NEIGHBORHOOD MATTERS: EXPLORING THE RELATIONSHIPS BETWEEN NEIGHBORHOOD SOCIAL RISK AND MEDICAL SPENDING IN A MEDICAID POPULATION

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ABSTRACT

Background: It is well established that attributes of neighborhoods are associated with individual-level health outcomes, however, little is known about the association between neighborhood social and economic resources and medical spending in low income populations.

Objective: This dissertation aims to: 1) describe a process for maximizing use of local neighborhood measures to construct multidimensional indices that may be used in community health planning and research; 2) Evaluate the associations between medical spending and neighborhood social and environmental resources across the distribution of medical spending; and, 3) Examine how different domains of neighborhood social and economic resources are associated with medical spending.

Methods: The first study demonstrates a methodology for reducing a large number of local community measures into 7 domains of neighborhood risk as well as a single multidimensional index that reflects social and environmental resources within neighborhoods. The second study examines the association between high, medium, and low values of the neighborhood social and environmental index across the distribution of medical spending among individuals enrolled in a single Medicaid Managed Care plan in Baltimore, Maryland using quantile regression methods. The third study capitalizes on the neighborhood domain-specific indices created in paper 1 to examine the association between each domain and medical spending.

Results: In paper one we successfully created indices of crime, housing, employment and workforce, education, living environment, and income and wealth at the level of the neighborhood, as well as an overall neighborhood social and environmental resource index. In paper two we find that neighborhoods with low versus high values of the neighborhood resource index were associated with higher individual-level medical spending across all quantiles of spending, even after adjusting for age, gender, morbidity and race. In paper 3 we find the domains of crime, housing, and employment and workforce were also associated with variation in medical spending.

Conclusions:

Study findings indicate that neighborhood-level measures could be informative to value based contracts, for risk adjustment purposes, and to guide interventions that address neighborhood factors that are associated with disparities in health outcomes.

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CHAPTER 1: INTRODUCTION AND BACKGROUND

CHAPTER 1.1: INTRODUCTION

The US healthcare system is widely espoused as being among the best in the world for clinical research and advances in medicine, however it is also known for its high spending per capita and relatively poor health outcomes[1-6]. The US's unusually high spending and poor health outcomes are especially notable in light of comparatively lower spending on social services[1,5-9]. This observation suggests that investing in healthcare services without addressing social factors that affect health outcomes and spending may not be enough to change commonly measured population health outcomes and reduce the cost of healthcare spending in the US[10,11].

Past research has shown that population health outcomes are the product of a group of individual's life experiences formed through families, schools, communities, and the broader social and environmental context in which they are raised[12-15]. Evidence suggests that health behaviors explain 30 -50%, social risk factors explain 15- 40%, environmental factors explain 3- 10%, and medical care explains 10-20% of variation in health outcomes such as life expectancy and premature mortality[1,16]. To date, however, few studies have examined the extent to which variation in social risk factors contributes to medical spending.

As healthcare reform efforts continue to focus on curbing rising healthcare spending by focusing on delivery of high value care and improving population health outcomes across the US, a focus on the social risk factors is becoming more prominent, raising new questions as to the nature of the social risk factors that are associated with the medical spending (here defined as total medical cost of care incurred by the insurer, not including out of pocket spending). Measuring social risk factors can be thought of at two levels: those measured at the individual level (factors such as gender, age, race, income, and education) and those measured at the neighborhood level (factors such as availability of healthy food, crime rates, green space and walkability, availability and quality of housing, etc). Some social risk factors can be measured at both individual and neighborhood level, for example, one could measure individual level income and average neighborhood income, and each level could influence outcomes differently. Individual factors such as age, gender, race, and ethnicity have begun to be used more commonly in models explaining total cost of health care [17]. However, to date there is less evidence as to which neighborhood level social risk factors relate to medical spending.

In order to reduce medical spending, to target resources in ways that produce the largest return on investment, and to improve the value of health care delivered, new research is needed to better identify which social risk factors, particularly at the neighborhood level, are associated with high healthcare spending. Identifying the neighborhood level social risk factors which are related to medical spending has the potential to improve risk adjustment methods for patient populations for payment and intervention purposes, as well as to improve targeting of resources and alignment of incentives across sectors. Strong interest in improving predictive models to better identify future high risk and high cost patients also leads to new questions about which neighborhood level social risk factors should be included in such models. Perhaps even more importantly, identifying neighborhood factors associated with medical spending may incentivize payers to invest more in working with communities, which shifts attention from tertiary approaches that address people who are already sick to approaches that change these circumstances through prevention.

This dissertation aims to identify the significance and relative contribution of neighborhood level social risk factors to medical spending across geographies defined by community statistical areas (CSAs), which are small clusters of neighborhoods for which data can be consistently measured over time without concern for smaller level neighborhood boundaries changing year to year [18]. Further, this dissertation aims to identify the specific neighborhood level social risk factors which are associated with medical spending for individuals insured by a single health care payer in Baltimore city.

In this dissertation, I use principal components analyses to develop domain specific indices and a multidimensional summary neighborhood index to capture the variation in social and environmental resources across neighborhoods. Next, I use these indices to examine associations between the overall neighborhood index representing multiple dimensions of neighborhood social risks and medical spending across CSAs. Finally, using the domain specific neighborhood level indices in addition to more commonly measured social risk factors such as age, gender, race, and measures of health, the last study in this dissertation compares the significance of different neighborhood constructs and medical spending to determine which neighborhood constructs may be most useful for risk adjustment models and for further exploration of pathways by which neighborhoods may affect medical spending.

The results of this dissertation will provide important information regarding how to better target resources to reduce medical spending, as well as to potentially help align incentives between healthcare payers, community organizations, public health departments, and social service organizations working to create healthier more sustainable communities. Further, better understanding neighborhood level social risk factors and their relationship to medical spending can have important policy implications, as it can be used to help align incentives across payers, providers, and patients through better risk adjustment methodology and improved targeting of resources to individuals and communities which may benefit most.

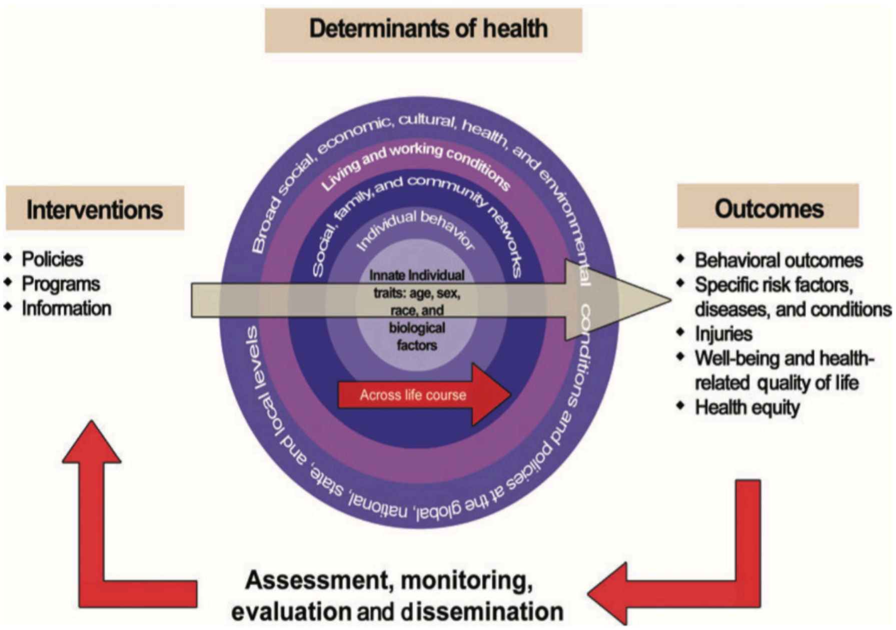
CHAPTER 1.2: BACKGROUND

The Social Determinants of Health

The Socio-Ecological Framework

Since the late 20th century, there has been a strong assumption from the general public and policy makers that population health outcomes were determined mostly by health care services[8,16]. However, in recent decades, numerous studies have confirmed what public health workers from the 19th century had already known - that social risk factors -- factors such as income, occupation, education, and social and physical environments -- significantly influence health outcomes[7,16,19-23]. That these factors are interconnected and multifactorial has been depicted in various conceptual frameworks and models[21-27 16]. One of the best known theoretical models is the Socio-Ecological Framework, which has been recognized by the World Health Organization, the Centers for Disease Control and Prevention (CDC) and the Institute of Medicine, among others for highlighting the way that multiple layers of health determinants contribute to health outcomes[5,16,28,29]. See Figure 1.1 below for an example of a Socio Ecological Framework taken from the National Research Council at the Institute of Medicine.

Figure 1.1: The Socio-Ecological Framework [5]



Generally, the social determinants of health are explained in 4 dimensions of complexity: that multiple determinants of health contribute to health outcomes, that multiple dimensions of health are influenced by determinants (including morbidity, functioning, and well-being, for example), that multiple causal pathways exist which influence how determinants interact with and influence each other, and that there are multiple levels of influence of determinants, meaning individuals, relationships, communities, and society each affect each other[16]. The social determinants of health are typically grouped into five major categories: genetics (some individuals are predisposed to be more susceptible to negative social and environmental influences), behavior, social circumstances, environmental and physical influences, and medical care[16].

Evidence on the Social Determinants of Health and Health Outcomes

While quantifying the effects of the social determinants of health is challenging, multiple studies have estimated the relative contribution of the determinants to health outcomes[9,16,30-34]. These studies generally support the finding that health behaviors explain 30 -50%, social circumstances explain 15- 40%, environmental factors explain 3-10%, and medical care explains 10-20% of variation in health outcomes[16], although this work has generally examined measures of mortality and quality of life as the outcomes of interest. To date, few studies have examined medical costs as they relate to neighborhood determinants of health.

