neighborhoods east of Troost Ave. in KCMO, which are predominantly Black communities subject to historic racial residential segregation and discriminatory disinvestment. Interestingly, the BPR model assigned parts of Hickman Mills, the Grandview Triangle, and Choteau community districts to c8, as well as parts of WYCO west of I-635. These areas were identified as potential hot spots in terms of both the rate of pediatric asthma ACVs per capita and high-risk asthma prevalence in Chapter 2, and they show within-community variation in HAZ scores at the parcel level in map 3.4.

The distinction between the above-average risk census tract clusters in comparison with the below-average risk group provide additional insight into the contextual factors that may be driving the burden in pediatric asthma. For example, c8 shares a number of similarities with c1 and c3 in the below-average risk group across the HAZ and HRE domains, and in terms of the indicator for linguistic isolation in the SHV domain. What distinguishes c8 from c1 and c3 is the consistently high levels of social disadvantage measured by the majority of the SHV domain indicators and the location of the c8 census tracts, which are concentrated in historically segregated neighborhoods of KCMO. This suggests that the combination of social disadvantage - especially a large racial-ethnic minority population – and location are driving the consistently high rates of pediatric asthma ACVs per capita in c8 census tracts, while privilege in terms of wealth and a largely White (non-Latinx) population are acting as protective factors in c1 and c3.

C9 includes most of the census tracts with extremely high rates of pediatric asthma ACVs per capita. In terms of the model covariates, c9 is distinguished by very high mean levels of renter

occupancy, the most consistently high levels of HAZ domain indicators, and noticeably higher property values. Census tracts in c9 are concentrated in parts of the East Side, Greater Downtown, and Midtown community districts in KCMO, and it includes the Central Business District in WYCO. The location of the census tracts in c9 and the relatively high HAZ and HRE scores suggest that this group of tracts is characterized by more commercial and industrial land use and a lower proportion of residential housing. The extremely high rates of pediatric asthma ACVs per capita in c9 are likely related to significant vulnerability and poor asthma control for children living in low-income or other unstable housing such as homeless shelters, which are present in this cluster but not captured by the aggregate SHV indicators.<sup>70</sup>

## **Discussion**

### **Summary of Findings**

The findings from this chapter offer insight into the depth and severity of the disparity in pediatric asthma between socially disadvantaged and privileged communities, highlighting the possibilities for more effective and sustainable research and intervention strategies. The results of the EJSM scanning exercise, descriptive analysis, and the BPR model provide evidence that the distinct combination of risk factors potentially contributing to pediatric asthma vary significantly within and between different communities. It is clear, however, that different forms of social disadvantage are driving the high rates of pediatric asthma ACVs per capita in some communities, while privilege in terms of wealth and a largely White (non-Latinx) population are acting to protect others (Kranjac et al. 2017). These patterns are consistent with findings that the cumulative and combined effects of historic racial residential segregation and other forms of social disadvantage act to subvert health and prosperity (Kershaw et al. 2017).

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<sup>70</sup> Results from Chapter 2 suggest that pediatric asthma patients with a history of housing instability are subject to more frequent ACVs. Extremely high rates of pediatric asthma ACVs per capita in some areas may be a consequence of churning in the population due to housing instability, where socially disadvantaged children are frequently moving to and from areas with low-income rental housing opportunities.

The SHV domain indicators for the percent minority, the percent below 200% poverty, median home value, and educational attainment have the most consistent and strong association with the rate of pediatric asthma ACVs per capita relative to the other EJSM domain indicators. All three of the above-average risk clusters have much larger minority populations than any of the other risk groups, with the highest rates of asthma in historically segregated or immigrant communities also burdened by different types of environmental exposure and social disadvantage, which is consistent with findings in the literature (Smiley 2019).

That each community faces a different set of socioeconomic, demographic, and environmental risk factors emphasizes the importance of community engagement in the process of identifying what might be driving inequitable health outcomes and in designing place-based interventions. For example, census tracts in the above-average risk cluster c7 are concentrated in a number of different immigrant communities throughout the Old Northeast neighborhoods of KCMO, and most of the community districts east of I-635 in WYCO. Research, intervention, and resource development in these areas would need to cater to the very specific needs of different communities within c7; even with similar population-level risks and vulnerabilities, non-English speaking immigrant and refugee communities require culturally-competent care (Bell and Condren 2018; Brotanek et al. 2005; Alzaye et al. 2019).

The risk of exposure to hazards often intersects with discriminatory economic development, which is closely associated with social disadvantage and health inequities (Martenies et al. 2017; S. M. Wilson 2009). For example, census tracts in the community districts divided by 71 Highway all fall in above-average risk clusters. Completed in the early 2000's, 71 Highway was built through the center of historically Black residential neighborhoods in the East Side, Brush Creek South, and East Myer community districts. The decades-long planning involved the purchase of a large swath of residential parcels from neighborhood residents, which were left vacant for significant periods of time before the full construction process began (Hogan 2014). Both the parcel- and tract-level HAZ

domain maps indicate that the highway acts as the primary residential hazard for these neighborhoods, which are also burdened by deficits in housing quality and stability (Mid-America Regional Council (MARC) 2016). The concentration of pediatric asthma in this neighborhood context means that, even when there are clear modifiable risk factors such as housing quality, access to care, or exposure to environmental hazards, it is not likely that these risk factors alone will be sufficient targets for policy and intervention to sustainably reduce the health disparity over time (Hicken 2015). Instead, modifiable risk factors should be addressed through research and intervention strategies designed to mitigate the impact of social disadvantage, leveraging existing resources toward place-, culture-, and person-specific solutions (Lion and Raphael 2015).

### **Limitations & Opportunities for Improvement**

The results from this chapter highlight a number of limitations and opportunities for improvement in terms of both the EJSM and BPR model specification. The standard series of indicators used to develop the EJSM help to characterize general risk and vulnerability, but there are issues with data quality and resolution. The placement of air quality monitors, for example, is designed to capture peak concentrations of pollution downwind of population centers (Loperfido and Guttorp 2008). Consequently, intermediate HRE indicators developed from regional monitor data may understate the presence and health impact of ambient air pollution in the urban core community districts. Furthermore, local risk factors tied to social disadvantage like housing quality and stability may not be adequately represented in available population-level indicators.

While the high-resolution HAZ domain is designed to compensate for the constraints of the HRE indicators, it was difficult to find consistent data to represent sensitive land use polygons - parcels or otherwise - and local hazards at the address-level for the full study area. Environmental exposure variables developed for the patient-level analysis in the following chapter will focus on standardized indicators of traffic, rail, and point sources of pollution to account for the limited availability and quality of hazardous land use data. Future research should validate the spatial

resolution and currency of commonly available, local datasets like parcel land use files and explore other data sources consistently available over large areas and multiple municipalities.

Future iterations of the EJSM for low-level health analyses can also incorporate data from local studies and would benefit from collaborative partnerships with advocacy groups focused on environmental justice. For example, the Kansas City Transportation and Local-Scale Air Quality Study (KC-TRAQS) is a long-term project involving the collection of high-resolution air quality data through stationary and mobile monitors in WYCO neighborhoods near a major railyard and related industry. The study identified complex patterns in the intra-urban variation in air pollution exposure from multiple hazards, providing opportunities for further research on the spatial extent and health impact of local sources of air pollution (Kimbrough et al. 2019). Similarly, CleanAirNow supports ongoing air quality monitoring in the Kansas City area through community-based participatory research (CBPR) and in partnership with regional environmental, educational, and other advocacy groups (Templeton 2018). These types of organizations and resources may be able to help facilitate and design CBPR exercises to review, modify, and validate the results of the EJSM, guiding future data collection and indicator specification.

There are also opportunities to improve the cumulative impact score in the EJSM scanning exercise. While there are a number of ways to estimate the cumulative impact of different risks and vulnerabilities, a simple additive approach was employed given the importance of transparency and accessibility in the first full application of the EJSM for this study. Future research using similar risk assessment methods should consider alternative measures of cumulative impact to maintain the heterogeneity and detail of each category of indicators.

The results of the analyses in this chapter highlight the importance of spatial scale in an investigation into health inequities given local variation in both the burden of pediatric asthma and possible contributing risk factors. Though the census tract geography was useful for this exploratory exercise, census tracts may obscure important patterns in social disadvantage and the burden of

pediatric asthma in rural communities with relatively low population density. Future iterations of the EJSM should explore options for indicator specification at different spatial scales – especially social geographies such as neighborhoods – to improve the use of these methods for communities throughout the region (Weiss et al. 2007).

Additional research can be done to test the robustness of the BPR model results and to learn more about which risk factors are driving the mixtures. While consistent patterns in the covariate levels may indicate which variables are driving the cluster assignment - for example, the SHV indicators for the percent minority and percent below 200% poverty - variable selection and Bayesian Model Averaging techniques can be used to test these relationships (Papathomas et al. 2012).<sup>71</sup> Furthermore, because the BPR model can be expanded to include as many covariates as needed, future research can incorporate more problem- or place-specific covariates into the model, which might improve the results and provide greater insight into the role of intersectionality in health inequities. In terms of an investigation into the racial disparity in pediatric asthma, the variable for the percent minority, for example, could be split up into distinct measures of race and ethnicity to better characterize the context of pediatric asthma in different communities (Green, Evans, and Subramanian 2017). Finally, this methodological approach can be applied to predictive scenarios to further assess model convergence and help to inform research and intervention strategies (Liverani, Lavigne, and Blangiardo 2016).

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<sup>71</sup> An example of the results for the continuous variable selection method are presented in the appendix to this chapter. The results suggest relatively weak correlation between Traffic Proximity and Volume, Percent Age 6 and Under, and Percent Age 60 and Over and cluster assignment at each sweep (see table A.3.5). When applied to the same model, the continuous variable selection method produces a profile of 8 clusters instead of 9, with a slightly different pattern in cluster assignment. Map A.3.16 show the location of the clusters. The most notable difference between the standard model results with 9 clusters and the continuous variable selection results is that the census tracts with extremely high rates of ACVs are not separated out in a distinct cluster. Because the continuous variable selection method affected cluster assignment in this way it suggests that, while the relationship with cluster assignment and asthma risk may not be as strong as the other EJSM domain indicators, these three covariates contain important information about what contextual factors - including development patterns - may distinguish census tracts with different levels of asthma risk. Further research should be done to explore variable selection methods for learning more about what variables are driving the mixtures.

## **Conclusion**

Together, the EJSM and BPR cluster analyses offer a flexible and transparent means of exploring patterns in the relationship between pediatric asthma and different combinations of risk and vulnerability throughout the Kansas City region. This initial demonstration of concept provides insight into the problem and signals for how to design subsequent research and intervention strategies. Future initiatives should integrate these analytical exercises with local knowledge through CBPR to ‘ground truth’ the results; to validate and improve the findings through stakeholder knowledge and direct observation (J. Sadd et al. 2014). The following chapter will move the analysis from the population-level to the patient-level to investigate pediatric asthma in the context of the home environment.

## **Supplemental Materials**

The following narrative covers the data processing steps used to develop the intermediate indicators in the high-resolution HAZ domain for KCMO and WYCO:<sup>72</sup>

### ***Residential Land Use Parcels***

The sensitive land use polygons are represented by residential parcels in this study. The parcels for both WYCO and KCMO were sorted by land use codes for existing residential parcels and copied to create new polygon feature classes using the ArcMap desktop application. The parcel layers were then merged to create a single feature class representing residential land use throughout the EJSM study area.

### ***Hazardous Land Use - General***

Land use codes in the parcel geography were used to create a base indicator of general hazardous land use, including heavy industry, manufacturing, power generation, airports, and other non-

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<sup>72</sup> The high-resolution HAZ domain was designed to identify general hazardous land use within communities for scanning purposes; it is not intended for use in low-level analyses requiring precision exposure estimates. The purpose of developing the trial, high-resolution HAZ domain in the context of this study is as a demonstration of concept and a review of available data. Future research should incorporate stakeholder and expert input to expand and improve the high-resolution HAZ estimates for the full study area.

commercial indicators of potential emissions to the environment. Railroad lines and railroad land use parcels are likely to overlap - railroad lines are typically built on property designated for railroad land use - but do not necessarily represent additional or independent sources of pollution. To prevent over-counting railroad features near residential parcels, these observations were subset from the parcel sample and included in the intermediate HAZ indicator for railroads, described below.

### ***Hazardous Land Use – Railroad Lines and Nodes***

Air pollution from railroad traffic and land use is a significant hazard throughout the Kansas City region. For example, the Armourdale, Santa Fe Industrial, Turner, and Argentine community districts in WYCO have been the subject of recent research on the intra-urban variation in air pollution from railyards and related facilities, which found elevated levels of air pollution posing a risk to respiratory health for residents in the area (Global Community Monitor 2015). Both rail lines and nodes were included as separate features to capture the potential impact of railroad land use on health. First, the 2015 Mid-America Regional Council (MARC) street centerline geography was sorted by transportation type to identify active railroad lines. A 10ft buffer of the railroad line geography produced a polygon layer, which was merged with the subset of railroad land use parcels to capture their full spatial extent. Railroad nodes are recognized as an indicator of concentrated railroad traffic and elevated levels of pollution from related industry such as railroad stations and maintenance sites (INSPIRE Registry 2019; Hagler and Tang 2016). Rail nodes were mapped as point sources of pollution using the site latitude and longitude recorded by the National Transportation Atlas Database (NTAD).

### ***Regulated Facilities***

National Emissions Inventory (NEI) data was collected as an indicator of potential point sources of pollution from EPA regulated facilities. The NEI includes duplicate observations for a single facility if it is regulated for more than one activity or type of emission. These duplicate points were removed based on the site identification number and geographic coordinates. Regulated facilities



included in the NEI are likely to be located on parcels designated for industrial or other hazardous land use activity. NEI points were consolidated with the general hazardous land use indicator if the features intersected.<sup>73</sup> This prevents over-counting point sources of pollution and provides a better representation of the spatial extent of active facilities during this period compared with a single point based on latitude and longitude alone.

### ***Intermodal Terminal Facilities***

Intermodal terminal facilities were geocoded using the site latitude and longitude recorded by the NTAD to represent point sources of pollution from the intersection of multiple modes of transportation. Like the NEI sample, intermodal terminal facilities were consolidated with the general hazardous land use geography if the features intersected to prevent over-counting point sources of pollution and to improve the representation of this type of land use in space.

### ***Highways & Freeways***

Traffic-related air pollutants (TRAPs) are concentrated near major highways, roadways, and principle arterials, which have been linked to increased risk of asthma exacerbation, particularly in socially disadvantaged neighborhoods (Li et al. 2011; Kim et al. 2004; Pratt et al. 2014). Line features with a federal functional classification of 1 or 2 were selected from the Highway Performance Management System (HPMS) geography as an indication of elevated levels of TRAPs near residential parcels. Because the line feature class representing single highway or roadway features will often include multiple segments, the HPMS segments were dissolved if they were assigned the same identifier and functional classification to prevent over-counting the number of unique traffic features around residential parcels.

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<sup>73</sup> The NEI is one data source for validating and improving the representation of hazardous land use throughout the study area. This dataset alone, however, does not provide enough information to define the relative impact of different types of activities or emissions from a single facility on nearby sensitive receptors. Because of this, the dataset was only used to identify unique features representing general hazardous land use. Case study and other highly localized analyses should review available data, pollutant modeling techniques, and alternative scoring methods to improve the accuracy of exposure estimates based on hazardous land use.

## CHAPTER 4

### 4. A PATIENT-LEVEL ANALYSIS OF PEDIATRIC ASTHMA, HOUSING CONDITIONS, AND HOUSING INSTABILITY IN THE KANSAS CITY REGION

#### **Introduction**

The findings from Chapters 2-3 illustrate significant variation in both the burden of pediatric asthma and the different risk factors that may be contributing to disease incidence rates in socially disadvantaged communities throughout the Kansas City region. While the analysis of population-level indicators is an important first step toward understanding what may be driving population health disparities, it does not provide information about the person-specific social determinants of health (SDOH) and environmental exposure both in and around the home that may contribute to a patient's asthma symptoms. In this chapter, the focus is shifted from the population-level to the patient-level to investigate the relationship between pediatric asthma and various risk factors in the immediate context of the patient's home environment. Indicators of patient social disadvantage, housing instability, housing conditions, and environmental exposure near the home are modeled using the Bayesian Profile Regression (BPR) methodology introduced in Chapter 3 to gain insight into the combination of risks and vulnerabilities that may contribute to the frequency of pediatric asthma acute care visits (ACVs) in the parcel-geocoded asthma patient sample.<sup>74</sup>

The retrospective pediatric asthma sample introduced and explored in Chapters 2-3 was provided by Children's Mercy Kansas City Hospitals and Clinics (CMH) as a part of their partnership with the UMKC Center for Economic Information (UMKC-CEI) on the KC-HEART project; a Healthy Homes Technical Grant funded by the Department of Housing and Urban Development (HUD) (#MOHHU0016-13). The major objective of the KC-HEART project was to collect address-level data to investigate the impact of housing conditions on pediatric asthma, blood-lead poisoning,

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<sup>74</sup> The asthma patient and encounter samples in this chapter are referred to as 'parcel-geocoded' to distinguish them from the centerline-geocoded asthma samples reviewed in Chapters 2-3. Acute care visits (ACVs) were defined in Chapter 2. ACVs include asthma-related emergency department (ED) visits, observation stays, and hospitalizations.

and childhood injuries. Parcel data for external housing conditions was collected by the UMKC-CEI through their Neighborhood Housing Conditions Survey (NHCS); a window survey conducted for different target areas in the Kansas City region from 2000-2012. The patient's residential address was used to match NHCS structure conditions data with asthma encounters occurring during the same period via an iterative geocoding process.<sup>75</sup> The resulting dataset is unique in its spatial resolution and extent, and in its potential as a reproducible means of studying the health impact of both social disadvantage and exposure to environmental triggers in and around the home.

The NHCS was conducted intermittently and while the survey format itself was consistent, the survey areas were not. The majority of the NHCS surveys targeted the urban core of Kansas City, MO (KCMO) and Wyandotte County, KS (WYCO). Parts of Johnson County, KS (JOCO) and other municipalities in Jackson County, MO were surveyed in different years as well, providing some coverage outside of the urban core. The uneven sampling of NHCS parcels - and, consequently, asthma patients - throughout the full study area resulted in a relatively homogenous sample, which may be subject to greater multicollinearity given the co-location of high rates of pediatric asthma, social disadvantage, and environmental exposure (Bravo et al. 2016).<sup>76</sup>

The Bayesian Profile Regression (BPR) introduced in Chapter 3 is a non-parametric Dirichlet Process Mixture Model (DPMM) that uses the patterns inherent in multicollinearity to identify distinct clusters of patients based on both a covariate profile and a response, or 'disease', sub-model. The covariate profile is jointly fitted with the response sub-model through iterative Markov Chain Monte Carlo (MCMC) sampling. The BPR identifies the best partition of clusters within the sample – the partition with the lowest uncertainty in cluster assignment – informed simultaneously by the response and covariate sub-models. Unlike standard statistical methods, the BPR model does not

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<sup>75</sup> The full geocoding process and additional details regarding the KC-HEART project are documented in a recent publication authored by research associates from the UMKC-CEI (B. Wilson, Wilson, and Martin 2019).

<sup>76</sup> Refer to the discussion in Chapter 3 regarding complex patterns in the distribution of risk factors and measures of vulnerability throughout the Kansas City region.

require a fixed number of clusters be determined in advance, it can include a large number of highly correlated covariates, and it can handle missing covariate values (Liverani, Hastie, and Richardson 2015).

In this chapter, the BPR response sub-model is based on the count of previous acute care visits (ACVs) in the previous 365 days; a cumulative indicator of asthma control and health care utilization rates, both of which are associated with different aspects of social disadvantage and physical environmental exposure (Chung, Hathaway, and Lew 2015; Newman et al. 2014). The covariate profile developed for the parcel-geocoded pediatric asthma sample includes indicators of patient history and characteristics, Neighborhood Housing Conditions Survey (NHCS) structure conditions ratings for residential parcels, and indicators of environmental exposure to pollution from traffic and industry near the patient's home address. Variables for patient history and characteristics were derived from the CMH electronic health records (EHR) for the parcel-geocoded patient sample. These include indicators for patient social disadvantage measured by race, ethnicity, and medical coverage type, as well as standard indicators of sex and age, which are closely related to pediatric asthma severity and phenotype (Dharmage, Perret, and Custovic 2019).

The NHCS structure conditions data is a primary focus of this investigation given the unique circumstances of Kansas City's geography and social history, the role of housing as one of the dominant sources of exposure that may contribute to asthma symptoms, and the potential to use housing conditions as a viable target for policy and intervention to reduce health risk (Morawska et al. 2013; Hughes et al. 2017; Ganesh et al. 2017). Housing conditions are suspected to impact child asthma health outcomes through elevated exposure to environmental triggers sourced within the home, such as mold and pests (Heinrich 2011; Vesper et al. 2017). Furthermore, exposure to air pollution or other environmental triggers may interact with certain housing conditions where, for example, substandard roof and window conditions may increase exposure to outdoor air pollution by trapping it in the home (Tong et al. 2016; Jacobs 2011).

Four environmental exposure covariates were developed to capture elevated levels of air pollution from traffic and industry near a child's home address through proximity and density estimates. Multiple studies have found an increased risk of asthma exacerbation for children living near major roads (McConnell et al. 2006; Jerrett et al. 2008; Kim et al. 2004; Li et al. 2011). Freight traffic on both highways and railroads is associated with elevated levels of diesel particulate matter (PM) and other traffic-related air pollutants (TRAPs), which have been linked to respiratory health problems (G. Norris et al. 1999; Brugge, Durant, and Rioux 2013; McCreanor et al. 2007; Zhang et al. 2009). The proximity of schools and residential housing to railyards and railroads has been identified as a contributor to high rates of poorly controlled asthma, with the greatest impact in socially disadvantaged communities (Spencer-Hwang et al. 2015; Juhn et al. 2010). Recent research has also found a strong relationship between the frequency of asthma exacerbations and traffic density near a patient's residential address, providing a high-resolution indicator of both the extent and relative impact of nearby roadways (Lindgren et al. 2016). Furthermore, while the findings from Chapter 3 indicate that transportation is likely to be the major source of local air pollution in the Kansas City region, there is substantial evidence that pollution from industry and hazardous land use also increases respiratory health risk and disproportionately impacts socially disadvantaged communities (Herrera et al. 2016; Patel et al. 2011; California Air Resources Board 2005; De Sario et al. 2018; Prieto-Parra et al. 2017; Moody and Grady 2017).

An important component of this investigation is patient history of transience, or housing instability, measured by the count of unique addresses recorded for each patient during the period in which they experienced their maximum count of previous ACVs. This variable demonstrates significant potential as a means of identifying high-risk patients using standard EHR, and it may improve analyses focused on asthma triggers in and around the home by capturing the relative duration of exposure to measured housing conditions and pollutants.<sup>77</sup> Furthermore, housing

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<sup>77</sup> The housing instability measure introduced in Chapter 2 is based solely on available CMH EHR for a patient,

instability itself is an issue tied to financial insecurity and social disadvantage generally, and has been cited as a contributing factor in health disparities (Christian 2017; Buckner 2008). The BPR model is tested with and without the count of unique addresses as a covariate to gain insight into the combinations of risks and vulnerabilities associated with the frequency of ACVs among distinct groups within the sample given the patient's history of housing instability. The results of each model trial are presented in tables and maps summarizing patient cluster characteristics, which are reviewed independently and then compared with one another.

## **Materials and Methods**

### **Tools & Software**

R/RStudio and ArcGIS Pro are the primary tools used for data collection, processing, and analysis, which were introduced in Chapters 2-3. Additionally, the Viridis R package introduced in Chapter 3 is used to color tables and maps to aid with scanning for patterns in the data. The Viridis color palette is robust to color blindness and is perceptually uniform, “meaning that values close to each other have similar-appearing colors and values far away from each other have more different-appearing colors, consistently across the range of values” (Rudis, Ross, and Garnier 2018).

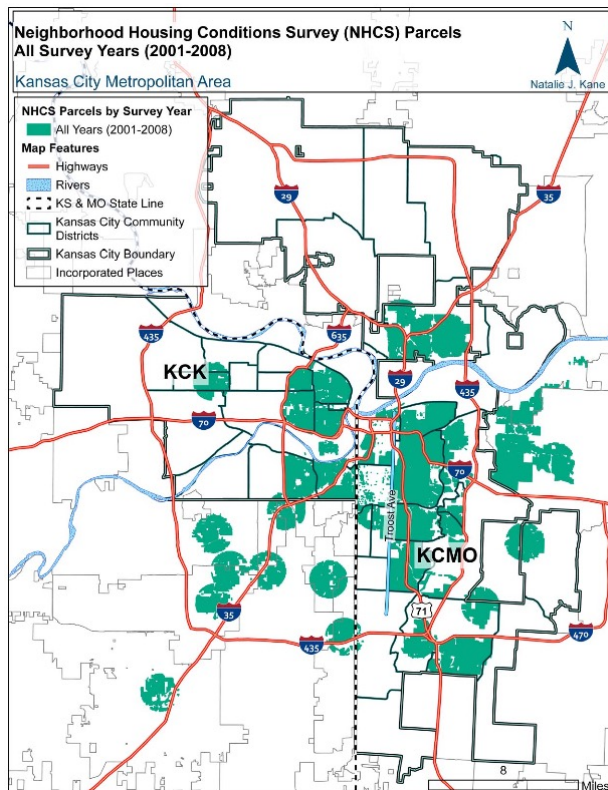
### **Data & Study Area**

The Neighborhood Housing Conditions Survey (NHCS) parcel conditions data collected between 2001 and 2008 were included in this investigation to capture parcel-geocoded asthma patient and encounter samples from throughout the full study area. The complete sample of parcels surveyed by the NHCS from 2001-2008 is symbolized in map 4.1.

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which may lead to sample selection bias where children who are in-network are more likely to be observed, as are children with more frequent ACVs. Despite these limitations, excluding the housing instability measure may obscure important patterns in the relationship between pediatric asthma and prolonged exposure to stationary risk factors (e.g. proximity to freight routes near the patient's home and substandard housing conditions) among children who have not moved; patients without housing instability are likely to be exposed to the measured risk factors for a longer period of time compared with patients who move frequently. Consequently, the impact of different combinations of stationary risk factors in and around the home may vary depending on patient history of transience (McConnell et al. 2006).

Map 4.1. Neighborhood Housing Conditions Survey (NHCS) Parcels, 2001-2008



## Data Collection & Processing

### *Parcel-Geocoded Pediatric Asthma Data*

The asthma encounters geocoded to the NHCS parcel geography during the 2001-2008 study period were processed according to the steps detailed in Chapter 2.<sup>78</sup> 95 observations were associated with invalid structure conditions ratings and deleted from the sample, leaving a total of N=6,554 unique asthma-related encounters geocoded to the NHCS parcel geography.<sup>79</sup>

<sup>78</sup> The data processing steps include removal of duplicate encounters, identification of a unique patient sample based on patient Medical Record Number (MRN), basic demographic variable specification, and the estimation of patient history variables for health care utilization and housing instability. Refer to the Data Collection and Processing section of Chapter 2 for details.