Given the significant contribution of behaviors and social circumstances to health outcomes, a large body of research has specifically focused on the effects of neighborhood factors, such as poverty, education, racial and ethnic composition, employment, housing, and stability of residence on various health outcomes, including mental health, early childhood outcomes, birth outcomes, intimate partner violence, obesity, all-cause mortality, and more general health outcomes[35,36]. Although robust evidence has established the association between neighborhood factors and health, the mechanisms by which neighborhoods affect health is less well understood [37,38].

Neighborhood factors affect health through complex pathways that involve exposure to educational and economic opportunities, exposure to stress, availability of healthy food options and areas to walk and exercise, exposure to crime, and exposure to environmental toxins such as lead and pollution, which all in turn impact health related behaviors, health outcomes, and the costs associated with it[37,38]. For example, neighborhood factors like "walkability" may directly affect physical activity, which in turn affects physical health[37,38]. Complex conceptual models articulate pathways by which neighborhood factors affect physical activity, stress, diet, smoking, sleep, and other health related behaviors, which may in turn affect health outcomes such as cardiovascular disease[37]. However, challenges in examining the causal pathways by which neighborhood factors affect health include the complexity of multiple mechanisms and pathways, variation among individual exposures and behaviors as well as duration of residential exposure, varying length of time that it takes for neighborhood affects to shape health, lack of information on the spatial scales that are relevant to health outcomes, and the many confounding and mediating variables that exist when examining this relationship[37,38].

This dissertation does not seek to explain causal pathways between neighborhood social risk factors, morbidity, and medical spending. Instead, the studies included in this dissertation seek to demonstrate the value of measuring neighborhood social risk in order to better understand the outcome of medical spending from a payer perspective. The purpose of this study is therefore to examine the associations between neighborhood level social risk factors, individual level risk factors, and medical spending from a payer's perspective.

CHAPTER 1.3: LIMITATIONS OF CURRENT EVIDENCE

While systematic reviews of neighborhood factors and health have found moderate to strong evidence for neighborhood effects on health outcomes and utilization[35], to date, there are a lack of studies examining how neighborhood factors are related to medical spending. Key gaps in the literature addressed in this dissertation include:

1. Data on neighborhood social risk factors vary in availability, geographic unit, and construct, making usability for community research more difficult. Availability

of studies detailing a flexible process for conducing principal components analysis on a large set of measures that can include community input allows for creation of different domains of neighborhood risk that can be used alone or aggregated into a single index for use in community outcomes research.

2. Despite a general acceptance that the social determinants of health play a large role in health outcomes, few studies to date have explored how neighborhood social and environmental resources affect medical spending across the distribution of spending. Aim 2 will examine the relationships between high, medium, and low categories of neighborhood social and environmental resources and across the distribution of medical spending.
3. To date, most area level neighborhood indices focus on only socioeconomic variables such as housing, income and wealth, and education. Other domains known to influence health outcomes, such as crime and physical environment, may also explain additional variation in medical spending. Determining which domains of neighborhood factors conceptually represent neighborhood social risk and which of these domains have the largest association with medical spending could inform creation of neighborhood indices with more meaningful associations with medical spending, and could encourage payers to partner with other sectors to achieve improvements in these areas.

CHAPTER 1.4: AIMS AND HYPOTHESES

Aim 1

To identify domains of neighborhood social risk, drawing on large set of variables describing neighborhood factors and following a conceptually driven approach using factor analysis.

Hypotheses:

1. Scores for domain specific indices will vary by neighborhood depending on the domain; neighborhood rankings will not be uniform across constructs measured.
2. A final neighborhood social and environmental resource index will include multiple constructs of neighborhoods, including constructs like crime and living environment that are not often included in area deprivation indices.
3. A final neighborhood social and environmental index will be highly correlated with outcomes known to be related to neighborhood deprivation.

Aim 2

To determine the strength of the association between a neighborhood level social and environmental risk score and medical spending across the distribution of medical spending after adjusting for individual and neighborhood level factors known to influence medical spending among residents of Baltimore City insured by a single Medicaid Managed Care Organization.

Hypotheses

1. As neighborhood social and environmental resources get less favorable, there will be a statistically significant increase in medical spending even after adjusting for other individual and neighborhood level factors known to influence medical spending.

2. The relationship between neighborhood social and environmental resources and medical spending will persist across quantiles of medial spending, even after adjusting for other individual and neighborhood level factors known to influence medical spending.

<u>**Aim 3**</u>

To identify domains of neighborhood social risk that have significant associations with medical spending after adjusting for individual and neighborhood level factors known to influence medical spending among residents of Baltimore City insured by a single Medicaid Managed Care Organization.

Hypotheses:

1. Multiple domains of neighborhood level social risk will be significantly associated with medical spending.
2. Domains of neighborhood-level social risk outside of just those traditionally measured using census data will have a significant relationship with medical spending

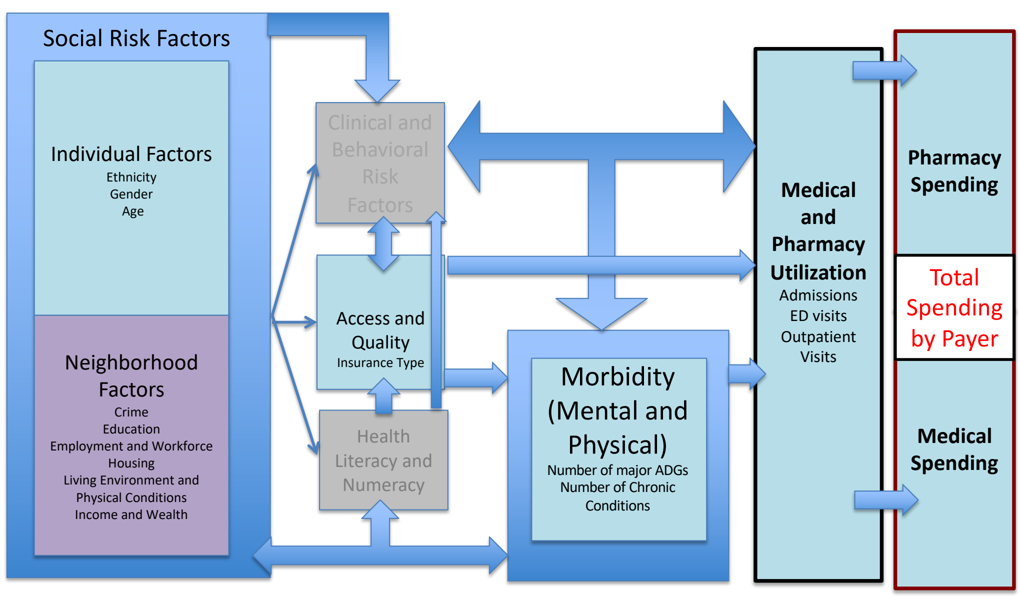
CHAPTER 2: METHODS BACKGROUND

CHAPTER 2.1: OPERATING FRAMEWORK

The conceptual model that guided this research is derived from the National Academy of Science, Engineering, and Medicine's (NASEM) Report, "Accounting for Social Risk Factors in Medicare Payment" which was developed to describe how social risk factors affect health outcomes, including resource use, in Medicare's value based purchasing programs[1]. To see the original model, please refer to Appendix 2.1. The NASEM identified the following social risk factors: socioeconomic position, race, ethnicity and cultural context, gender, social relationships, and residential and community context, due to their conceptual and empirical association with outcomes related to value based payments, through a pathway involving individuals' access to care, health literacy, and clinical and behavioral risk factors[1]. Further, each of these factors has been established as affecting healthcare use, morbidity, and resource use, preceding care delivery, not a consequence of the quality of care, not typically modified through clinical practice, and meeting practical considerations related to feasibility of data collection[1].

While the original conceptual model was developed for studying factors influencing performance of indicators for value-based payments, the model is highly relevant to this dissertation as it articulates factors that conceptually and empirically affect access and behaviors, morbidity and subsequent medical spending. The NASEM model maps indicators that precede care delivery to outcomes, and also focuses on individual measures as well as community level measures, making it a good fit for measuring the impact of neighborhood factors on individual level medical spending. This model was also selected because it accounts for the types of measures that exist and can be measured, ensuring that the findings have practical application and can be used in a real-world setting. This model includes neighborhood social risk factors that can be modified or addressed at some level, and also focuses on factors that have existing evidence linking them to outcomes. See Figure 2.1 for the operational model for this research.

<u>Figure 2.1: Social Risk Factors Operational Model</u>
Adapted from: National Academies of Sciences, Engineering and Medicines' Social Risk Factor Model [1]



CHAPTER 2.2: STUDY DESIGN AND DATA SOURCES

Study Design

This study is comprised of retrospective, secondary data analyses that combine publicly available data sources with a limited data set extracted from administrative data at Johns Hopkins HealthCare LLC (JHHC). The analytic dataset was constructed by linking individual level claims and enrollment data from JHHC to the CSA level social risk factor data from the Baltimore Neighborhood Indicators Alliance (BNIA), using geocoded addresses to match individuals to the CSA in which they reside.

Data Sources

The study sample comprised 9,783 individuals enrolled in the Priority Partners Managed Care Organization who were between the ages of 18-64 in calendar year 2016 and were identified as living in any of 55 Baltimore City community statistical areas. Table 1 provides additional information on each dataset, the years of information that were available at the time the study was initiated, and the level at which the data is aggregated.

Table 2.1: Datasets, Domains, Years, and Geographic Level

Dataset	Domain Covered	Years Available	Level
JHHC	Demographic data, home addresses, morbidity, cost outcomes	2005-2016	Individual
Baltimore Neighborhood Indicators Alliance	Census Demographics Housing and Community Development Children and Family Health Crime and Safety Workforce and Economic Development Sustainability Education and Youth Arts and Culture	2010-2015	Community statistical area (collection of adjacent census blocks which are based on US census tracts and remain consistent from year to year)

Johns Hopkins HealthCare Claims Data

Johns Hopkins HealthCare (JHHC) is jointly owned by the Johns Hopkins Health System and the Johns Hopkins University School of Medicine, and manages medical care contracts for 4 different health plans: Johns Hopkins Employer Health Programs (EHP), Priority Partners (Medicaid), Johns Hopkins US Family Health Plan (USFHP), and Johns Hopkins Advantage MD (Medicare). As such, JHHC contains longitudinal data in the form of enrollment data (including addresses), demographic data such as age, gender, race, and claims data, which provides measures of morbidity and spending associated with services.

Baltimore Neighborhood Indicators Alliance (BNIA)

BNIA began as a 2-year planning process in which nonprofit organizations city government agencies, neighborhoods, and foundations were convened to bring together data to inform city decision making. In 2002, BNIA brought together focus groups to come to consensus on neighborhood goals and indicators that should be collected. The first "Vital Signs for Baltimore Neighborhoods Report" was released in 2002, and each year since 2002.

Analyses in the report are organized at the community statistical area (CSA) level, which is a collection of adjacent census blocks which are based on US census tracts and remain consistent from year to year. There are 55 CSAs in Baltimore City which each consist of 1-8 census tracts with a total population range between 5,000 and 20,000 individuals[2]. CSA boundaries align with Census Tracts, and reflect the city planner's understanding of resident and institution perceptions of the boundaries of the community. Each CSA defines a relatively demographically homogenous area[2]. Data issued by the BNIA is publicly available, covers the domains of: Census Demographics, Housing and Community Development, Children and Family Health, Crime and Safety, Workforce and Economic Development, Sustainability, Education and Youth, Arts and Culture, and combines data from numerous sources (see Appendix 2.2 for list of measures and sources)[2]:

Study Sample

While originally, data across multiple types of health insurance plans were to be included in analyses (N=27,909), initial exploratory analyses of the analytic dataset suggested that without the ability to control for individual level income, neighborhood variables may simply serve as a proxy for the socioeconomic status of the individual: a known predictor of health outcomes. Therefore, to prevent confounding by individual level income, I chose to control for income by narrowing our study sample to only include Medicaid Managed Care enrollees (N=17,189). By limiting the sample to only individuals with Medicaid, I effectively control for low income related to programmatic eligibility (138% of the Federal Poverty line for parents and adults, 259% of the poverty line for pregnant women), and ensure comparable access to Medicaid-funded services across the study population. I also chose to focus on adults within the Medicaid population (N=9,783) rather than children (N=7,406) in this study, since evidence shows the differing pathways through which neighborhoods may affect child utilization and costs as compared to adults, and payers are generally more concerned with adults, who tend to have greater medical spending[3]. Pregnancies were excluded from main models (N=644), and included only in sensitivity analyses, given a strong existing literature showing that neighborhoods have effects on pregnancies and outcomes, and that pregnancies have high medical expense. Further, the mechanisms by which neighborhood factors affect pregnancies may be different than those that affect chronic conditions. Therefore, I excluded pregnancies from main models in order to ensure that neighborhood associations with medical spending are not due to higher rates of costly pregnancies alone.

The final sample included 9,783 adults (18+) who were insured by JHHC's Priority Partners Medicaid Managed Care Plan, the largest Medicaid Plan in Baltimore City. All subjects had a valid Baltimore City address on file at JHHC and had been continuously enrolled in a JHHC plan with no more than a 30-day gap for a full 12-month (January1-Dec 31st, 2016) study period. The sample size for this study was calculated to be sufficient for multilevel models with two levels (level 1 comprised of individuals and level 2 comprised of neighborhood level variables), where literature on the topic generally indicates a minimum threshold of 50 groups at level 2, with a minimum of 30 individuals in each group representing level one [4]. Although the number of individuals per CSA varied, on average, there were 188 individuals per CSA, with 9,783 individuals spread across 55 CSAs. Our study sample was sufficiently powered to detect effect sizes at $p<0.05$ for fixed effect quantile regression and two part models.

Analytic Dataset

The dataset that was used for this study was comprised of combined measures from JHHC and the CSA level BNIA data from 2015, linked using geocoded addresses of each individual insured by JHHC who met study eligibility criteria. Measures were selected using a modified version of the NASEM Social Risk Factors Model (Figure 2) which classified domains of social risk factors into individual and neighborhood levels[1]. See Table 2.2 for the data sources and analyses for each aim.

Table 2.2: Description of Datasets for Aims and Type of Analyses

Aim	Data	Analysis
1	Domains of neighborhood social risk from BNIA	Factor analyses
2	Full merged dataset with individual and multidimensional neighborhood index created from BNIA data in Aim 1	Quantile Regression
3	Full merged dataset with individual level data, multiple domain specific indices and multidimensional neighborhood index created from BNIA data in Aim 1	Two Part Models

CHAPTER 2.3: AIM 1 MEASURES AND METHODS BACKGROUND

Measures

Neighborhood Level

Aim 1 drew upon 137 measures from the BNIA representing different domains of neighborhood-level social risk. The full list of measures included in Aim 1 is available in Appendix 2.2.

Methods Background

Chapter 3 provides details on how principal components analyses (PCA) were used to create neighborhood domain specific and multidimensional indices. Kaiser Myer Olkin (KMO) Measure of Sampling Adequacy tests were used to ensure the groupings of indicators were appropriate for PCA[2]. The KMO test measures sampling adequacy for the model, and measures proportion of variance among indicators that may be common variance. KMO test values range from 0 to 1, and generally assumes that scores >0.5 indicate adequacy for PCA, with KMO values above 0.8 indicating ideal samples[2]. After reducing numbers of indicators by domain through removal of redundant indicators (defined as measures with correlations greater than 0.8), KMO tests were conducted after PCAs on each domain and for the overall neighborhood social and environmental index to ensure appropriateness of the remaining samples for PCA. The KMO values calculated after PCA on each domain (using only non -redundant indicators), are listed in Table 2.33. For more on methods used to calculate each index score, see Chapter 3.

Table 2.3: KMO test values calculated after PCA for each Domain:

Domain	Number of Indicators	Kaiser Myer Olkin Value
Crime	5	0.65
Education	10	0.78
Housing	14	0.68
Employment and Workforce	8	0.61
Living Environment	9	0.54
Income and Wealth	5	0.56
Social Resources	7	0.65
Baltimore Neighborhood Social and Environmental Index	18	0.86

CHAPTER 2.4: AIM 2 MEASURES AND METHODS BACKGROUND

2.4.1: Measures

Dependent Variable

The main dependent variable of interest for Aim 2 was medical spending, which was measured at the individual level (per person per year) based on medical claims paid in CY2016, excluding any out of pocket costs for individuals. Spending for long term care and psychiatric-specific outpatient visits and inpatient stays were not available or included in this analysis, as these services are reimbursed separately. Using quantile regressions (see Chapter 4 below for more detail) allowed us to test for significant associations at percentiles of medical spending rather than at the mean (which can be highly skewed by outliers). Therefore, it was not necessary to recode outliers in our outcome variable. To address the large number of individuals with zero medical spending, I limited the sample to only individuals with spending greater than zero, then ran sensitivity analyses using two part models to test whether the relationship between our independent and dependent variables persist after including both individuals with zero spending and individuals with non-zero spending in the model.

Independent Variable

The independent variable of interest in the second aim was our multidimensional neighborhood social and environmental index, categorized into high, medium, and low resource neighborhoods for the purposes of exploring whether or not there were associations between different levels of neighborhood resources and medical spending. Given the research questions centered on whether or not the associations between medical spending and neighborhood social and environmental resources were significant and varied across quantiles, grouping individuals into high, medium, and low resource neighborhoods rather than using the continuum of neighborhood resource scores allowed a larger number of individuals per neighborhood grouping at each quantile of spending, thus maximizing available sample. Further, results involving comparisons of high, medium, and low resource neighborhoods are conceptually simpler to interpret. I used fully adjusted regression models to compare the model fit for the full social and environmental index, three categories of the index, four categories of the index, or five categories of the index, and found the three category structure had the lowest log likelihood and AIC values, although the values were very similar (See Table 2.4).

Table 2.4: Model Fit for Structure of Neighborhood Index Comparing Log Likelihood and AIC Values*

Structure of Baltimore Neighborhood Social and Environmental Index (BNSEI) Variable	Log Likelihood Value	Akaikes Information Criteria (AIC) Value
Continuous BNSEI Index	-11,951	23,922
3 Categories of BNSEI	-11,948	23,919
4 Categories of BNSEI	-11,948	23,920
5 Categories of BNSEI	-11,950	24,016

Control Variables

I selected several control variables in my models, guided by the conceptual framework. Morbidity was measured at the individual level using two measures calculated from the Adjusted Clinical Group System (ACG), a statistically valid, case-mix methodology that allows calculation of scores representing multimorbidity and describes and predicts a population's past, concurrent, or future healthcare utilization and spending[5]. (See Chapter 4 for more details on these variables). Individual level age, gender, and race were also gathered from JHHC claims data. Age groups were divided into three age bands: 18-34, 35-54, and 55+. Gender was coded as binary (male or female). Sensitivity analyses that include pregnancy demonstrate that when included, low neighborhood social and environmental resource index values predict higher medical spending at each quantile as compared to neighborhoods with high resources (see Appendix 41.). These differences remain significant across quantiles, as well as in part two of the two part model output, where both the low and medium resource neighborhoods on average are significantly associated with higher medical spending than high resource neighborhoods (see Appendix 4.2). Including pregnancies in two part models with each neighborhood domain modeled separately did not result in any significant changes in association between neighborhood domain and medical spending. (see Appendix 5.10).