<sup>79</sup> NHCS parcel classification codes were used to flag invalid conditions ratings. Parcel-geocoded encounters were removed from the sample if they were assigned a '0' or a '6' in the structure profile category; a structure profile rating of '0' indicates that the parcel was not surveyed, and a rating of '6' indicates that there was no structure on the parcel. Refer to tables A.4.37-A.4.40 in the *Parcel Classification* section of the Chapter 4 appendix for details.

A total of N=3230 patients were selected from the cleaned, parcel-geocoded asthma encounter sample using the child’s unique Medical Record Number (MRN). Following the data processing steps in Chapter 2, the patient records for the parcel-geocoded encounter associated with a child’s maximum count of previous acute care visits (ACVs) in a year period were used to specify the patient variables outlined in table 4.1.

Table 4.1. Pediatric Asthma Patient Variables

Variable	Values
Age (in years)	Min: 2 years Max: Under 19 years
Sex	1 - Female 0 - Male
Race and Ethnicity	1 - White (non-Latinx) 2 - Latinx (any race) 3 - Black (non-Latinx) 4 - Multi-Racial, Asian, or Native American Indian (non-Latinx) 5 - Unknown
Medical Coverage Type	1 - Medicaid or Other State Coverage 2 - Private Insurance 3 - Self-Pay
Patient Count Variables - Previous 365 Days	Acute Care Visits (max count per patient) Unique Residential Addresses

***Neighborhood Housing Conditions Survey (NHCS)***

There are three major categories of NHCS parcel conditions ratings: structure, grounds, and public infrastructure.<sup>80</sup> Through the NHCS window survey, parcels were assigned a rating from 1-5 for the conditions in each category, where:<sup>81</sup>

<sup>80</sup> While the parcel structure conditions ratings are the primary focus of this investigation, the public infrastructure and grounds conditions are reviewed in subsequent descriptive statistics to assess the quality and limitations of the NHCS dataset generally.

<sup>81</sup> The specific ratings criteria for each condition were based on local housing codes and designed with stakeholder input. The condition ratings criteria are summarized by category in the UMKC-CEI’s NHCS



- 1 = *Severely deteriorated*
- 2 = *Seriously deteriorated*
- 3 = *Substandard*
- 4 = *Good*
- 5 = *Excellent*

Two sets of structure conditions ratings were developed for the parcel-geocoded asthma patient sample. The first is a set of categorical variables with 5 levels ranging from severely deteriorated to excellent based on the NHCS ratings criteria for each structure condition.<sup>82</sup> The second is a composite structure conditions variable indicating the percent of substandard or worse structure conditions ratings (*conditions ratings*  $\leq$  3) for each parcel.

### ***Environmental Exposure***

Following methods used by Lindgren et al. (2016), the National Highway System (NHS) 2011 spatial data – a consistent indicator of major roads and traffic volume across state lines – was used as the input in the ArcGIS Pro Kernel Density tool to develop an estimate of traffic density for the full study area.<sup>83</sup> The annual average daily traffic (AADT) recorded for NHS segments was selected as the population field to weight the density estimates by a measure of traffic volume. The output of the Kernel Density tool was a raster dataset with cells representing the relative traffic density per square meter, which is symbolized in appendix map A.4.25.<sup>84</sup> The sample of parcel-geocoded asthma patients were assigned the raster value for traffic density based on the location of

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Ratings Guide included in the Chapter 4 appendix tables A.4.39-A.4.58.

<sup>82</sup> The primary ratings range from 1-5 – severely deteriorated to excellent – though in some cases parcels were assigned a 6 (not applicable) or a 7 (un-ratable), depending on the circumstance. A rating of 6 is associated with conditions that do not apply to a parcel, for example public sidewalk conditions for a parcel that has no public sidewalk. A rating of 7 is typically assigned to parcels if the roof of a structure is not visible from the street and is unable to be rated. These observations were treated as missing values and assigned an ‘NA’. Refer to appendix tables A.4.44-A.4.48 for additional details.

<sup>83</sup> The NHS is “a national dataset including all highways identified as Interstate, Principal Arterial – Other Freeways and Expressways, Principal Arterial – Other, and lower level roadways that are part of the National Highway System” (U.S. Department of Transportation Federal Highway Administration 2018).

<sup>84</sup> Default settings were used for the remaining parameters in the Kernel Density tool: the cell size was set to the maximum of inputs; auto commit: 1000; tile size: width/height=128; output cell size: 1477.25.

the patient's home address using a series of tools in ArcGIS Pro. First, the Feature to Point tool was used to assign a point feature class to the centroid of each parcel. A raster density value was then assigned to each parcel centroid using the Extract Values to Points tool, which was matched with the parcel-geocoded asthma sample by the unique parcel identifier.

The Near Distance tool in ArcGIS Pro was used to estimate the distance in feet from each parcel in the model sample to (1) the nearest freight route, and (2) the nearest railroad line.<sup>85</sup> The Freight Analysis Framework - Version 4 (FAF4) Network Assignment provides freight flow estimates for highways throughout the nation, including a line geography representing the highway freight routes (U.S. Department of Transportation - Federal Highway Administration (FHWA) 2012). Because the spatial resolution of the FAF4 dataset is less accurate than the NHS at the local level, segments were selected from the NHS geography and flagged as freight routes to develop a higher resolution freight traffic indicator for proximity estimates (U.S. Department of Transportation Bureau of Transportation Statistics 2017).<sup>86</sup> The final highway freight route geography is symbolized in appendix map A.4.26. The 2011 National Transportation Atlas Database (NTAD) railroad line geography symbolized in appendix map A.4.27 was used to estimate proximity to the nearest railroad from the patient's residential address (U.S. Department of Transportation Bureau of Transportation Statistics 2011).

The datasets used to represent potential point sources of pollution in the Kansas City region were derived from the U.S. Environmental Protection Agency (EPA) Facility Registration System (FRS) and the 2011 NTAD (U.S. Environmental Protection Agency Facility Registry Service (FRS)

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<sup>85</sup> The method parameter in the Near Distance Tool was set to 'geodesic'.

<sup>86</sup> The NHS segments were flagged as freight routes based on matching values in the FAF4 linear referencing system (LRS) national route identifier, segment begin and end points, and AADT fields (U.S. Department of Transportation Federal Highway Administration (FHWA) 2016). The freight route flag was used to subset the NHS data to obtain a consistent geography representing segments at least partly identified as freight routes in the FAF4 dataset.

2019).<sup>87</sup> The FRS data was used to identify facilities in the Air Facility System (AFS) and Emission Inventory System (EIS) programs with a 'create date' during or before 2010, which was recommended by EPA administrators for the FRS program (U.S. Environmental Protection Agency (EPA) 2015).<sup>88</sup> Intermodal terminal facilities and railway nodes were selected from the 2011 NTAD and merged with the FRS point feature class as additional indicators of stationary sources of air pollution.<sup>89</sup>

Default settings in the Kernel Density tool in ArcGIS Pro were used to create a raster dataset representing the density of point sources of pollution per square kilometer throughout the Kansas City study area. Given the lack of information about the relative impact and degree of pollution from different types of facilities, however, the focus of the density estimates for point sources of pollution are on the spatial distribution of unique facilities and are not weighted by a population measure (Buteau et al. 2019).<sup>90</sup> The raster density values symbolized in the appendix map A.4.28 were assigned to the parcel-geocoded asthma patient sample based on the patient's residential address according to the same procedures used in the traffic density analysis.

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<sup>87</sup> Different types of hazardous land use and their relationship with respiratory health were introduced in Chapter 3.

<sup>88</sup> FRS state single files for KS and MO were merged, then subset by program type (PGM\_SYS\_ACRNMS) and the facility registry identifier (REGISTRY\_ID) to include only unique AFS and EIS regulated facilities. The Delete Identical tool was used in ArcGIS Pro to remove duplicate facilities in this layer by location (latitude and longitude) and the NAICS code. Duplicates were removed to prevent biasing the results of the density analysis and to improve the representation of local variation in hazardous land use. The duplicates in the FRS feature class appeared to be associated with sprawling facilities such as feedlots, where multiple lots were registered to a single address. While none of these duplicates were within the study area, they do highlight potential limitations to the FRS and other regulatory datasets for this type of analysis requiring a high spatial resolution.

<sup>89</sup> Future research should explore the impact from different types of facilities (e.g. major vs. minor environmental interest types in the FRS dataset), but for the purpose of this analysis all AFS/EIS program facilities and NTAD point source indicators were grouped together in a single feature class for the kernel density analysis.

<sup>90</sup> For the default environment settings, the cell size was set to the maximum of inputs; auto commit: 1000; tile size: width/height=128. The area units parameter was set to kilometers, and the method was set to 'geodesic'.

## Sample Overview

### *Pediatric Asthma Encounters and Patients*

The location of the NHCS surveys is likely to have affected the distribution and characteristics of the parcel-geocoded asthma samples compared with the 2012 estimates reviewed in Chapter 2. The sample of parcel-geocoded asthma encounters is summarized by encounter severity in table 4.2.

Table 4.2. Parcel-Geocoded Pediatric Asthma Encounters by Severity Level, 2001-2008

	All Encounters	Severity Level: (1) Controlled	Severity Level: (2) Acute Care	Severity Level: (3) Hospitalization
<b>Sample Size</b>				
N (%)	6554 (100%)	3275 (50%)	2575 (39.3%)	704 (10.7%)
<b>Sex</b>				
Female	2,826 (43.1%)	1,479 (45.2%)	1,057 (41.0%)	290 (41.2%)
Male	3,728 (56.9%)	1,796 (54.8%)	1,518 (59.0%)	414 (58.8%)
<b>Age</b>				
2 - 6	2,816 (43.0%)	1,242 (37.9%)	1,257 (48.8%)	317 (45.0%)
7 - 10	1,718 (26.2%)	942 (28.8%)	595 (23.1%)	181 (25.7%)
11 - 14	1,283 (19.6%)	705 (21.5%)	452 (17.6%)	126 (17.9%)
15 - 18	737 (11.2%)	386 (11.8%)	271 (10.5%)	80 (11.4%)
<b>Race and Ethnicity</b>				
White (Non-Latinx)	873 (13.3%)	470 (14.4%)	308 (12.0%)	95 (13.5%)
Latinx (Any Race)	661 (10.1%)	338 (10.3%)	270 (10.5%)	53 (7.5%)
Black (Non-Latinx)	4,741 (72.3%)	2,350 (71.8%)	1,878 (72.9%)	513 (72.9%)
Other or Multiracial (Non-Latinx)	187 (2.9%)	74 (2.3%)	81 (3.1%)	32 (4.5%)
Unknown	92 (1.4%)	43 (1.3%)	38 (1.5%)	11 (1.6%)
<b>Medical Coverage Type</b>				
Medicaid	4,967 (75.8%)	2,541 (77.6%)	1,941 (75.4%)	485 (68.9%)
Commercial Insurance	1,179 (18.0%)	572 (17.5%)	436 (16.9%)	171 (24.3%)
Self Pay	403 (6.1%)	161 (4.9%)	194 (7.5%)	48 (6.8%)
Unknown	5 (0.1%)	1 (0.0%)	4 (0.2%)	0 (0.0%)

The parcel-geocoded asthma encounter sample is fairly similar to the 2012 encounter sample in terms of the proportion of the encounters by severity and patient sex, though it has a much higher proportion of low-income and minority patients. For example, 72% of the 2001-2008 parcel-geocoded asthma encounters were for Black patients and 76% of the encounters were for patients covered by Medicaid. In contrast, 48% of all encounters in 2012 were for Black patients and 65% of

the encounters were covered by Medicaid.<sup>91</sup> These patterns are repeated in the parcel-geocoded patient sample summarized by the frequency of previous ACVs in table 4.3.

Table 4.3. Parcel-Geocoded Pediatric Asthma Patients by History of Acute Care, 2001-2008

	All Patients	ACV Count: 0	ACV Count: 1	ACV Count: 2+
<b>Sample Size</b>				
N (%)	3230 (100%)	916 (28.4%)	1390 (43%)	924 (28.6%)
<b>Sex</b>				
Female	1,390 (43.0%)	436 (47.6%)	575 (41.4%)	379 (41.0%)
Male	1,840 (57.0%)	480 (52.4%)	815 (58.6%)	545 (59.0%)
<b>Age</b>				
2 - 6	1,409 (43.6%)	325 (35.5%)	651 (46.8%)	433 (46.9%)
7 - 10	782 (24.2%)	251 (27.4%)	294 (21.2%)	237 (25.6%)
11 - 14	654 (20.2%)	203 (22.2%)	292 (21.0%)	159 (17.2%)
15 - 18	385 (11.9%)	137 (15.0%)	153 (11.0%)	95 (10.3%)
<b>Race and Ethnicity</b>				
White (Non-Latinx)	461 (14.3%)	145 (15.8%)	220 (15.8%)	96 (10.4%)
Latinx (Any Race)	306 (9.5%)	78 (8.5%)	134 (9.6%)	94 (10.2%)
Black (Non-Latinx)	2,335 (72.3%)	662 (72.3%)	978 (70.4%)	695 (75.2%)
Other or Multiracial (Non-Latinx)	93 (2.9%)	23 (2.5%)	47 (3.4%)	23 (2.5%)
Unknown	35 (1.1%)	8 (0.9%)	11 (0.8%)	16 (1.7%)
<b>Medical Coverage Type</b>				
Medicaid	2,370 (73.4%)	680 (74.2%)	974 (70.1%)	716 (77.5%)
Commercial Insurance	620 (19.2%)	183 (20.0%)	284 (20.4%)	153 (16.6%)
Self Pay	239 (7.4%)	53 (5.8%)	131 (9.4%)	55 (6.0%)
Unknown	1 (0.0%)	0 (0.0%)	1 (0.1%)	0 (0.0%)

The descriptive statistics for high-risk patients in the parcel-geocoded asthma sample are summarized by the count of previous addresses – the indicator for patient housing instability – in table 4.4.<sup>92</sup> The patterns in table 4.4 indicate that coverage by Medicaid – a proxy for socioeconomic status (SES) – may provide a relatively strong signal of both asthma severity and housing instability compared with the 2012 high-risk asthma patient population reviewed in Chapter 2. Additionally, it

<sup>91</sup> See table 2.3 in Chapter 2.

<sup>92</sup> Patients are considered ‘high-risk’ if they experienced 2 or more ACVs in a year period.

was found that 12 of the NHCS parcels in the 2001-2008 model sample were matched with more than one pediatric asthma patient, highlighting the relevance of housing instability, particularly in the primary NHCS survey areas.

Table 4.4. High-Risk Pediatric Asthma Patients by the Count of Unique Addresses, 2001-2008

	High-Risk Patients	Address Count: 1	Address Count: 2	Address Count: 3+
<b>Sample Size</b>				
N (%)	924 (100%)	697 (75.4%)	205 (22.2%)	22 (2.4%)
<b>Sex</b>				
Female	379 (41.0%)	289 (41.5%)	82 (40.0%)	8 (36.4%)
Male	545 (59.0%)	408 (58.5%)	123 (60.0%)	14 (63.6%)
<b>Age</b>				
2 - 6	433 (46.9%)	331 (47.5%)	90 (43.9%)	12 (54.5%)
7 - 10	237 (25.6%)	161 (23.1%)	71 (34.6%)	5 (22.7%)
11 - 14	159 (17.2%)	128 (18.4%)	28 (13.7%)	3 (13.6%)
15 - 18	95 (10.3%)	77 (11.0%)	16 (7.8%)	2 (9.1%)
<b>Race and Ethnicity</b>				
White (Non-Latinx)	96 (10.4%)	82 (11.8%)	11 (5.4%)	3 (13.6%)
Latinx (Any Race)	94 (10.2%)	78 (11.2%)	14 (6.8%)	2 (9.1%)
Black (Non-Latinx)	695 (75.2%)	510 (73.2%)	169 (82.4%)	16 (72.7%)
Other or Multiracial (Non-Latinx)	23 (2.5%)	18 (2.6%)	5 (2.4%)	0 (0.0%)
Unknown	16 (1.7%)	9 (1.3%)	6 (2.9%)	1 (4.5%)
<b>Medical Coverage Type</b>				
Medicaid	716 (77.5%)	529 (75.9%)	168 (82.0%)	19 (86.4%)
Commercial Insurance	153 (16.6%)	129 (18.5%)	21 (10.2%)	3 (13.6%)
Self Pay	55 (6.0%)	39 (5.6%)	16 (7.8%)	0 (0.0%)
Unknown	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)

### ***NHCS Structure Conditions Ratings***

The difference between the general patient population explored in Chapter 2 and the parcel-geocoded pediatric asthma sample is likely a consequence of the uneven distribution of parcels surveyed by the NHCS during the 2001-2008 study period; areas burdened by relatively high rates of housing code violations, vacancy, and substandard housing conditions were more likely to be surveyed, and were also more likely to be subject to greater social disadvantage. These patterns are reflected in table 4.5, which shows that the distribution of the parcel-geocoded asthma patient sample

by race, ethnicity, and medical coverage type varies considerably depending on the NHCS survey year.

Table 4.5. Parcel-Geocoded Asthma Patients by NHCS Survey Year, 2001-2008

	2001	2002	2003	2004	2005	2006	2007	2008
<b>Sample Size</b>								
N (%)	1181 (36.6%)	260 (8%)	114 (3.5%)	85 (2.6%)	338 (10.5%)	395 (12.2%)	420 (13%)	437 (13.5%)
<b>Sex</b>								
Female	507 (42.9%)	109 (41.9%)	54 (47.4%)	37 (43.5%)	122 (36.1%)	182 (46.1%)	202 (48.1%)	177 (40.5%)
Male	674 (57.1%)	151 (58.1%)	60 (52.6%)	48 (56.5%)	216 (63.9%)	213 (53.9%)	218 (51.9%)	260 (59.5%)
<b>Age</b>								
2 - 6	479 (40.6%)	111 (42.7%)	43 (37.7%)	39 (45.9%)	148 (43.8%)	173 (43.8%)	185 (44.0%)	231 (52.9%)
7 - 10	297 (25.1%)	65 (25.0%)	27 (23.7%)	25 (29.4%)	76 (22.5%)	86 (21.8%)	97 (23.1%)	109 (24.9%)
11 - 14	268 (22.7%)	60 (23.1%)	27 (23.7%)	12 (14.1%)	68 (20.1%)	82 (20.8%)	81 (19.3%)	56 (12.8%)
15 - 18	137 (11.6%)	24 (9.2%)	17 (14.9%)	9 (10.6%)	46 (13.6%)	54 (13.7%)	57 (13.6%)	41 (9.4%)
<b>Race and Ethnicity</b>								
White (Non-Latinx)	125 (10.6%)	58 (22.3%)	13 (11.4%)	39 (45.9%)	136 (40.2%)	11 (2.8%)	31 (7.4%)	48 (11.0%)
Latinx (Any Race)	50 (4.2%)	61 (23.5%)	4 (3.5%)	3 (3.5%)	20 (5.9%)	14 (3.5%)	31 (7.4%)	123 (28.1%)
Black (Non-Latinx)	977 (82.7%)	132 (50.8%)	95 (83.3%)	39 (45.9%)	168 (49.7%)	356 (90.1%)	343 (81.7%)	225 (51.5%)
Other or Multiracial (Non-Latinx)	16 (1.4%)	7 (2.7%)	1 (0.9%)	4 (4.7%)	10 (3.0%)	9 (2.3%)	11 (2.6%)	35 (8.0%)
Unknown	13 (1.1%)	2 (0.8%)	1 (0.9%)	0 (0.0%)	4 (1.2%)	5 (1.3%)	4 (1.0%)	6 (1.4%)
<b>Medical Coverage Type</b>								
Medicaid	891 (75.4%)	167 (64.2%)	93 (81.6%)	47 (55.3%)	170 (50.3%)	311 (78.7%)	338 (80.5%)	353 (80.8%)
Commercial Insurance	189 (16.0%)	70 (26.9%)	14 (12.3%)	35 (41.2%)	155 (45.9%)	56 (14.2%)	49 (11.7%)	52 (11.9%)
Self Pay	101 (8.6%)	23 (8.8%)	7 (6.1%)	3 (3.5%)	12 (3.6%)	28 (7.1%)	33 (7.9%)	32 (7.3%)
Unknown	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (0.3%)	0 (0.0%)	0 (0.0%)	0 (0.0%)

For example, 40% of parcel geocoded patients in the 2005 sample were White (non-Latinx) and 40% were Black (non-Latinx). In contrast, only 11% of the parcel geocoded patients in the 2001 sample were White (non-Latinx), while 83% were Black (non-Latinx). Appendix maps A.4.17-A.4.24 show the spatial distribution of NHCS parcels by survey year. NHCS parcels surveyed in 2001 were concentrated in largely minority and low-income areas of the urban core and aging suburbs north of the Missouri river in KCMO. In contrast, the 2005 NHCS survey targeted parcels throughout different suburbs of the Kansas City region, including samples in parts of JOCO and WYCO in Kansas, in KCMO north of the Missouri River, and in the Independence and Raytown municipalities in Jackson County, Missouri.<sup>93</sup>

<sup>93</sup> See the discussion in Chapter 3 for more details regarding the distribution of socially disadvantaged communities throughout the Kansas City region and how it relates to historic racial residential segregation.

Table 4.6 shows the percent of the parcel-geocoded asthma patient sample by NHCS conditions ratings in all three categories.

Table 4.6. Percent of NHCS Conditions Ratings by Category in the Parcel-Geocoded Asthma Patient Sample, 2001-2008<sup>94</sup>

Conditions	Substandard			Good-Excellent		NA
	1	2	3	4	5	
<b>Structure</b>						
Roof	1	6	38	39	12	4
Foundation	0	1	9	40	50	0
Windows and Doors	0	1	12	39	47	0
Porch	0	3	20	37	39	1
Exterior Paint	1	4	26	41	27	0
<b>Grounds</b>						
Private Sidewalks and Driveways	5	6	27	37	24	0
Lawn	0	1	11	33	55	0
Vehicles	0	1	4	9	87	0
Litter	0	1	5	16	77	0
Open Storage	0	1	5	17	78	0
<b>Infrastructure</b>						
Public Sidewalks	7	4	11	23	24	31
Curbs	5	7	12	32	34	9
Streetlights	0	0	0	2	96	0
Catch Basins	0	0	1	1	8	90
Street Condition	0	1	5	40	54	0

Table 4.6 suggests skewed structure conditions ratings in the parcel-geocoded patient sample; the majority of the variation in structure conditions ratings is between ratings 4 (good) and 5 (excellent). Compared with the structure category, the conditions in the infrastructure and grounds categories show less variation in the parcel-geocoded patient sample overall.<sup>95</sup> The distribution of

<sup>94</sup> The color coding in table 4.6 was developed using the Viridis package introduced in Chapter 3 and covered in the Tools and Software section of this chapter. Colors are assigned to cells based on their value, which is used to help with scanning for patterns in the data.

<sup>95</sup> The distribution of conditions ratings by survey year in appendix figures A.4.1-A.4.16 suggest that the quality and availability of the grounds and public infrastructure categories depends on regional development patterns. For example, the infrastructure ratings for public sidewalks in figure A.4.11 shows that over 60% of the sample in the 2005 and 2006 survey years are missing data for public sidewalk ratings, meaning that there were no public sidewalks to rate for those parcels. Appendix maps A.4.21 and A.4.22 suggest that the surveys conducted between 2005 and 2006 were in relatively low-population density suburbs and rural communities outside of KCMO and WYCO where it may be less common to have sidewalks on both sides of every



ratings and missing data by category may be related to regional development patterns, highlighting additional caveats to this type of indicator that should be taken into consideration when interpreting the data analysis results.<sup>96</sup>

### *Environmental Exposure Covariates*

The descriptive statistics for each of the environmental exposure covariates assigned to the parcel-geocoded asthma patient sample are provided in table 4.7.

Table 4.7. Environmental Exposure Covariate Values Assigned to the Parcel-Geocoded Asthma Patient Sample, 2001-2008

	All Patients	ACV Count: 0	ACV Count: 1	ACV Count: 2+
<b>Sample Size</b>				
N (%)	3230 (100%)	916 (28%)	1390 (43%)	924 (29%)
<b>Density of Point Sources (per sq km)</b>				
mean (sd)	1.7 (1.3)	1.6 (1.3)	1.7 (1.3)	1.7 (1.4)
min	0.0	0.0	0.0	0.1
max	9.1	8.3	8.8	9.1
<b>Traffic Density (AADT per sq m)</b>				
mean (sd)	28.0 (45.0)	30.1 (49.9)	27.2 (43.6)	27.3 (42.0)
min	0.0	0.0	0.0	0.0
max	483.1	387.7	303.2	483.1
<b>Proximity to Freight Lines (US Feet)</b>				
mean (sd)	1,558.7 (1,187.9)	1,573.0 (1,224.5)	1,585.4 (1,170.1)	1,504.4 (1,177.0)
min	14.4	26.5	14.4	21.6
max	6,903.2	6,903.2	6,296.9	6,550.2
<b>Proximity to Railroads (US Feet)</b>				
mean (sd)	4,738.8 (2,777.6)	4,826.1 (2,889.9)	4,708.4 (2,760.1)	4,698.1 (2,690.0)
min	0.0	71.8	0.0	118.1
max	17,522.7	17,522.7	17,483.7	15,008.7

residential street. Other ratings are highly skewed and provide little detail about actual patient living conditions. For example, the vast majority of the sample in each survey year is assigned a 5, or an excellent rating, for streetlights in appendix figure A.4.14.

<sup>96</sup> The Chapter 3 results suggest that certain indicators not directly related to the incidence or severity of pediatric asthma may guide cluster assignment by providing information about development patterns and the location of vulnerable populations. Including unrelated or auxiliary NHCS conditions ratings in the patient-level analysis, however, may bias the results or add noise to the model where data is missing due to development patterns, or where ratings provide little information about what distinguishes different patient living conditions.

The only consistent relationship between environmental exposure and the frequency of ACVs in the sample overall is captured by the measure for proximity to railroads. Given the spatial distribution and relative homogeneity of the parcel-geocoded asthma sample, however, the aggregate summary statistics are not likely to provide much information about how environmental exposure may actually impact or relate to pediatric asthma severity.

### Model Specification

The BPR model specified in Chapter 3 was modified to facilitate an exploratory analysis of the parcel-geocoded pediatric asthma patient sample. The dependent variable in this chapter - the patient history of acute care visits (ACVs) - is modeled as a Poisson distributed variable in the response sub-model, and the covariate model is built to allow for a mixture of both discrete and continuous random variables.<sup>97</sup> The cluster assignments in the model output are used to explore how different combinations of covariates relate to the asthma patient history of ACVs, providing insight into both protective factors and risk factors, and informing subsequent research, intervention, and patient treatment strategies.