Racial data were available, but had many missing values. Due to the importance of including race in examining the associations between neighborhoods and medical spending, I imputed the missing values for race. Missing data on race were initially tested to determine whether data were missing at random and whether or not the missing data correlated with the outcomes of interest. In this case, missing data were not missing at random, and the data missing were correlated with the outcome. Therefore, I imputed the missing data using multiple imputation methods in Stata version 15.1 to identify if a missing person was likely to be "black" or "non-black". See Appendix 2.5 for a table comparing demographics and medical costs by black, non-black, or missing. Initially, there were 6,835 individuals with "black" listed as race, and 1,401 with other race categories listed, including white, Asian, Hispanic (non-black), and Pacific Islander. I combined all races except for black into a "non-back" category due to low numbers. Further, 1,547 individuals were missing race data, and therefore these values were imputed through a logistic imputation equation that contained the following predictors: medical spending, gender, age (by decade), neighborhood social and environmental resource score, the racial diversity score of the neighborhood, chronic condition count, major ADG count, and whether or not there was a hospital in the CSA. 10 imputations were run with a random seed set to 54,321. The race variable was insignificant in most models prior to imputation, and remained insignificant after imputation, however there was a correlation between individuals missing data and costs prior to imputation. It is expected that a mechanism which created missing data may be linked to cost, but when allocated to a category of race, this link was attenuated. After imputation, 16%-19% of the imputed sample were identified as other, and 84-81% were identified as Black.

Two additional neighborhood level control variables were also included in Aim 2 analyses: a racial index representing a measure of neighborhood segregation (the odds of choosing two people at random from the same neighborhood and having them each be a different race or ethnicity)[2] available from BNIA data, and a variable identifying whether or not a hospital was located in an individuals' neighborhood, which was used to control for any relationship between higher utilization related to close proximity to a hospital and emergency room. This variable was derived by assigning all major hospitals in Baltimore City to the CSA in which they reside, and creating a binary variable indicating for each CSA whether or not there was a hospital in that CSA. Ten CSAs across Baltimore City had at least one hospital in the neighborhood, and 16.5% of the study sample lived in a CSA which had a hospital in it.

2.4.2: Methods Detail Aim 2

The initial analysis plan for Aim 2 was to use multilevel models to test associations between the index of neighborhood social and environmental resources and medical spending, conditional on covariates. Using exploratory analyses, I determined that that the outcome data (medical spending) was skewed right, with a high proportion of zeros as I would expect from health spending data. Results of the Breusch Pagan test of heteroscedasticity confirmed data were heteroscedastic (p=0.00). Because of this, I initially created and tested multiple structures for our outcome variable to account for the issues of a large number of zeros and right skew, including creation of binary variables indicating if someone incurred high medical spending or not at different levels (top 10% of high medical spending, top 25%, top 50%), and also created a continuous variable to account for the skew using the log of medical spending.

Due to the nested nature of the data (individuals in CSAs), I also used multilevel models to examine the extent of clustering at the neighborhood level using our binary and continuous medical spending outcomes. First, empty models with different structures of the outcome of medical spending (90/10, 75/25, 50/50, continuous) and associated model specification (logistic versus linear multilevel models) clustered at the neighborhood level were run, and the ICCs were calculated to determine appropriateness of using a multilevel model based on clustering at the neighborhood level. The ICCs for each model were less than 0.003, indicating a minimal clustering effect at the neighborhood level. Models adjusting for the neighborhood social and environmental resource index level, age group, gender, presence of the hospital in the CSA, segregation, and morbidity also demonstrated very small ICCs, indicating that it would be appropriate to use a single level model to estimate medical spending outcomes. Further, I found that the size of the neighborhood effect varied based on which outcome structure used (90/10, 25/75, 50/50, continuous), which suggested use of quantile regression models to examine whether associations vary across quantiles of medical spending. Quantile regression tests are also appropriate for skewed data, allowing us to use the full distribution of medical spending as our outcome for individuals with nonzero spending[70].

I tested whether fixed or random effect models are more appropriate by performing Hausman tests. Using CSAs as the grouping variable, and testing medical spending as the outcome, I found that fixed effects models are more appropriate than random effect models (p=0.3032) (see Appendix 2.8 for more details). Based on these analyses, I chose to use fixed effects quantile regression models with robust errors (to account for heteroscedasticity) for analyses in Aim 2, and used random effects models as sensitivity analyses. For the full description of methods using quantile regressions, please see Chapter 4.

CHAPTER 2.5: AIM 3 MEASURES AND METHODS BACKGROUND

2.5.1: Measures

Dependent Variable

The main dependent variable of interest for Aim 3 was medical spending, however, I chose to top code outliers for use in Chapter 5 analyses (two part models) by reassigning all values greater than two standard deviations above the mean to that value of (medical spending at two standard deviation above the mean equaled $48,894). Two part models account for the issue of a large number of zeros in our dependent variable, and top coding ensured that outliers would not affect results in part two of the model.

Independent Variables

Multiple indices of neighborhood domains and the social and environmental resource index created in Aim 1 were the independent variables in Aim 3. Indices representing Crime, Education, Housing, Living Environment and Physical Conditions, and Income and Wealth were converted into z scores with a mean of zero and standard deviation of 1 prior to use, with low scores indicating the most favorable conditions, and higher scores indicating less favorable conditions. I chose to use the full range of values in Aim 3 rather than grouping into high, medium, and low as was done in Aim 2 in order to capitalize on the range of values across CSAs. I excluded data from CSAs with less than 10 individuals in alignment with CMS's policy on suppressing groups with less than 10 individuals[10], leaving 52 CSAs with unique index values for use in Aim 3. The number of individuals remaining after excluding the smallest CSAs was 9,772. For details on the creation of these indices, please refer to Chapter 3.

Control Variables

As in Aim 2, I use chronic condition count as a main control for morbidity, and use major ADG count to control for morbidity in sensitivity analyses. I also use the same specifications for age, gender, race, and to control for whether or not a hospital was located in the individual's CSA as in Aim 2. While in Aim 1 the intent was to examine whether or not high, medium and low values of neighborhood social and environmental resources were significantly associated with medical spending across the distribution, in Aim 3, I seek to compare the added value of including different domains of neighborhood social risk factors to models of medical spending for the purposes of understanding which could be used in predictive models or to better target interventions. Therefore, in addition to the measures used in Aim 2, I control for a measure of segregation (rather than just racial diversity as used in Aim 2) in all models to determine which domains of neighborhood social risk are still significantly associated with medical spending even after segregation is controlled for. Segregation measures are widely available and included in many existing neighborhood indices, and already have a strong literature tying them to health outcomes[11,12].

In Aim 3, I used dissimilarity indices as our measure of segregation. Dissimilarity indices measure the proportion of individuals of a given race that would have to change their area of residence to achieve even distribution, and are a widely accepted method for capturing variation across the various constructs that comprise segregation [11]. The dissimilarity index was calculated on a scale of 0 to 100, with larger numbers indicating higher levels of segregation. I calculated a dissimilarity index score for each CSA by taking the absolute value of the difference between the proportion of white individuals in each CSA and the proportion of black individuals in each CSA (measured at the CSA level from BNIA data), and dividing this value by 2[11]. The mean score across all CSAs in our sample was 33%, with a range of 3.8% - 48.5%.

2.5.2: Methods Detail Aim 3

Building on the lessons learned from Aim 2, I chose to use two part models to test associations between neighborhood domain indices and medical spending in Aim 3 for several reasons. First, two part models allowed me to test whether or not neighborhood domains were significantly associated with likelihood of having any medical spending, as well as the odds of having higher spending among individuals with medical spending greater than zero. Second, two part models allowed me to account for the large number of individuals in the population with zero spending in addition to those who had incurred medical costs. Finally, I established in Aim 2 that neighborhood social and environmental resources were significantly associated with medical spending across the distribution, and therefore could justify using the mean values of medical spending in the second part of the two part model, with robust errors to account for right skew. For more details on the methods from Aim 3, please see Chapter 5.

CHAPTER 3. MANUSCRIPT 1

CREATION OF A COMPREHENSIVE NEIGHBORHOOD SUMMARY INDEX TO CHARACTERIZE NEIGHBORHOODS IN BALTIMORE CITY USING DATA REPRESENTING MULTIPLE DOMAINS OF NEIGHBORHOOD SOCIAL RISK

ABSTRACT

Background: Data on neighborhood social risk factors vary in availability, geographic unit, and construct, making usability for community research more difficult. The authors developed a process for capitalizing on available community data with flexibility for inclusion of local knowledge to create domain specific indices and an overall social risk index to summarize multidimensional neighborhood data in ways that can be used for a variety of community research purposes.

Methods: A series of principal components analyses were used to distill 137 measures of neighborhood social risk into distinct domains. The authors validated the indices using health outcomes known to be associated with neighborhood risk factors.

Results: The authors identified 7 neighborhood domains, including: crime (5 indicators), education (10 indicators) employment and workforce (8 indicators), housing (15 indicators), living environment and physical conditions (9 indicators), social resources (7 indicators), and income and wealth (4 indicators) – as well as a single composite Baltimore Neighborhood Social and Environmental Index (BNSEI) of 18 indicators representing 6 neighborhood domains. The BNSEI was highly correlated with health outcomes known to be linked to neighborhood social risk.

Conclusions: We describe a flexible method for creating neighborhood indices that allows communities to make use of local data to identify measures of social and environmental resources that may be used for a variety of community research and planning purposes.

CHAPTER 3.1: INTRODUCTION

There is a growing appreciation that social risk factors -- factors such as income, occupation, education, and social and physical environments – affect health.[7,16,19-23] These factors can be measured at the individual level, family level, or larger geographic level, such as neighborhoods, zip codes, or regions. As social risk factors cluster within neighborhoods, and intervening at the neighborhood level can have broad public health effects, understanding and addressing neighborhood level social determinants has been an area of active interest [36]. Neighborhood factors affect health through multiple pathways, that include the quality and availability of educational and economic opportunities, exposure to stress, availability of healthy food, areas to walk and exercise, exposure to crime, and exposure to environmental toxins such as lead and pollution, among others[45].

As local areas across the US seek to address determinants such as education, food availability, crime, and housing, among others, to improve health[6,15] determining priority areas of intervention is often difficult [6,12,15]. Available data is often limited to relatively large geographic areas that may mask important variation between communities[33,46]. Tools such as the County Health Rankings, which have proven effective in large-scale public health initiatives, provide both an overall rank and more nuanced information on how different domains affect health outcomes. However, county level measures are often not sufficiently granular to guide neighborhood-level efforts[47]. Collectively, these issues underscore the need for systematic, reproducible approaches to maximizing use of local neighborhood data for community led cross sector collaboration. Empowering communities to capitalize on available data to identify, prioritize, track and intervene on social risks in their communities is the basis of public health practice, and the process described here is one way for communities to arrive at actionable information which can be used to align vision, financing, and leadership across sectors.

While many established approaches have been used to measure neighborhood socioeconomic status and environmental conditions, the utility for individual communities is limited, as measures typically identify global disparities, as opposed to providing granular, actionable information related to particular domains (categories of indicators), such as crime, education, or housing. Another limitation is that existing approaches are not readily accessible to community partnerships that may have idiosyncratic local information – or that are lacking expertise to compile items into meaningful domain specific indices.

To address this gap, we describe an approach to leveraging local data to develop multifaceted neighborhood social and environmental indices with specific neighborhood domain scores, while also allowing for flexibility to use community knowledge to direct development of scores. The approach we describe could be replicated by public health departments, community organizations with technical expertise, or other community partners with technical skillsets, with the aim of capitalizing on local data to share information for improving communities. We discuss applications of these type of indices for research and policy purposes, underscoring the utility of these indices as a tool in the public health process of Monitor, Review, Act cycles from which multiple sectors can examine data on communities, overlay their own knowledge of the issues, and subsequently, prioritize areas for intervention. Utilizing a rich community dataset available for Baltimore City, Maryland, we describe a process to use existing neighborhood level data to develop domain specific and overall neighborhood indices and describe their utility. Although this paper focuses on 55 Community Statistical Areas (CSAs) across the city of Baltimore, the approach that we describe is applicable to any definition of neighborhood, and can be applied regardless of the number of indicators and domains available as long as more than one domain is represented by the data available.

CHAPTER 3.2: METHODS

Overview

This paper describes a method for compiling domain-specific and overall index score summarizing available neighborhood social and environmental indicators[48]. While each geographic area will have access to different types of data representing different types of domains, the approach we describe is readily transportable to other areas, regardless of the number of indicators and domains available. Rather than focusing on foundational aspects of combining, cleaning, aggregating, or addressing outliers in constructing an analytic dataset, we instead describe the method for pruning and aggregating large numbers of indicators representing different concepts into a reduced set of items more appropriate for principal components analysis (PCA). The methods proposed here, while arguably simpler for non-statisticians than other methods such as structural equation modeling and hierarchical clustering, require use of statistical packages such as Stata (used in the example here) or R (available free online) and at least minimal technical expertise to implement.

We rely on a multistep process adapted from the methodology proposed by Lalloue et al. as shown in Figure 3.1 and further detailed in the text that follows. Although the methods are informed by the literature, we follow an empirically-guided approach to reducing a large set of indicators, utilizing all available data rather than reducing it to only measures that are commonly used in the literature. We do not tailor the index to focus specifically on indicators that relate to health outcomes, as our purpose is to construct a neighborhood index with broader utility. We also create a process where community knowledge can be used to guide inclusion of indicators, so that local knowledge can be combined with empirical evidence to drive indices. Each of the steps is described in greater detail in the following text.

Study Setting and Geographic Area

This study was carried out in Baltimore City, the largest city in the state of Maryland. Baltimore has an ethnically and economically diverse population of about 600,000 individuals[49] and comprises distinct neighborhoods marked by variable cultures and backgrounds. The diversity and juxtaposition of wealth and community resources in Baltimore City makes it an interesting geographic area to study the effects of neighborhood social and environmental factors on health outcomes. Further, a rich community level dataset available from the Baltimore Neighborhood Indicators Alliance (BNIA) creates an opportunity to construct a neighborhood social and environmental index comprising established domains of neighborhood socioeconomic status as well as novel domains not previously examined.

Neighborhood level data available for Baltimore City is measured at the Community Statistical Area level (CSA). CSAs are small clusters of neighborhoods for which data can be consistently measured over time[18]. Baltimore City is comprised by 55 CSA, each of which consist of 1-8 census tracts with populations ranging between 5,000 and 20,000 individuals[18]. CSA boundaries align with Census Tracts, and reflect city planner understanding of resident and institution perceptions of the boundaries of the community. Each CSA defines a relatively demographically homogenous area[18]. It is important to note that although Baltimore measures neighborhoods at the level of the CSA, the definition of communities and neighborhoods, as well as the types of indicators and domains that are available for any given community may differ. However, the approach that we describe is applicable to any definition of neighborhood, and can be applied regardless of the number of indicators and domains available as long as more than one domain is represented by the data available.

Data Sources and Measures

Data related to neighborhood social risk was obtained from the Baltimore Neighborhood Indicators Alliance (BNIA). The BNIA resulted from a 2-year planning process in which nonprofit organizations, city government agencies, neighborhoods, and foundations were convened, participated in focus groups, and came to consensus on neighborhood goals and indicators that should be collected to inform city decision making[18]. This work led to the development of a "Vital Signs for Baltimore Neighborhoods Report," first released in 2002, and subsequently each year since[18].

The BNIA data involves multiple modes of data collection including email, direct data entry, online downloads, and secure File Transfer Protocol (FTP) from a variety of community data sources (see Appendix 2.2 for list of all sources by indicator). External data is gathered and standardized in the BNIA Data Warehouse[18]. Data issued by the BNIA are open source, publicly available, and organized at the community statistical area (CSA) level. We draw from 137 indicators across 8 domains of neighborhood indicators from 2015[18]. For the full list of indicators and their assigned domains, please refer to Appendix 3.1. The dataset has been extensively cleaned by the BNIA so that no significant outliers exist in publicly available data, which includes no missing data points in the 2015 dataset.

Construction of Indices

Step 1: Selecting Domains and Organizing Indicators

As there is no consensus regarding the salient measures of social and environmental domains of neighborhoods, our first step was to identify domains and categorize available indicators (see Figure 3.1). Identified domains of neighborhood social and environmental resources in the BNIA varied from the prevailing literature. For example, indicators such as “Liquor Outlet Density” and “Average Healthy Food Availability Index” originally labeled as “Health” in the BNIA may instead reflect available resources. A review by Messer at al (2006) identifies domains most commonly used to represent concepts of neighborhood deprivation, including: poverty/income, racial/ethnic compositions, education, employment, occupation, housing/crowding, residential stability, economic inequality, affluence, and racial desegregation[36,48]. Domains such as crime, social resources, and living environment/physical conditions, while less commonly used in neighborhood indices, have also been linked to health outcomes[35,50,51]. We relied on the literature to categorize indicators by domains in this analysis (see Table 3.1 for the original and reorganize domains), but our approach affords communities flexibility to categorize indicators into relevant domains based on local knowledge. The health domain was purposefully excluded as measures of health were operationalized as outcomes rather than characteristics of neighborhoods. Demographics, including age and race, were also excluded from constructing our indices, since these variables are fixed and not considered “actionable” indicators for communities.

Step 2: Pruning Redundant Indicators

Our second step involved quantitative reduction of indicators that represented redundant concepts within each domain using principal components analysis (PCA). This method has been used in other literature as an appropriate way to prune a large number of indicators to create an index that maximizes variation with a subset of indicators[48]. In order to assess redundancy, we examined correlation matrices for all indicators within the same domain. Following Lalloue, indicators with a correlation 0.8 or higher were identified as redundant. While there is no consensus on minimum ratios or sample size for PCA, there is general agreement that larger sample sizes (greater than 50) and ratios of subjects to indicators (5:1) is best, which meant the number of indicators available from BNIA needed to be significantly pruned to be appropriate for a PCA with 55 CSAs[52].

For the purposes of this manuscript, PCA (using Stata 13.1) was performed for each group of redundant or linear indicators to determine which indicators among the redundant sets had the highest correlation with the first component. Theoretically, the first component identified from PCA represents the key concept encompassed by the set of indicators, so selecting the indicator with the greatest correlation to the first component reduces redundant indicators while retaining the key concept represented by the group. From the initial 137 indicators in the BNIA dataset, 58 indicators remained. A full list of indicators retained in each domain is presented in Appendix 3.1.

An alternate method for reducing redundant indicators without use of PCA would be to select the indicator from the redundant group that the team feels is most relevant or important to retain from local knowledge, priorities, or amenability to intervention.