The following represents the likelihood for the full profile regression model, with  $f_Y$  as the response model, and  $f_X$  the covariate model:<sup>98</sup>

$$p(D_i|Z_i, \Theta, \Lambda, W_i) = f_Y(y_i|\Theta_{Z_i}, \Lambda, W_i)f_X(x_i|\Theta_{Z_i}, \Lambda)$$

Where:

$D = (Y, X)$ , such that the data contain information for both a response,  $Y_i$ , and covariates  $X_i$  for each individual,  $i$ ,

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<sup>97</sup> The ‘mixed mixtures’ covariate model was used in this chapter given the exploratory nature of the exercise, and because limited or inconsistent information is available on how each covariate relates to the disease response, making it difficult to discretize all variables. While the results of this exercise may provide a basis for discretizing some of the continuous variables, future initiatives should investigate alternative model and variable specification options in general through multi-disciplinary research.

<sup>98</sup> The model specification was derived from the primary publication on the PReMiuM R package for Bayesian Profile Regression (BPR) (Liverani, Hastie, and Richardson 2015).

$Z_i$  is a cluster allocation variable,  
 $\Theta_{Z_i}$  is a cluster specific vector of parameters,  
 $\Lambda$  is a vector of global parameters, and  
 $W_i$  are fixed effects for each individual.<sup>99</sup>

### ***Covariate Model***

The covariate ‘mixed mixtures’ model,  $f_X$ , is built to fit both continuous and discrete categorical variables:<sup>100</sup>

$$p(D_i|Z_i, \Theta_{Z_i}, \Lambda) = p(D_i^1|\mu_{Z_i}, \Sigma_{Z_i})p(D_i^2|\phi_{Z_i})$$

The covariate model for the mixture of discrete random variables,  $D_i^2$ , was specified in Chapter 3 and is written:

$$p(D_i|Z_i, \Theta_{Z_i}, \Lambda) = f(D_i|\Phi_{Z_i}) = \prod_{j=1}^J \phi_{Z_i,j,X_{i,j}}^{101}$$

The covariate likelihood for the subset of continuous random variables,  $D_i^1$ , where  $\mathbf{D} = \mathbf{X}$ , assuming  $\mathbf{X}$  takes the form of a mixture of Gaussian distributions, is as follows:

$$p(X_i|Z_i, \Theta_{Z_i}, \Lambda) = f(X_i|\mu_{Z_i}, \Sigma_{Z_i}) = (2\pi)^{-\frac{J}{2}}|\Sigma_{Z_i}|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}(X_i - \mu_{Z_i})^T \Sigma_{Z_i}^{-1}(X_i - \mu_{Z_i})\right)$$

With prior distributions for each cluster  $c$ ,  $\mu_c \sim Normal(\mu_0, \Sigma_0)$  and  $\Sigma_c \sim InvWishart(R_0, \kappa_0)$ .

### ***Response Model***

In the Poisson response sub-model,  $f_Y$ , each individual is associated with an offset  $E_i$  and an additional parameter  $\theta_c$ :<sup>102</sup>

<sup>99</sup> As in Chapter 3, no fixed effects were specified for the BPR model trials in Chapter 4.

<sup>100</sup> It should be noted that in the mixed mixtures covariate model, the authors are assuming, conditional on cluster assignment, that the discrete and continuous data are independent. Future research should review alternative model and variable specification to account for these limitations given the available data.

<sup>101</sup> Refer to the Model Specification section of Chapter 3 for the discrete mixtures covariate model details.

<sup>102</sup> Because the response variable measures the count of ACVs recorded during a 365-day period, the offset is the same duration for all patients in the sample and  $E_i = 1$ .

$$f_Y(y_i | \Theta_{Z_i}, \Lambda, W_i) = p(Y_i | \theta_{Z_i}, \beta, W_i) = \frac{\mu_i^{Y_i}}{Y_i!} \exp\{-\mu_i\}$$

Given the Poisson parameter  $\lambda$  and a global parameter vector,  $\Lambda = \beta$ , which is the length of the vector of fixed effects,  $W_i$ :

$$\mu_i = E_i \exp\{\lambda_i\}, \text{ for } \lambda_i = \theta_{Z_i} + \beta^T W_i$$

For  $\theta_c$  and  $\beta$ , the prior models are specified as t-location distributions with a default specification of 7 degrees of freedom: for each cluster,  $\theta_c \sim t_v(\mu_\theta, \sigma_\theta)$ , and for each fixed effect  $l$ ,  $\beta_l \sim t_v(\mu_\beta, \sigma_\beta)$ . Finally, the model was specified to allow for extra variance in the response given evidence of overdispersion.<sup>103</sup>

### ***Variable Specification***

The full set of model variables introduced in the Data Collection & Processing section are specified as follows:

*Dependent Variable,  $y_i$ :*

$y_i$  the maximum count of acute care visits (ACVs) over a 365-day period associated with each parcel-geocoded asthma patient in the 2001-2008 sample

*Categorical Discrete Covariates,  $D_i^2$ :*

#### **Patient Characteristics**

$x_{i1}$  patient sex with two levels, where 1 = female and 0 = male

$x_{i2}$  indicator for race and ethnicity with 4 levels, where 0 = White (non-Latinx), 1 = Latinx, 2 = Black (non-Latinx), and 3 = Asian, Pacific Islander, Native American, or unspecified

$x_{i3}$  medical coverage type with 3 levels, where 0 = Medicaid or other state coverage, 1 = commercial or private insurance coverage, and 2 = self-pay (no state or commercial medical coverage)

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<sup>103</sup> Overdispersion is a common violation of the assumption that the variance is equal to the mean in a Poisson distribution. The AER package in RStudio was used to test the sample for overdispersion by fitting the data with a Poisson generalized linear regression model, then using the model sample estimates in the dispersiontest() function, which tests the null hypothesis  $H_0: dispersion = 1$  against the alternative hypothesis  $H_1: dispersion > 1$ . The results of the test reject the null hypothesis with sample  $dispersion = 1.49$  and a  $p\text{ value} = 3.304e - 08$ , suggesting the model does exhibit overdispersion.

### Parcel Structure Conditions Ratings<sup>104</sup>

- $x_{i4}$  Roof conditions rating (5 levels)
- $x_{i5}$  Foundation and walls conditions rating (5 levels)
- $x_{i6}$  Windows and doors conditions rating (5 levels)
- $x_{i7}$  Porch conditions rating (5 levels)
- $x_{i8}$  Exterior Paint conditions rating (5 levels)

### Continuous Covariates, ( $D_i^1$ ):<sup>105</sup>

#### Patient Characteristics

- $x_{i9}$  an indicator of housing instability measured by the count of unique addresses associated with each patient during the period in which they experienced their maximum count of ACVs
- $x_{i10}$  age of patient at the time of the encounter (in years)

#### Parcel Structure Conditions Ratings

- $x_{i11}$  the percent of structure conditions rated as substandard or worse (*NHCS Rating*  $\leq 3$ )

#### Environmental Exposure Covariates

- $x_{i12}$  Density of point sources of pollution per square kilometer
- $x_{i13}$  Traffic density measured by the annual average daily traffic (AADT) per square meter
- $x_{i14}$  Distance to the nearest freight route (US Feet)
- $x_{i15}$  Distance to the nearest railroad line (US Feet)

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<sup>104</sup> The categorical covariates for NHCS structure conditions ratings are based on the 5 ratings criteria, discussed in the Data Collection & Processing section of this chapter. The 5 levels range from 1 (severely deteriorated) to 5 (excellent).

<sup>105</sup> As mentioned above, some variables were treated as continuous given limited information on the relevant ranges of values to use for creating a discrete categorical variable. Future research can test alternative models using only discrete categorical covariates, which would be aided by multidisciplinary collaboration. For example, input from environmental scientists on the relevant ranges of impact for proximity to railroads can be used to inform a discrete categorical covariate for  $x_{i15}$ .

## ***Model Trials***

Two BPR model trials were tested:<sup>106</sup>

Model 1: *Excluding* the housing instability variable,  $x_{i9}$

Model 2: *Including* the housing instability variable,  $x_{i9}$

The BPR results for each model trial are presented by cluster risk group in risk profile box plots, summary statistics, and maps showing the spatial distribution of parcel-geocoded patients based on cluster assignment.<sup>107</sup> If there are no clear risk groups, the patient clusters are compared with one another based on relative risk.<sup>108</sup> The results for each model trial are reviewed individually and then compared with one another based on changes in patient cluster assignment.

## **Results**

For each trial, the initial model chain was run for 20,000 iterations with a burn-in sample of 10,000 and default hyperparameter values, documented in the PReMiUM R package details (Liverani, Hastie, and Richardson 2015). Trace plots for  $\alpha$  - the concentration parameter for the Dirichlet distribution - and for the number of clusters do not provide evidence against convergence of the

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<sup>106</sup> As is discussed in the introduction to this chapter, housing instability is a suspected health risk factor and may also act as a measure of the relative duration of patient exposure to both environmental triggers and housing conditions. To the author's knowledge, however, there were no examples in the literature at the time of this study of measuring housing instability using electronic health records (EHR), let alone testing the relationship between this type of indicator and pediatric asthma. The model was run with and without the housing instability variable,  $x_{i9}$ , given the exploratory nature of the measure. This is the only variable excluded from the model because the other covariates were selected based on existing evidence of their relationship with pediatric asthma risk and examples of their use in similar studies.

<sup>107</sup> The risk profile box plots included in the BPR output from the PReMiUM R package provide a detailed summary of cluster characteristics based on the posterior distribution of each sample. Risk groups are identified based on whether the 95% credible interval of the posterior distribution for each patient cluster is fully below the average (blue), includes the average (green), or is fully above average (red) risk in terms of the frequency of ACVs; the response.

<sup>108</sup> The clear definition of risk groups, while useful for exploratory analysis, is not the focus of this investigation. That clusters of patients with a similar risk of ACVs are separated into distinct groups may provide insight into the different combinations of risks and vulnerabilities relating to pediatric asthma, which can provide valuable place- and person-specific targets for research, intervention, and patient treatment strategies; for translational research.

chains to the posterior in either model trial.<sup>109</sup> Despite the homogeneity of the model sample, clear and distinct patterns emerge shedding light on both risk factors and protective factors relating to the frequency of pediatric asthma patient ACVs in the surveyed population.

### **Model 1**

The results of the BPR for the Model 1 trial identified 8 distinct clusters of patients. The risk profile box plots for each cluster in appendix figures A.4.29-A.4.30 show that the model identified only 2 fully below-average risk clusters; clusters 1 and 3. While there are no clear above-average risk clusters, the distribution of risk still varies between the average-risk (green) clusters, providing a basis for separating out relative risk groups for comparison. The distribution of covariate values by patient cluster are summarized in table 4.8 with clusters organized from low to high risk in terms of the mean count of ACVs, and maps 4.2-4.10 show the general location of the patients by their residential address within the NHCS parcel survey area.<sup>110</sup>

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<sup>109</sup> See appendix figures A.4.31-A.4.32 for the Model 1 trace plots, and A.4.36-A.4.37 for the Model 2 trace plots.

<sup>110</sup> The cells in table 4.8 are colored by value using the Viridis R package following the same method used in the Chapter 3 BPR analysis. Rows for common variables were assigned colors based on the same range of values so that they are comparable to one another. If a range of values was unique to a variable – for example, the first row showing the mean count of asthma ACVs – the colors were based on the range of values in that row alone.

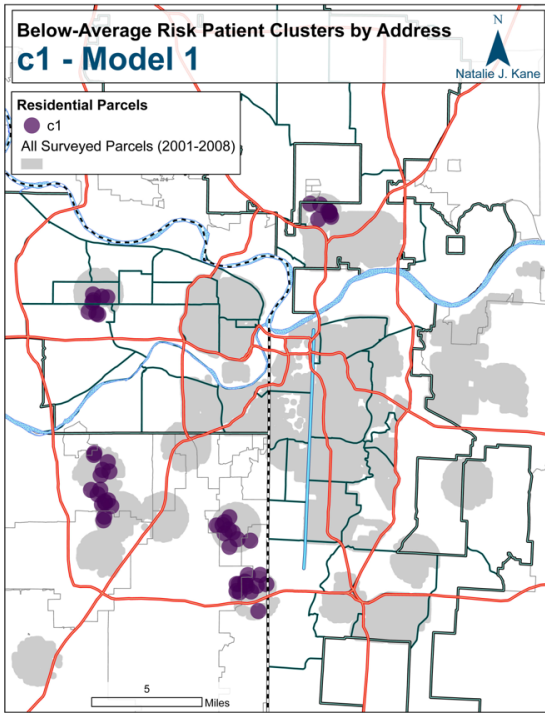
Table 4.8. Response and Covariate Profile Summarized by Patient Cluster – Model 1<sup>111</sup>