Often, neighborhood representatives have a good understanding of the types of indicators which affect their daily lives and longer term health outcomes, and the knowledge which neighborhood representatives bring to the table may be used to inform the pruning of indicators. Indicators that neighborhood representatives feel are important may be retained even if another indicator in the redundant set is empirically selected through PCA.

Step 3: Constructing Domain-Specific Scores

Step 3 involves conducting principal components analyses on all remaining 58 indicators, sorted into the 7 domains identified in step one to calculate domain specific index scores . Following the methods set forth by Lallaoue et al., indicators that loaded higher than average on the first component within each domain were retained for use in Step 4 to calculate the BNSEI scores from a final list of indicators representing each of the 7 domains. In all cases, the first component of each domain explained the majority of the variation in the domain and had a greater eigenvalue then the rest of the components. The indicator loadings on the first component from each domain were used to calculate the domain specific index values. From the initial 58 indicators in the BNIA dataset, 31 indicators remained for PCA in step 4.

Step 4: Construct Overall BNSEI

The fourth step involved constructing the final BNSEI. PCA was conducted using the 31 indicators from 7 domains of neighborhood risk. All indicators that contributed more than the average correlation (indicators with correlations greater than 0.156) to the first component were retained. The only domain not represented after pruning this final list was the social resources domain, which did not contribute any indicators that loaded greater than average on the first component. This step yielded 18 indicators, and the final list of indicators and factor loadings are presented in Table 3.2.

To confirm that the sample size and correlation structure in the final reduced set of measures was large enough to produce reliable results, and that the proportion of variance in the selected indicators within each domain may be linked to underlying factors, the Kaiser Meyer Olkin (KMO) Measure of Sampling Adequacy test was used. Generally, a KMO value must be 0.5-0.6 to be considered adequate; in this case, the KMO value for the final PCA was 0.87, which indicates an adequate sample for principal components analyses[53].

A final PCA was conducted on the remaining 18 indicators to compute the BNSEI score for each CSA. The BNSEI score was calculated by estimating the first component score for each CSA based on loadings of all 18 indicators (Appendix 3.2). and loaded on the first component with correlations ranging from -0.2713 to 0.2747. In total, the first component explained 60% of the total variance in the list of indicators, and could be interpreted according to the meaning of the indicators remaining as representative of concepts of neighborhood social and environmental risk. BNSEI scores were standardized in STATA by converting the scores to z scores in order to create an index with an average of zero and a standard deviation of 1. Scores on the standardized index ranged from a high score of 2.38 for the “Greater Roland Park” CSA to a low score of –1.61 for “Southwest Baltimore” CSA. Higher scores indicate a more positive and resource rich neighborhood context.

Validating the Indices

To assess whether the final index is valid and aligns with existing evidence on neighborhood social and environmental indices and health outcomes, BNSEI scores were examined in relation to two health indicators that are strongly linked to socioeconomic status and area deprivation: life expectancy and percent of births delivered at term[36,54,55]. We expected areas of higher neighborhood socioeconomic status to be strongly correlated with life expectancy, and rates of births delivered at term (37-42 weeks)[36,54,55]. Correlation matrices for life expectancy were computed for the overall BNSEI and domain-specific scores for each CSA (see Table 3.3). While we expected the overall neighborhood index to correlate highly with life expectancy, the relationship of domain-specific scores, such as housing, crime, living environment, and education were expected to be more variable. High correlations between each of the neighborhood domains and between each neighborhood domain and life expectancy would indicate that domain specific scores did not contribute much value to understanding variation in neighborhood social and environmental factors.

One common way to display the results of neighborhood indices is by mapping neighborhoods by index scores, since maps make information readily interpretable to multiple audiences[32,56]. For mapping purposes, the index scores were grouped into deciles by rank, such that the top decile (1st) represents the geographies with the highest scores, and the bottom decile (10th) represents the CSAs with the lowest scores. Deciles of BNSEI scores were computed and mapped to visually reflect geographic proximity of neighborhood-level social and environmental risk.

CHAPTER 3.3: RESULTS

The Baltimore Neighborhood Social and Environmental Index (BNSEI) is a multidimensional index of neighborhood social and environmental risk that is a composite of multiple domain-specific scores. From 137 indicators, we identified 7 domains of risk, including: crime (5 indicators), education (10 indicators) employment and workforce (8 indicators), housing (15 indicators), living environment and physical conditions (9 indicators), social resources (7 indicators) income and wealth (4 indicators), The final BNSEI reflects a composite score of 18 indicators comprising domains of: crime (2 indicators), education (5 indicators), employment and workforce (3 indicators), housing (4 indicators), living environment and physical conditions (1 indicators), and income and wealth (2 indicators).

Figure 3.2 displays a scatter plot of BNSEI scores and life expectancy and Figure 3.3 displays a scatter plot of the BNSEI score against full term births. As expected, BNSEI scores are highly correlated with life expectancy (correlation 0.89) and full term births (correlation = 0.66). Details regarding the rank of each CSA by domain as well as the overall BNSEI score are presented in Table 3.4.

The domain-specific maps produced in this study demonstrate variability in neighborhoods by domain. For example, the CSA Belair Edison ranked 4 for crime, indicating it is a lower crime area, but 9 in both housing and living environment/physical conditions. Neighborhoods that ranked in the lowest decile of the BNSEI were commonly adjacent to neighborhoods that ranked in the highest decile (Figure 3.4). However, neighborhoods in the lowest decile tended to cluster to the right and left of the center of Baltimore City, while neighborhoods falling into the highest deciles of the

BNSEI classification were located north of the city center and on the perimeter of the city.

CHAPTER 3.4: DISCUSSION

This paper describes the construction of a neighborhood social and environmental index that leverages rich local datasets to characterize neighborhoods within Baltimore City. Following a standardized approach set forth by Lalloue et al (2013), this paper uses an evidence based, statistically driven approach with flexibility for inclusion of local knowledge to narrow down a large set of indicators into a composite index that captures variation across multiple domains of actionable neighborhood indicators – as well as domain-specific indices that can be used to better understand variation among domains within and across communities[36,48]. The final BNSEI contained 18 indicators across 6 of the neighborhood domains. Communities seeking to capitalize on existing data about their own neighborhoods may find this approach useful for building evidence to pair with associated narratives about neighborhood priorities to gather financial support for community improvements, as well as to promote cross sector action for targeted, collaborative improvement efforts.

One of the key lessons emerging from years of research on health and health outcomes is that the drivers of health are multifaceted and complex, and changing these factors must start with communities working together with various sectors towards a shared goal of reducing disparities and improving living conditions to promote health[57-59]. The indices described here could be used as a tool for communities to convene stakeholders across multiple sectors to start conversations around how best to partner for improving neighborhood risk factors, using an empirical approach to prioritization while also taking into account the importance of community members' own understanding and prioritization of neighborhood related factors for designing interventions.

A number of limitations merit comment. First, the indicators used in the BNSEI are specific to Baltimore City, represent a cross sectional view of the neighborhoods as of 2015 and are limited to 55 neighborhoods. Therefore, the factors that comprise the indices may not be stable over time or across settings. Although the methods may be transportable, the index itself represents results for Baltimore City and therefore the findings may not be applicable in other locations. Further, this study is limited by adherence to predefined definitions of neighborhoods, which may not reflect resident's true perceptions of what constitutes a neighborhood. We cannot comment on unmeasured factors such as social cohesion, transience, community based organizations providing resources, religious community networks, and health care availability, among others factors, since these were not represented in this dataset and could greatly influence index scores. The fact that the social resources domain was not represented in the final index, and was less correlated with other domain specific indices may be due to the absence of data reflecting important constructs as opposed to the lack of the relevance of this domain.

CHAPTER 3.5: CONCLUSIONS

With the push for community empowerment and cross sector collaboration to drive change in social determinants, and the need to address community factors to change the current trajectory of poor health outcomes and high spending in the US, use of local and multifaceted community data in ways that can be the impetus for change through community led, cross sector partnerships is needed more than ever[6,59]. Maximizing use of local data is key to helping guide cross sector efforts towards a shared vision and strategy for community improvements, and developing indices that are multifaceted as well as domain specific and actionable will be critical for better understanding of where to target resources. Further, using these indices in models of total cost of care and healthcare utilization will help inform payers seeking to reduce costs and improve quality of care, and could provide incentive for funders to work more closely with communities to address neighborhood factors related to health. Overall, the BNSEI will allow researchers to model the effects of neighborhood deprivation on a variety of outcomes in Baltimore City neighborhoods, which will be useful for both researchers and policy makers seeking to better understand the links between neighborhood factors and health related outcomes.