Asthma Risk and Covariates by Cluster	Total	Relative Risk by Cluster - 90% Credible Interval (IQR)							
		Below Avg.			Average			Above Avg.	
		C1	C2	C3	C4	C5	C6	C7	C8
Mean Count of Patient Asthma ACVs	1.27	0.8	0.89	1.19	1.24	1.32	1.33	1.39	1.45
Sample Size (%) (N=3230)	100%	2	1	34	6	21	23	5	7
<b>Sex (%)</b>									
Male	57	59	51	58	52	55	56	57	61
<b>Age (%)</b>									
2 - 6	44	47	49	48	44	40	39	39	50
7 - 10	24	24	43	23	21	24	26	22	27
11 - 14	20	20	9	19	23	22	21	23	15
15 - 18	12	8	0	10	12	14	14	15	8
<b>Race and Ethnicity (%)</b>									
White (non-Latinx)	14	85	14	12	7	13	12	9	29
Latinx (any race)	9	0	54	8	3	8	6	12	34
Black (non-Latinx)	72	10	29	74	89	77	80	78	27
Other or Multiracial (non-Latinx)	3	3	3	4	1	1	2	1	8
Unknown	1	2	0	2	0	1	1	1	2
<b>Medical Coverage (%)</b>									
Medicaid	73	10	74	72	83	72	74	88	81
Commercial	19	90	20	21	12	18	19	9	11
Self-Pay	7	0	6	7	4	10	7	4	8
<b>Average NHCS Ratings</b>									
Avg. % Substandard Structure Ratings	25	8	21	0	24	53	20	91	35
Roof	3.6	3.9	3.5	4.3	3.7	3.1	3.3	2.6	3.3
Foundation and Walls	4.4	5	4.5	4.7	4.4	3.9	4.5	3.3	4.2
Windows and Doors	4.3	5	4.2	4.7	4.4	3.8	4.5	2.9	4
Porch	4.1	4.8	4.3	4.7	4	3.4	4.3	2.9	3.9
Exterior Paint	3.9	4.6	4	4.5	4	3.1	4.1	2.9	3.4
<b>Environmental Exposure (Mean Decile Rank)</b>									
Density - Point Sources (per sq. km)	5.5	1.3	9.7	5.6	4.9	5.2	4.6	6.3	9.7
Density - Traffic (per sq. m)	5.5	4.3	9.1	5.1	10	5.2	5	6.2	5.1
Distance to Nearest Freight Route (ft)	5.5	8.9	2.1	5.7	2.8	5.7	5.8	4.1	6.4
Distance to Nearest Railroad (ft)	5.5	10	1.8	5.1	7.2	5.8	6	5.9	2.5

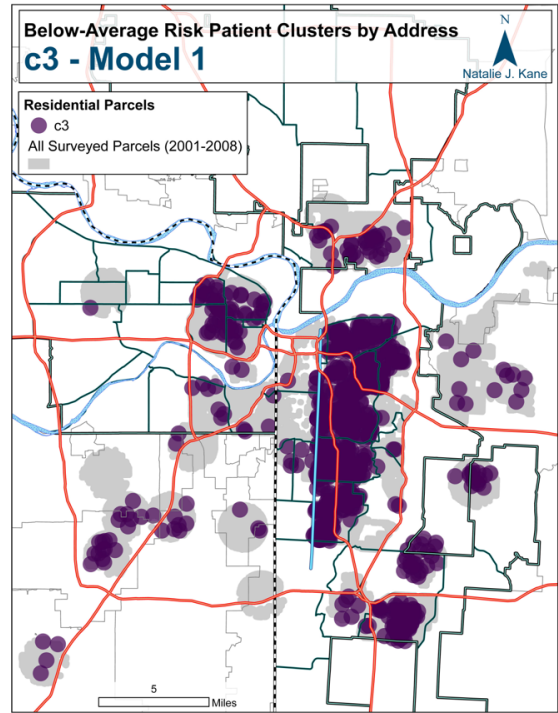
<sup>111</sup> The patient characteristics including sex, age, race and ethnicity, and medical coverage type are summarized by the percent of patients in each covariate category. The structure conditions variables are summarized by the mean percent substandard conditions ratings overall and the mean rating for each of the categorical structure conditions variables. To simplify the continuous environmental covariates for within- and between-cluster comparisons, the full model sample was assigned a decile rank (1-10) for the four covariates before estimating the cluster averages. Note that a high decile rank for the density covariates indicates elevated exposure, while high scores in the proximity estimates indicate greater distance between the patient’s address and land use hazard, which would suggest lower risk of exposure.



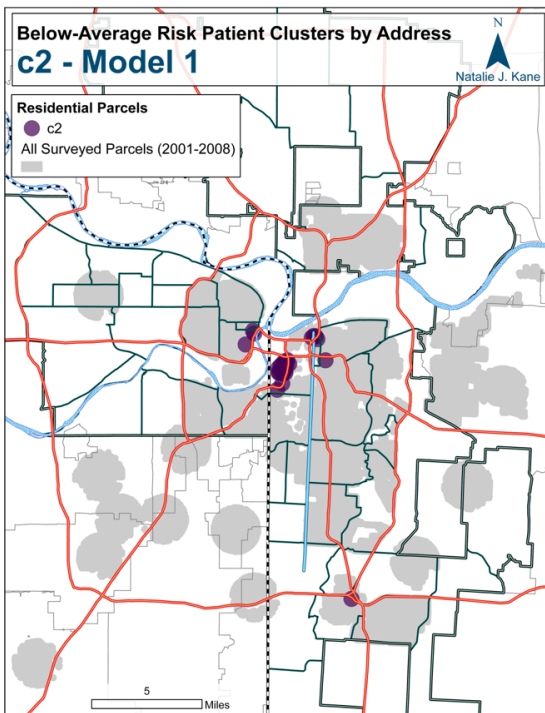
Map 4.2. Model 1 Patient Cluster 1 (c1)



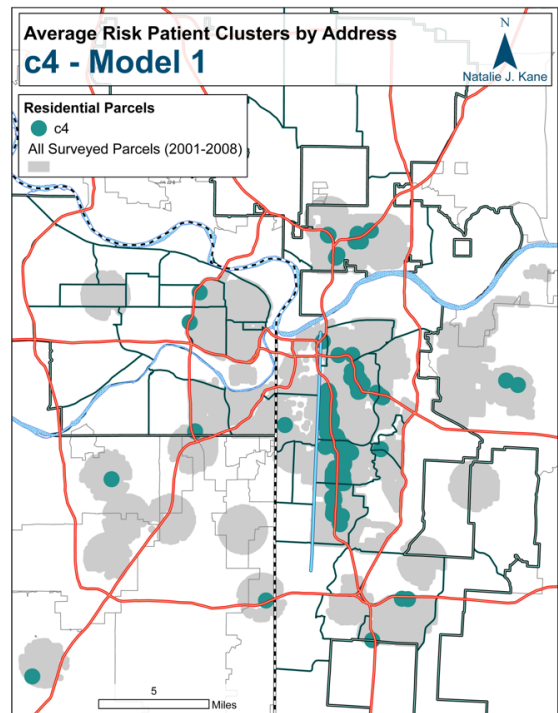
Map 4.4. Model 1 Patient Cluster 3 (c3)



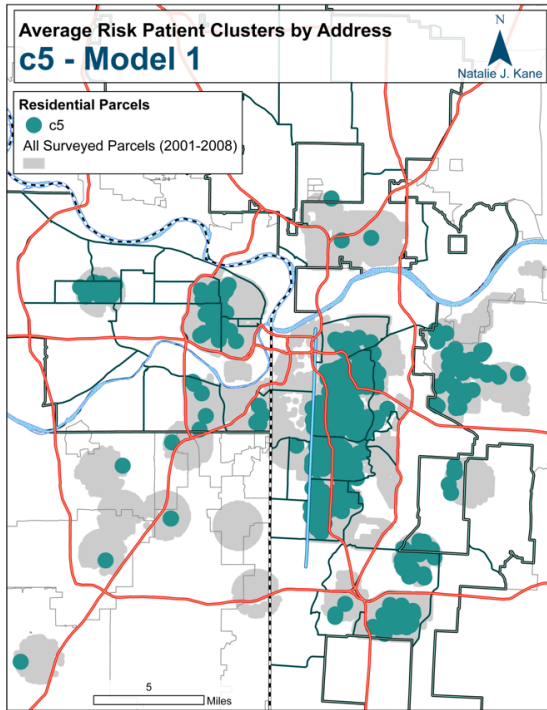
Map 4.3. Model 1 Patient Cluster 2 (c2)



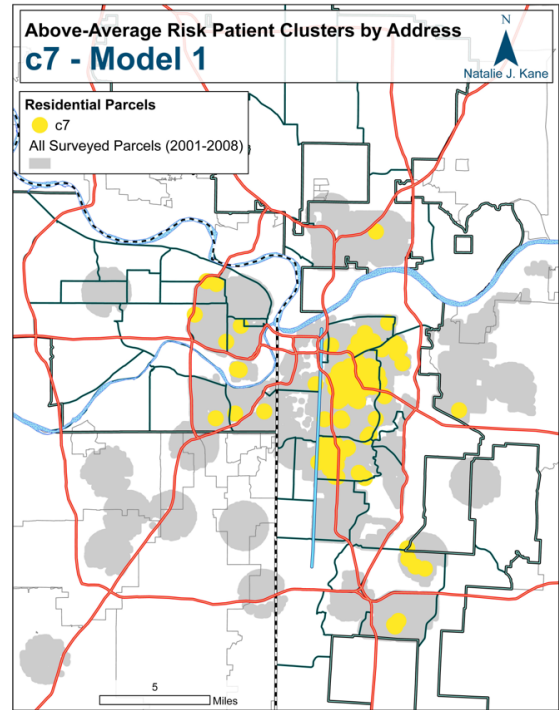
Map 4.5. Model 1 Patient Cluster 4 (c4)



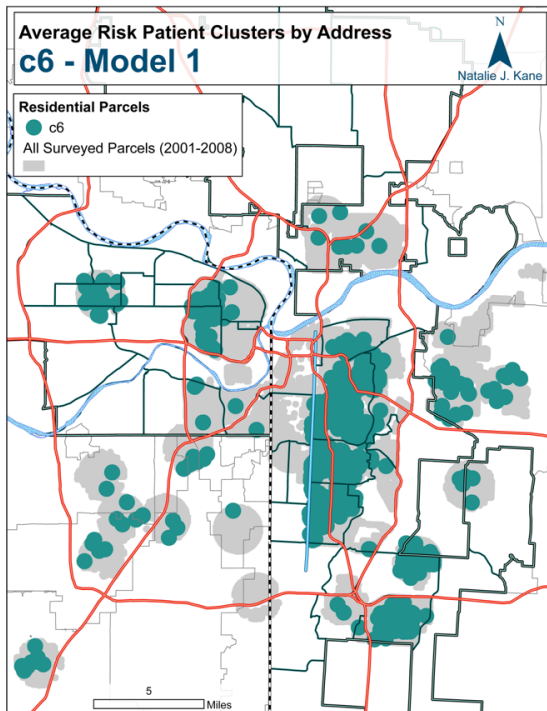
Map 4.6. Model 1 Patient Cluster 5 (c5)



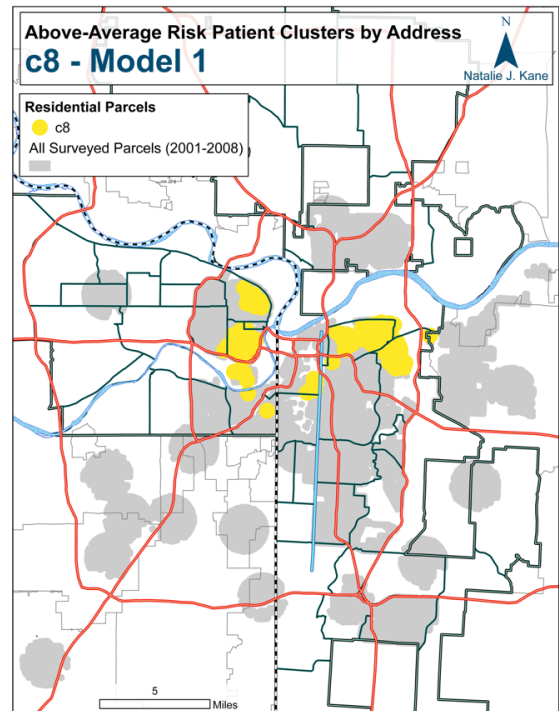
Map 4.8. Model 1 Patient Cluster 7 (c7)



Map 4.7. Model 1 Patient Cluster 6 (c6)



Map 4.9. Model 1 Patient Cluster 8 (c8)



Cluster assignment in Model 1 suggests that the lowest risk patient cluster, c1, is characterized by relative privilege in terms of race, ethnicity, socioeconomic status measured by commercial insurance coverage, and low environmental exposure both in and around the home. The patterns in map 4.2 show that c1 patients also live in wealthy suburbs of Kansas City identified as below-average risk populations in Chapter 3.

Cluster c3 might be characterized as the representative below-average risk Model 1 patient cluster in terms of its size, patient characteristics, environmental exposure, and frequency of ACVs. 34% of the patients in the full sample are assigned to c3, making it the largest of all 8 risk profile clusters. The patients in c3 are distinguished from the rest of the Model 1 clusters by the NHCS covariate levels; c3 has the most consistently high NHCS ratings of all clusters, with an average of 0% substandard structure conditions ratings. Map 4.4 shows that the patient sample assigned to c3 includes children living throughout most of the NHCS parcel survey area, though very few c3 patients live in the same survey areas as c1 patients.

While Model 1 did not identify any completely above-average risk clusters, the posterior distributions for the model clusters suggests consistently higher risk in clusters c7 and c8 compared with the rest of the sample.<sup>112</sup> Cluster c7 is comparable to the sample overall and most of the Model 1 clusters in terms of race and ethnicity, age, and sex. Aside from having the second highest mean count of ACVs, c7 is distinguished by the highest proportion of patients covered by Medicaid (88%) and the lowest ratings for all structure conditions, with an average of 91% rated substandard or worse. Map 4.8 shows that the patients assigned to c7 are concentrated in the East Side, Brush Creek South, and Old Northeast community districts in KCMO, with observations scattered throughout other parts of WYCO and Jackson County, MO. Notably, though, there are no observations for c7 in JOCO. This suggests that the higher average frequency of ACVs among c7 patients compared with the

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<sup>112</sup> Note that the order for the two highest risk clusters c7 and c8 in table 4.8 is reversed in the risk profile box plots for Model 1, which ordered clusters based on empirical distribution for cluster risk rather than the sample mean. See appendix figures A.4.29-A.4.30.

completely below-average risk clusters c1 and c3 may be related to a combination of both social disadvantage and substandard housing conditions.

## Model 2

In contrast to the Model 1 results, Model 2 produced a much more clearly defined set of risk groups – 3 fully below-average risk, 2 average risk, and 2 completely above-average risk patient clusters – suggesting that the addition of the housing instability indicator provided a very strong signal for cluster assignment.<sup>113</sup> Table 4.9 summarizes the covariate profile for each of the 7 patient clusters identified in Model 2, which included the count of unique addresses - the housing instability measure – as a continuous explanatory variable,  $x_{i9}$ . Maps 4.10-4.16 show the Model 2 patient clusters mapped by residential address within the NHCS parcel survey area.

The below-average risk cluster c1 has the largest sample of patients (35%) and the lowest mean count of ACVs (1.09) in Model 2. In terms of the covariate profile, c1 is distinguished by the lowest percent of patients covered by Medicaid (65%), the highest percent covered by commercial insurance (29%), and the lowest mean levels of environmental exposure of all 7 clusters. While c1 also has the highest percent of White (non-Latinx) patients (19%), it is still made up of mostly Black (non-Latinx) patients (75%). Except for roof conditions, c1 patients on average have structure conditions ratings in the good to excellent range ( $ratings \geq 4$ ).<sup>114</sup> Map 4.10 shows that, while the patients in c1 are located throughout the NHCS survey area, a significant proportion of c1 patients live in relatively wealthy suburbs and almost no c1 patients live in either the Old Northeast community district in KCMO or the Northeast community district in WYCO.

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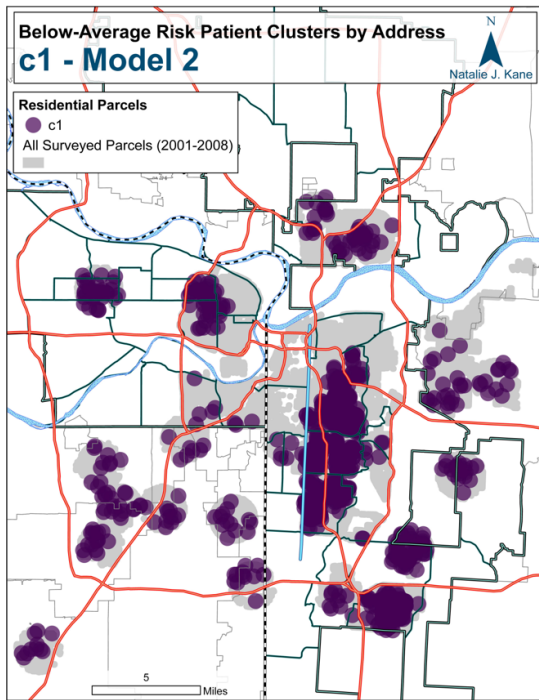
<sup>113</sup> Refer to the Model 2 risk profile box plots in appendix figures A.4.34-A.4.35 for details.

<sup>114</sup> According to the risk profile box plots in appendix figure A.4.34, the spread of the posterior distribution for c1 roof ratings is relatively narrow. This suggests that the slightly lower mean rating is not just due to a greater number of patients with missing roof ratings where the roof was not visible from the street in the NHCS survey. Additional descriptive statistics and data visualizations should be developed to review and verify the distribution of structure conditions ratings by cluster.

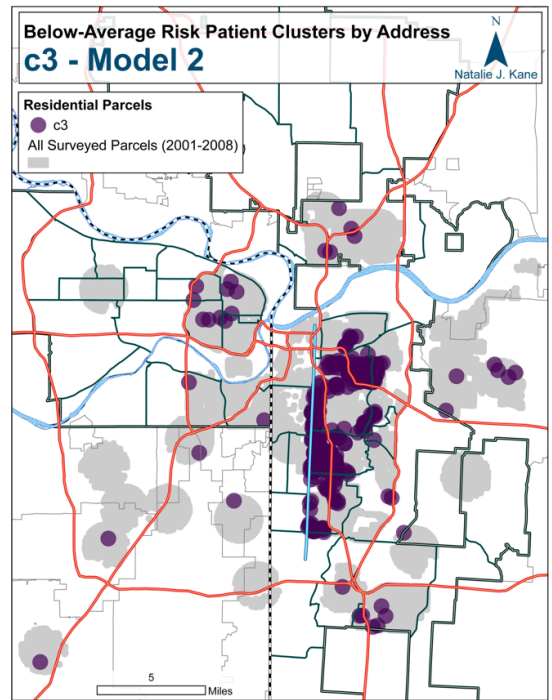
Table 4.9. Response and Covariate Profile Summarized by Patient Cluster – Model 2

Asthma Risk and Covariates by Cluster	Total	Relative Risk by Cluster						
		Below			Average		Above	
		C1	C2	C3	C4	C5	C6	C7
Mean Count of Patient Asthma ACVs	1.27	1.02	1.1	1.14	1.27	1.27	2.2	2.41
Sample Size (%) (N=3230)	100%	35	5	13	7	29	10	2
Avg. Count of Unique Addresses	1.13	1	1	1	1	1	2	2.58
<b>Sex (%)</b>								
Male	57	59	56	56	56	56	58	56
<b>Age (%)</b>								
2 - 6	44	44	42	42	52	43	42	45
7 - 10	24	24	21	21	22	24	31	28
11 - 14	20	21	27	23	15	19	17	16
15 - 18	12	11	10	13	11	13	11	11
<b>Race and Ethnicity (%)</b>								
White (non-Latinx)	14	19	10	8	11	16	9	5
Latinx (any race)	9	3	6	4	28	16	7	14
Black (non-Latinx)	72	75	83	85	50	64	80	80
Other or Multiracial (non-Latinx)	3	3	1	2	9	3	2	0
Unknown	1	1	0	2	1	1	2	2
<b>Medical Coverage (%)</b>								
Medicaid	73	65	79	79	75	77	79	88
Commercial	19	29	14	14	16	14	13	11
Self-Pay	7	7	7	7	9	9	8	2
<b>Average NHCS Ratings</b>								
Avg. % Substandard Structure Ratings	25	12	25	9	1	56	21	24
Roof	3.6	3.7	3.7	3.9	4.3	3.1	3.6	3.5
Foundation and Walls	4.4	4.6	4.4	4.7	4.7	3.8	4.5	4.3
Windows and Doors	4.3	4.7	4.2	4.6	4.6	3.7	4.4	4.4
Porch	4.1	4.5	4	4.4	4.6	3.4	4.1	4.2
Exterior Paint	3.9	4.3	3.9	4.3	4.4	3.1	3.9	4
<b>Environmental Exposure (Mean Decile Rank)</b>								
Density - Point Sources (per sq. km)	5.5	3.6	5.9	5.9	9.5	6.7	5.2	6
Density - Traffic (per sq. m)	5.5	4.1	10	7.4	5.9	5.3	5.7	7.8
Distance to Nearest Freight Route (ft)	5.5	7.1	2.5	2.8	5.7	5.4	5.2	3.9
Distance to Nearest Railroad (ft)	5.5	6.3	6.2	5.8	2.7	4.8	5.8	6.1

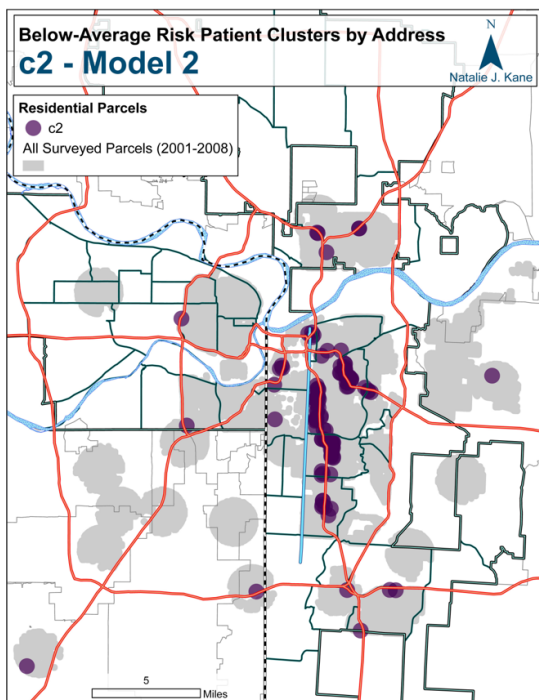
Map 4.10. Model 2 Patient Cluster 1 (c1)



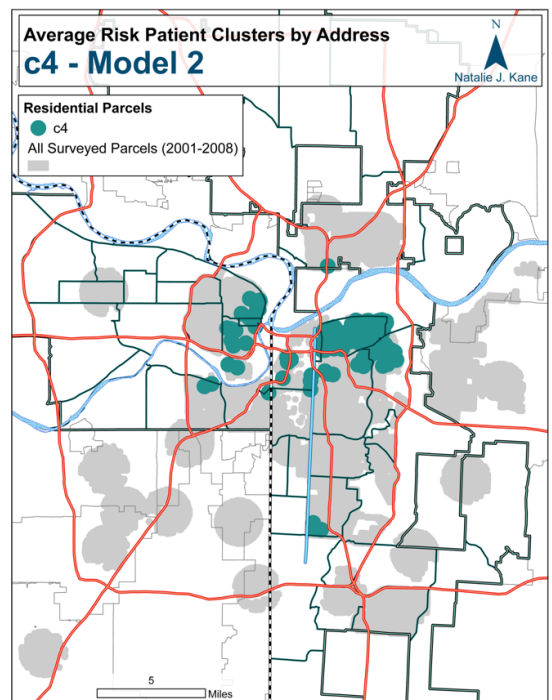
Map 4.12. Model 2 Patient Cluster 3 (c3)



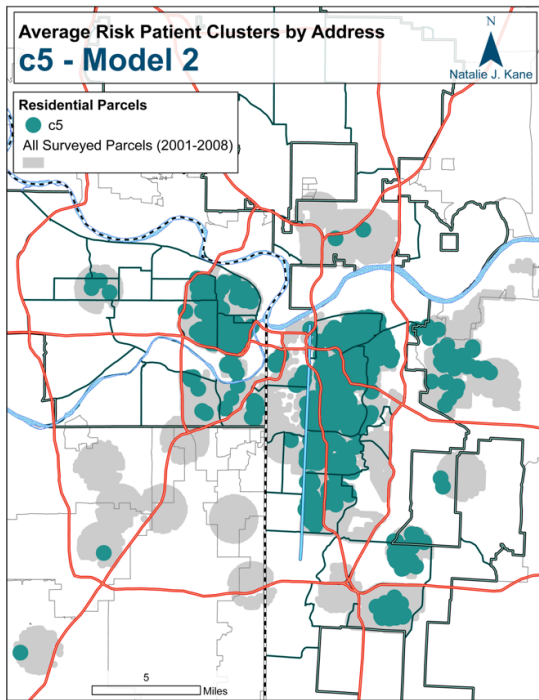
Map 4.11. Model 2 Patient Cluster 2 (c2)



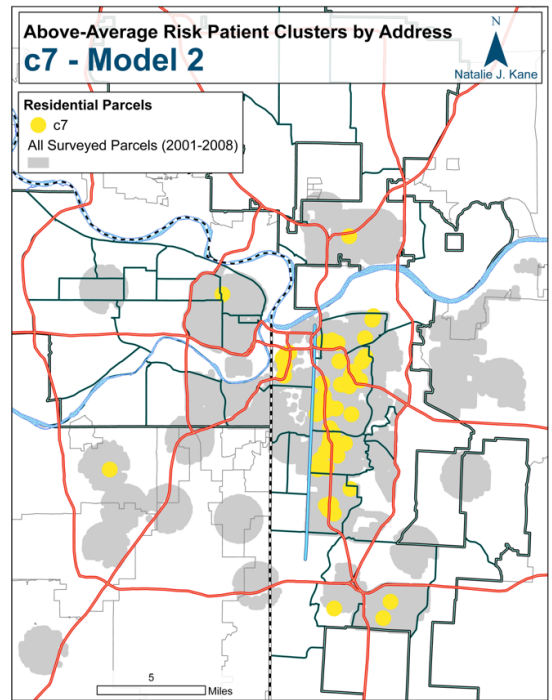
Map 4.13. Model 2 Patient Cluster 4 (c4)



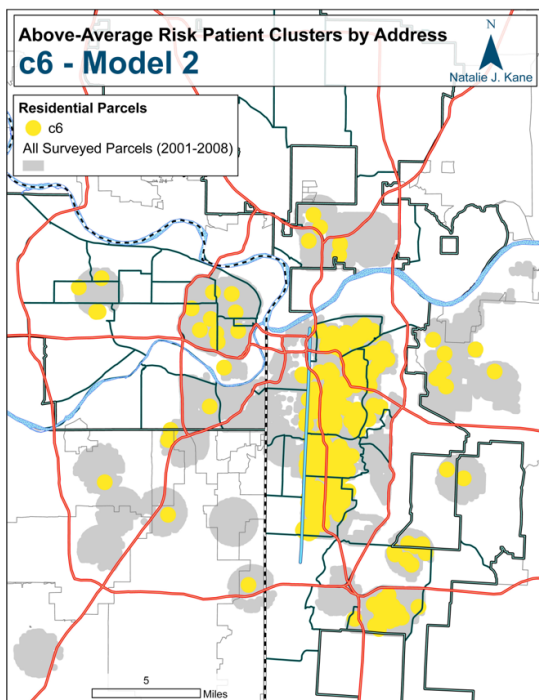
Map 4.14. Model 2 Patient Cluster 5 (c5)



Map 4.16. Model 2 Patient Cluster 7 (c7)



Map 4.15. Model 2 Patient Cluster 6 (c6)



29% of the full patient sample is assigned to the average-risk cluster c5 making it the second largest cluster in Model 2. Compared with the rest of the Model 2 clusters, c5 is characterized by the second highest percent of White (non-Latinx) and Latinx patients (16%) and the second lowest percent of Black (non-Latinx) patients (64%). Furthermore, c5 is distinguished by the lowest structure conditions ratings across the board – on average, 56% are rated substandard or worse. The c5 patient sample in map 4.14 is distributed fairly evenly across the NHCS survey area, though there are very few observations for patients living in the wealthier suburbs of JOCO or north of the Missouri river in KCMO.