CHAPTER 3 TABLES

<u>Table 3.1. Domains and Indicators Retained by Each Step of Index Construction</u>

BNIA* Identified Domains	Number of BNIA Indicators	Reassigned Domains for this Study	Number of BNIA Indicators Reclassified (Step 1)	Retained After Reducing Redundant Indicators (Step 2)	Retained After Creating Domain Scores (Step 3)	Retained After Creating Final Index (Step 4)
Crime	12	Crime	12	5	2	2
Education	22	Education	22	10	5	5
Workforce	18	Employment and Workforce	18	8	5	3
Housing	20	Housing	20	15	9	4
Sustainability	16	Living Environment and Physical Conditions	16	9	3	1
Arts	8	Social Resources	11	7	4	0
Demographics	24	Demographics	16	0	0	0
Health	17	Health	14	0	0	0
		Income and Wealth	8	4	3	2
Total	**137**	**--**	**137**	**69**	**36**	**18**

**Indicates original domains as grouped by the Baltimore Neighborhood Indicators Alliance*

<u>Figure 3.1: Construction of the Baltimore Neighborhood Social and Environmental Index Adapted from Lalloue et al (2013)[48]</u>

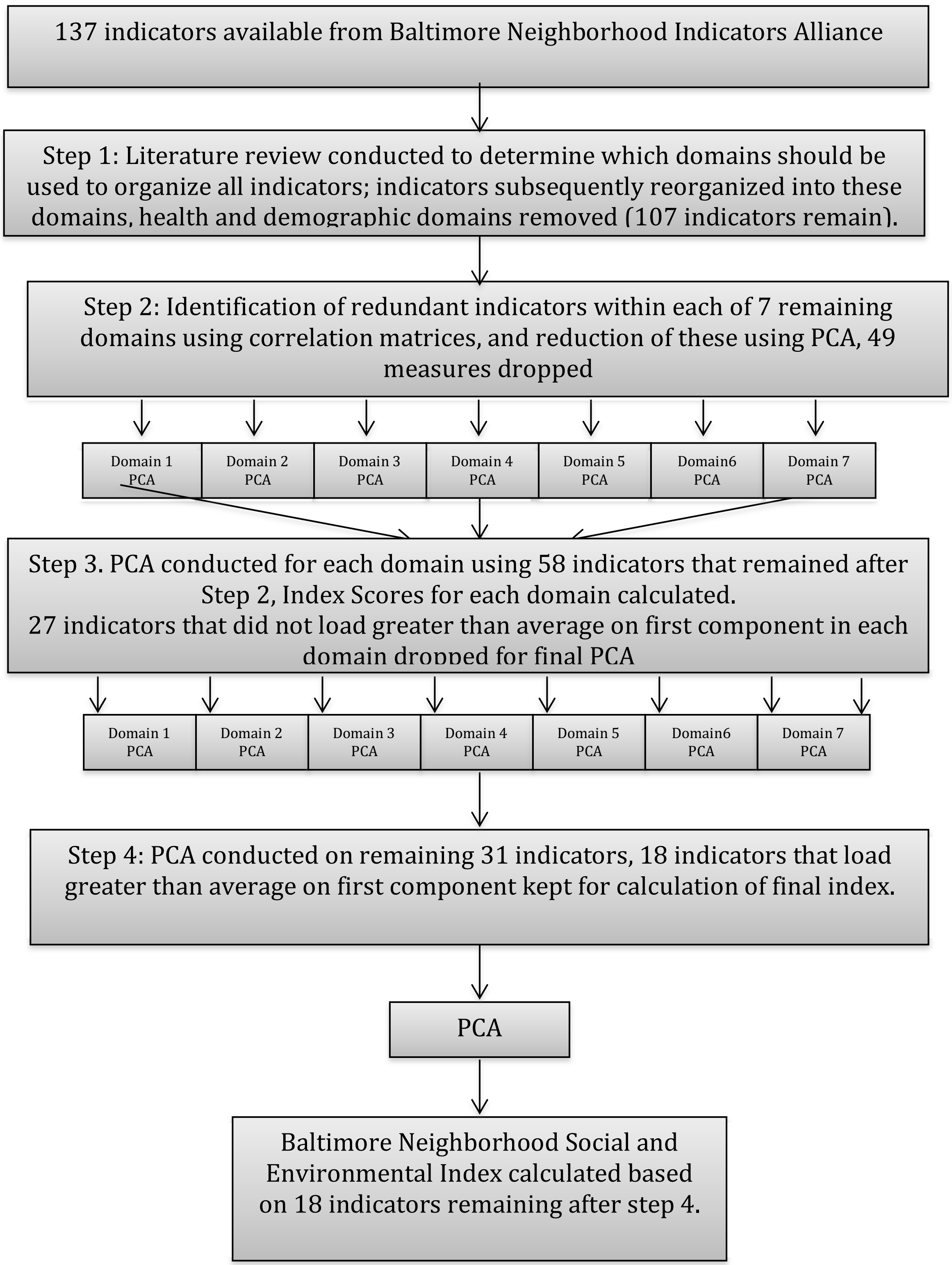
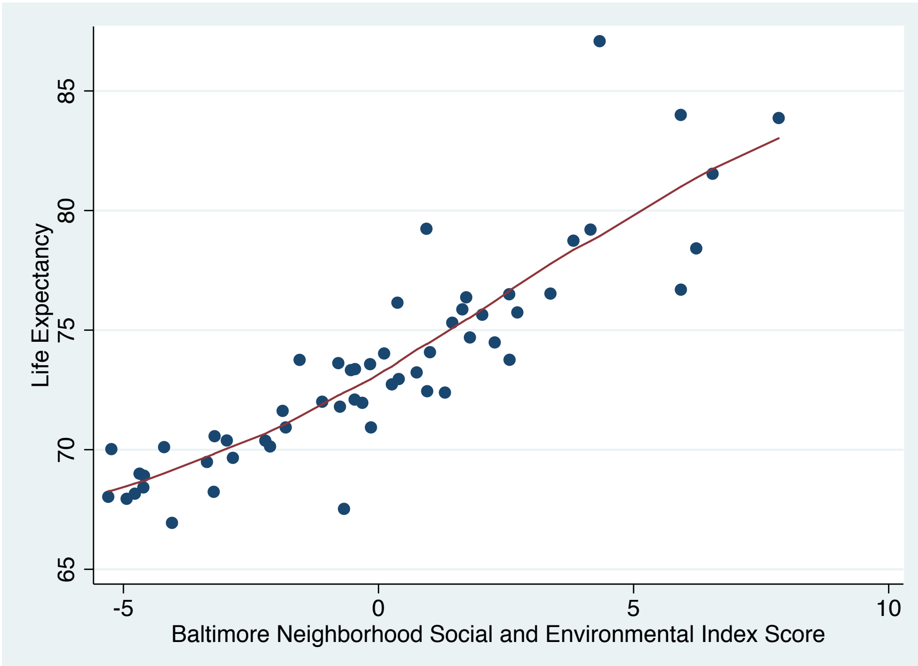
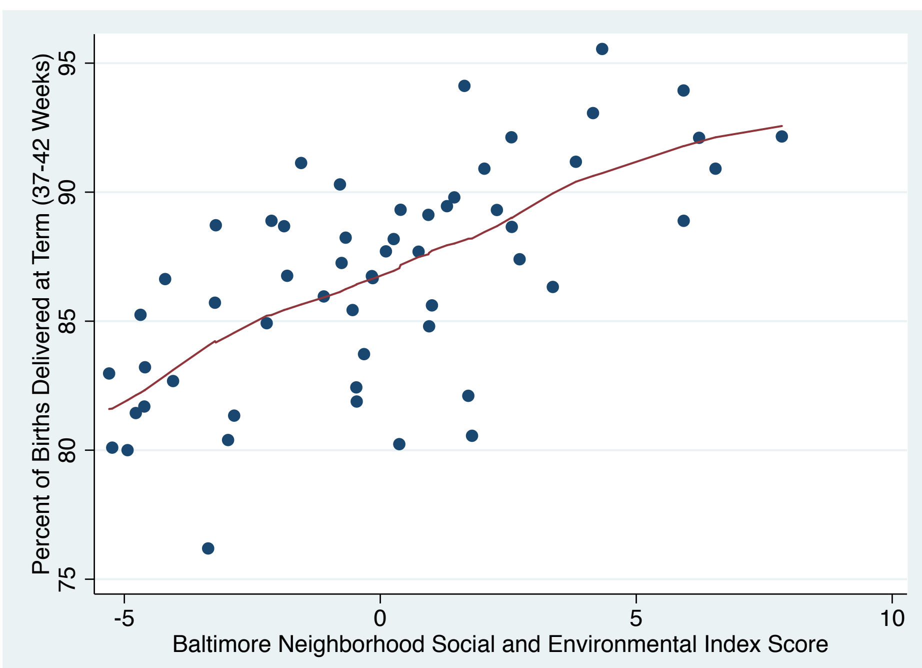


Figure 3.2: Validating BNSEI Against Life Expectancy*



**For the purposes of this graph, higher BNSEI score indicates improved social circumstances*

Figure 3.3: Validating BNSEI Against Full Term Births (37-42 weeks)*



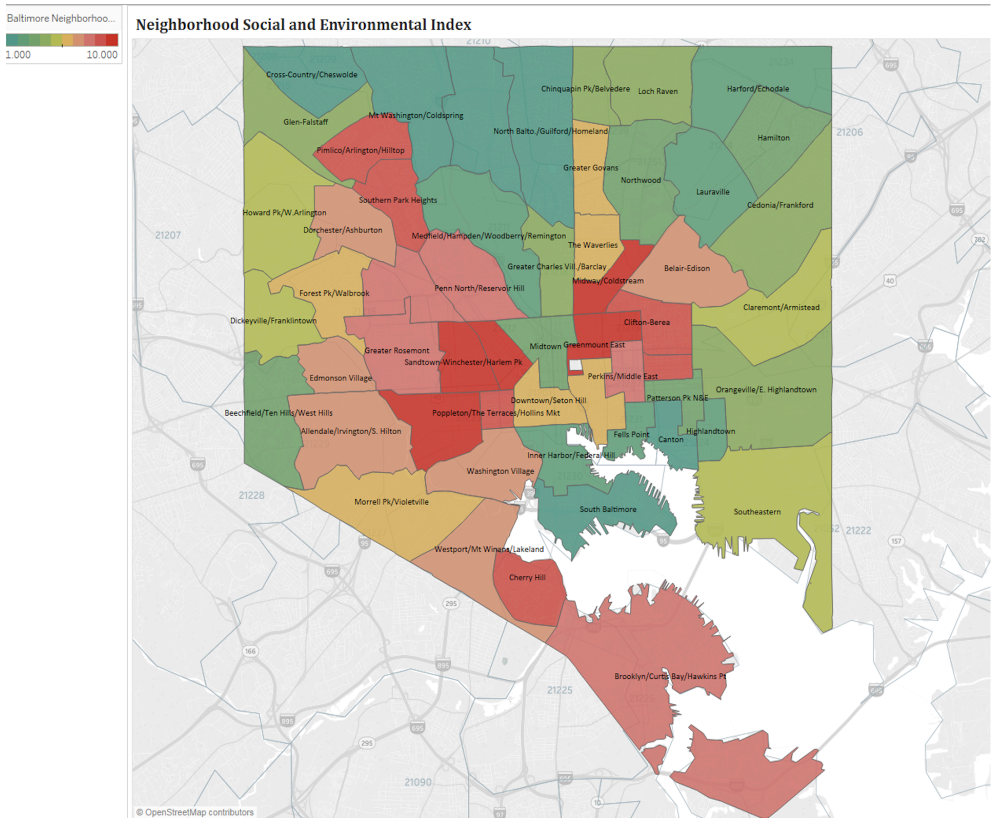
**For the purposes of this graph, higher BNSEI score indicates improved social circumstances*