Patients in the above-average risk clusters c6 and c7 are distinguished by significantly higher mean counts of previous ACVs and unique addresses compared with the rest of the Model 2 clusters. C6 and c7 are fairly similar in terms of the distribution of structure conditions ratings and the patient characteristics for sex, age, race and ethnicity. C6 has a lower average count of unique addresses (2) and ACVs (2.2) compared with c7, however, and is characterized by levels of environmental exposure consistent with the sample average. The distribution of c6 patients in map 4.15 mirrors that of c5; patients are fairly evenly distributed across the study area, with fewer observations in the relatively privileged suburbs of JOCO and KCMO north of the river.

With an average of 2.58 unique addresses, c7 is subject to the greatest levels of housing instability, has the lowest percent of White (non-Latinx) patients (5%), and the highest percent of patients covered by Medicaid (88%) of all 7 Model 2 clusters. Compared with c6, c7 also has relatively high levels among all four environmental exposure covariates, with the second highest average levels of traffic density. Map 4.16 shows that the patients in c7 are concentrated along major highways in the Old Northeast, Greater Downtown, East Side, and Brush Creek South community districts in KCMO.

### **Comparison of Model Trial Results**

While the results of each model trial may seem significantly different from one another, they



share similarities in cluster assignment for patients without a history of housing instability. In particular, the dominant patterns in both models suggest that, for the majority of patients *not* subject to housing instability, high structure conditions ratings in combination with relatively low environmental exposure are associated with the lowest risk asthma-related ACVs. These patterns are supported by table 4.10, which shows the percent of patients in the 8 Model 1 clusters that were assigned to each of the 7 Model 2 clusters.

Table 4.10. Percent of Patients in Model 1 Clusters by Model 2 Cluster Assignment

Model 2 Clusters	Model 1 Clusters							
	c1*	c2	c3*	c4	c5	c6	c7	c8
Below-Average Risk (%)								
c1	98	0	48	0	12	62	0	0
c2	0	49	0	61	0	0	1	0
c3	0	0	22	23	0	19	0	0
Average Risk (%)								
c4	0	14	18	0	0	0	0	8
c5	0	23	0	0	75	7	93	86
Above-Average Risk (%)								
c6	2	0	12	2	11	11	6	4
c7	0	14	1	14	1	1	1	2

*Note:*

\* Below-average risk profile clusters in Model 1.

For example, in Model 1, patient clusters c1, c3, and c6 all had consistently above-average structure conditions ratings. Table 4.10 shows that the majority of these Model 1 patient clusters were assigned to below-average risk clusters in Model 2, with 98% of the c1 patient cluster in Model 1 assigned to c1 in Model 2. Similarly, Model 1 patient clusters c5, c7, and c8 all had below-average structure conditions ratings. Table 4.10 shows that the majority of patients in these Model 1 clusters – 75% of c5, 93% of c7, and 86% of c8 – were assigned to cluster c5 in Model 2, which was distinguished by the lowest structure conditions ratings of all 7 clusters and the highest mean risk of

ACVs among the patient clusters without housing instability (c1-c5).

### **Discussion**

Despite the homogeneity of the patient sample, both model trials successfully identified multiple, distinct clusters of patients based on both their history of asthma-related ACVs and the covariate profile of person- and place-specific risk factors. The results of the first model trial excluding the housing instability variable indicate that, given the data, high structure conditions ratings are associated with a lower risk of ACVs among both socially disadvantaged and privileged children, and that the distinct risks and vulnerabilities affecting patients is tied to where they live.

Including the housing instability variable in Model 2 resulted in a much more definitive cluster assignment relating to the patient history of ACVs. The patterns in the Model 2 cluster assignment also suggest that low structure conditions ratings are related to an increased risk of ACVs, but only among children without housing instability. This is consistent with expectations given evidence of reduced time in the surveyed structure, affecting model results due to missing and inaccurate data on the living conditions and environmental exposure of children burdened by housing instability. These results support the use of electronic health records (EHR) to identify high-risk patients based on their history of ACVs and housing instability and offer insight into the impact of housing conditions on pediatric asthma. Furthermore, the methods, data, and findings from this analysis can be used to inform place- and person-specific research and intervention strategies addressing both the immediate risk factors and social disadvantage tied to population health disparities.

### **Limitations & Opportunities for Improvement**

The results of this analysis illustrate the benefit of the BPR methodology for distinguishing between otherwise homogenous groups to better inform person- and place-specific interventions, though there is room to improve on both the model design and diagnostics. While BPR model diagnostics are generally limited, additional steps can be taken to assess the stability of the model

results and the convergence of the chains to the posterior distribution (Papathomas et al. 2012). For example, multiple model trials can be run with different MCMC chain lengths - a different number of iterations – or with different initial values to compare the number of clusters and changes in cluster assignment as an indication of the quality of mixing and the stability of the model results (Molitor et al. 2010; Lim, Yoo, and Park 2018).<sup>115</sup>

The strengths of this analysis include the spatial resolution and detail of both patient EHR and housing conditions data, and consequently, environmental exposure estimates. Like the conclusions from Chapter 3, however, there are limitations to each resource that can be improved through coordinated data collection at the regional and local level, and through community-based participatory research (CBPR).

### ***Electronic Health Records (EHR)***

The CMH EHR for pediatric asthma encounters and patients is a very valuable resource for identifying vulnerable patients, communities, and the relationship between severe patient health outcomes and a wide range of risk factors. There are, however, two major deficits to this dataset, which highlight policies that may improve it. The first is that, while the CMH EHR includes hospitalizations, there is no way to identify patient deaths by asthma diagnosis code alone. For example, a child may experience a severe asthma attack, go into cardiac arrest, receive treatment via emergency medical services, and die in the field before reaching the hospital. Even if the emergency medical professionals can identify the cause as a respiratory condition, the EHR in their system and at the receiving hospital will document the primary diagnosis as cardiac arrest. Furthermore, there are no disease codes for death in the CMH EHR, so pulmonologists are mining CMH records for respiratory interventions and manually reviewing patient charts to identify asthma-related deaths in the Pediatric Intensive Care Unit (PICU).<sup>116</sup> This suggests that most asthma-related deaths occur in

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<sup>115</sup> Though it is beyond the scope of this dissertation, this type of exploratory review of the BPR model results will be tested and added to the chapter results before submitting the final draft for publication.

<sup>116</sup> These examples were provided in conversations with local Kansas City Fire Department (KCFD) and CMH

the field and are not documented as a part of the CMH data collection, research, or intervention strategies for pediatric asthma. An alternative approach that may capture asthma-related deaths in the available health records would be to identify patient EHR coded for cardiac arrest, then use patient identifiers to mine general EHR for previous asthma-related care.<sup>117</sup>

The second major deficit of the CMH EHR is related to the quality of the housing instability indicator. The variable developed in this chapter used all available asthma records to identify how frequently a patient changed their address. Future iterations of this measure should use all available CMH records – regardless of event type or diagnosis – to develop consistent measures of transience. Furthermore, data collection strategies can be modified to enhance this type of measure, provided practitioner and advocate input. For example, CMH practitioners can add questions to checkups to verify both the official or primary address for the child, as well as secondary addresses associated with homes, schools, or other locations where the child may spend most of their time. This would provide information about time activity patterns and indicators of other social or economic instability that may factor into the child’s level of asthma control and the most effective interventions.

### ***NHCS Structure Conditions Ratings***

The NHCS offers an affordable, standardized, and reproducible means of collecting data on external housing conditions at a fine spatial resolution. The results from this chapter illustrate the potential application of the NHCS to identify specific risks for vulnerable patients, which can be used as targets for practical interventions that may reduce exposure to asthma triggers in the home and alleviate the burden of substandard housing in socially disadvantaged communities. There are a number of ways, however, to improve the NHCS for health research and intervention. Future research should test the association between external housing conditions ratings and internal home assessment records; the specific triggers represented by the substandard structure conditions ratings related to

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staff.

<sup>117</sup> This query can be structured to exclude cardiac arrest encounters likely due to trauma or other comorbidities.

health risk are important for both intervention and policy design. This type of investigation would also help to tease out the degree to which housing conditions act as an additional signal of social disadvantage by race and place given development patterns throughout the region. Furthermore, there is little variation in substandard or worse ratings for some of the key structure conditions including the foundation, windows, and doors conditions, which suggests that they do not provide much information. Future research should investigate alternative survey designs and criteria for major external conditions ratings both to improve the quality of survey information and to capture conditions related to specific health risks.

### ***Environmental Exposure Data***

An important limitation of this analysis is the lack of access to consistent and meaningful environmental exposure estimates at a fine spatial and temporal resolution. Future iterations of this research would benefit from multidisciplinary collaboration and CBPR to collect additional data and improve modeled environmental exposure estimates. Additionally, future research should include estimates for environmental exposure with both a high temporal and spatial resolution to capture the impact of short-term events such as heat waves or air pollution exceedance days, which can contribute to more frequent asthma exacerbations (Pollock, Shi, and Gimbel 2017).

### **Policy Implications**

While the 2016 CMH Community Health Needs Assessment (CHNA) cites poverty, employment, and housing as some of the most important risk factors contributing to frequent ED visits, they are also considered the most difficult to address through CMH services (Children’s Mercy Kansas City 2016, 62). Historic economic policies such as the New Deal – as well as recent proposals for Green New Deal and Housing New Deal policies – highlight the possibilities to modify these risk factors through an adaptive management approach to federal fiscal and monetary policy.<sup>118</sup> For

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<sup>118</sup> The adaptive management and relevant economic policy frameworks are introduced in Chapter 1.

example, using EHR to identify patients subject to housing instability and related financial insecurity may provide a means of confidentially connecting at-risk families with federally-funded, locally-designed employment and housing opportunities to stabilize families and improve their ability to make the best use of available care. Furthermore, these services can be designed in the context of regional economic development and planning, where previous economic development strategies have acted to isolate socially disadvantaged communities, worsening health inequities and restricting the communities' means to address them over time (Morello-Frosch and Lopez 2006).<sup>119</sup> Building an adaptive information management and policy system to facilitate ongoing coordination of regional employment, housing, education, childcare, and healthcare services would help to rehabilitate communities burdened by social disadvantage, with the potential to move the mark on health disparities and sustainably reduce them over time.

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<sup>119</sup> Refer to the Background section in Chapter 1 for an overview of historic, uneven development in Kansas City and how it relates to population health. Specific examples of discriminatory economic development in Kansas City – for example, the construction of 71 Highway through historically segregated neighborhoods in KCMO – are also discussed in Chapters 2-3.

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## VITA

Natalie June Kane, formerly Natalie June Brown, was born on February 17<sup>th</sup>, 1992 in Nevada, MO. She was raised in rural Missouri until the age of 11 when she moved with her mother and brother to the Kansas City metropolitan area. She attended Shawnee Mission East High School in Prairie Village, KS, where she began studying Spanish and took an interest in the social sciences. During high school, Natalie attended Anthropology courses at the local community college and passed multiple Advanced Placement (AP) exams, giving her a head start on her college career.

After graduating from Shawnee Mission East in 2010, Natalie travelled to Luque, Paraguay for a summer study abroad program through the American Field Service (AFS), where she lived with a family for two months while volunteering at a local daycare. Natalie started her bachelor's degree at the University of Kansas in the fall of 2010 before transferring to the University of Missouri-Kansas City (UMKC) in the spring of 2011, enrolling in a double major degree program with a major in Environmental Studies, a major in Spanish Language and Literature, and a minor in Anthropology. She studied abroad for three months in southern Spain, spending a month as an English language tutor in the coastal town of Motril before completing her capstone coursework at la Universidad de Granada. Natalie graduated summa cum laude with departmental honors in December 2013.

During her undergraduate career, Natalie spent two years as an environmental coordinator intern at Kiewit Power Constructors where she gained an interest in economic policy and its role in environmental regulation. She enrolled in the Department of Economics MA program in the fall of 2014 and was awarded a research assistantship through the Global Institute for Sustainable Prosperity (GISP). After completing her MA in December 2015, Natalie enrolled in UMKC's iPhD program, studying Economics as her primary discipline and Geosciences as her co-discipline. During this time, she continued studies in Geographic Information Systems (GIS), receiving a Graduate Certificate in GIS in May 2017.

Natalie began an assignment as a Graduate Research Assistant (GRA) for the UMKC Center

for Economic Information (CEI) in 2015, using GIS and data analysis for a wide range of local, urban economic development and planning projects. Her background in economics and GIS led to her work on a joint project with Children's Mercy Kansas City, using HIPAA protected electronic health records (EHR) to investigate the relationship between housing, environmental exposure, and pediatric asthma in the region. Natalie's experience on this project provided the foundational skills and expertise to develop her dissertation, which uses data science and GIS as tools for understanding the racial disparity in pediatric asthma throughout the Kansas City region. She successfully defended her dissertation on April 17<sup>th</sup>, 2020 and is planning to pursue a career in public health research as a data scientist in Kansas City.