Table 3.2: Correlation Matrix of Domain-Specific Indices and Life Expectancy

	SOCIAL RESOURCES	CRIME	EDUCATION	HOUSING	LIVING ENVIRONMENT	INCOME	EMPLOYMENT	BNSEI*	LIFE EXPECTANCY
SOCIAL RESOURCES	1								
CRIME	0.4082	1							
EDUCATION	0.1558	0.6707	1						
HOUSING	0.0589	0.7527	0.8311	1					
LIVING ENVIRONMENT	0.0337	0.5651	0.6583	0.6655	1				
DEMOGRAPHICS	0.457	0.3452	0.5103	0.6533	0.5823				
INCOME	0.1732	0.533	0.797	0.8263	0.5159	1			
EMPLOYMENT	0.359	0.4183	0.7406	0.7523	0.6714	0.8105	1		
BNSEI*	0.0615	0.7767	0.9359	0.9272	0.7439	0.87376	0.8348	1	
LIFE EXPECTANCY	0.2499	0.7406	0.8639	0.8162	0.66	0.7409	0.6745	0.8850	1

Baltimore Neighborhood Social and Environmental Index

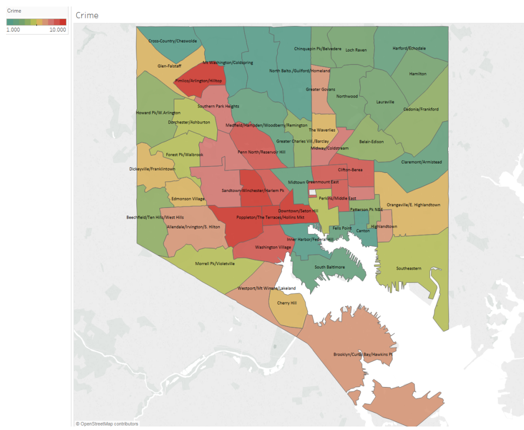
<u>Figure 3.4: Map of CSAs in Baltimore City by Baltimore Neighborhood Social and Environmental Index (BNSEI) Decile Score</u>



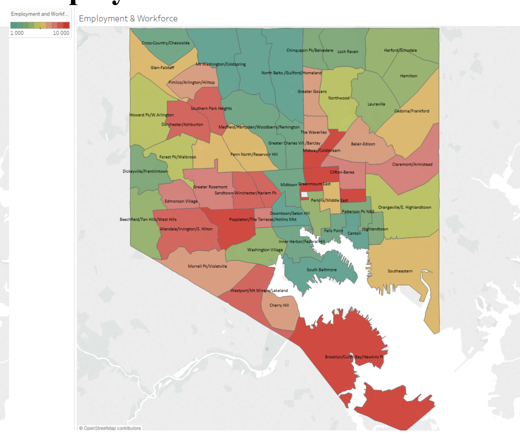
******Green indicates more favorable conditions as measured by neighborhood BNSEI score (on a scale of 1 to 10), red indicates least favorable*

Figure 3. 5: Map of CSAs in Baltimore City by Decile Specific Domain Indices*

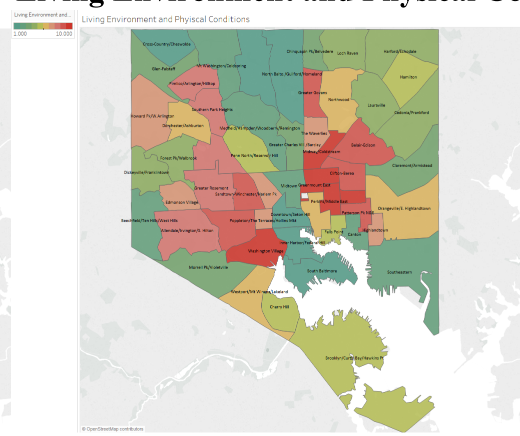
Crime



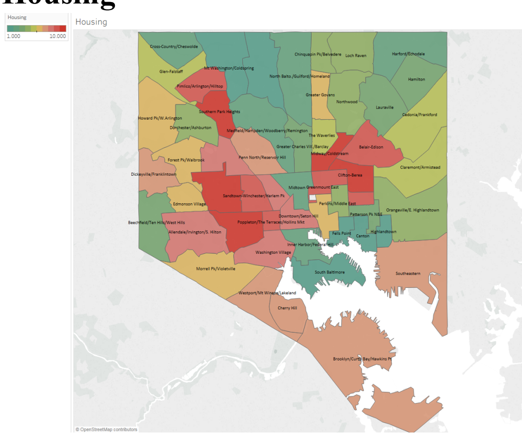
Employment and Workforce



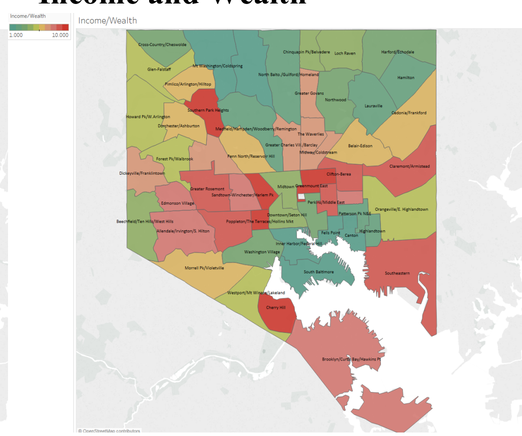
Living Environment and Physical Conditions



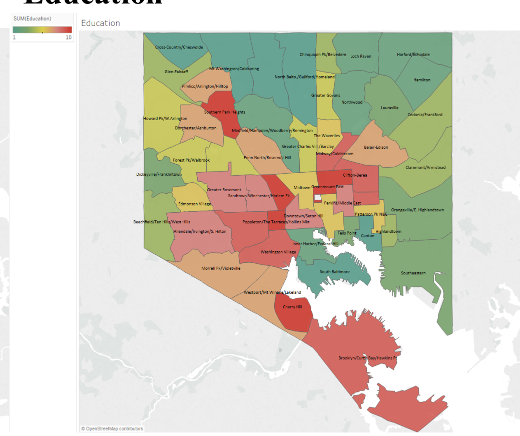
Housing



Income and Wealth



Education



*****_Green indicates more favorable conditions as measured by neighborhood BNSEI score (on a scale of 1 to 10), red indicates least favorable_

Table 3.3: Ranking Scores by Domain Index Decile for each CSA

CSA2010	SOCIAL RESOURCES	CRIME	EDUCATION	HOUSING	LIVING ENVIRONMENT AND PHYSICAL CONDITIONS	INCOME AND WEALTH	EMPLOYMENT AND WORKFORCE	BNSEI	LIFE EXPECTANCY
ALLENDALE/IRVINGTON/S. HILTON	6	7	8	8	8	8	9	7	7
BEECHFIELD/TEN HILLS/WEST HILLS	10	4	4	3	2	4	4	3	4
BELAIR-EDISON	5	4	7	9	9	6	7	7	6
BROOKLYN/CURTIS BAY/HAWKINS POINT	7	7	9	7	5	8	10	8	9
CANTON	1	1	1	1	2	1	1	1	2
CEDONIA/FRANKFORD	8	4	4	5	4	6	6	4	6
CHERRY HILL	4	6	10	7	5	10	7	9	9
CHINQUAPIN PARK/BELVEDERE	7	3	4	4	3	4	3	4	3
CLAREMONT/ARMISTEAD	8	2	4	5	3	9	8	5	7
CLIFTON-BEREA	3	9	9	10	9	9	8	9	10
CROSS-COUNTRY/CHESWOLDE	10	1	1	2	1	3	2	1	1
DICKEYVILLE/FRANKLINTOWN	9	6	3	7	4	7	3	4	5
DORCHESTER/ASHBURTON	8	5	7	4	6	6	9	6	5
DOWNTOWN/SETON HILL	1	10	8	8	1	4	1	6	10
EDMONDSON VILLAGE	7	6	6	6	7	8	8	7	7
FELLS POINT	2	2	3	1	5	1	2	2	2
FOREST PARK/WALBROOK	7	5	5	6	4	5	5	5	4
GLEN-FALLSTAFF	9	6	4	5	3	5	6	4	1
GREATER CHARLES VILLAGE/BARCLAY	4	4	5	3	3	7	2	4	4

GREATER GOVANS	**6**	**7**	**5**	**6**	**9**	**7**	**7**	**6**	**5**
GREATER MONDAWMIN	**7**	**8**	**5**	**8**	**8**	**7**	**6**	**8**	**8**
GREATER ROLAND PARK/POPLAR HILL	**5**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
GREATER ROSEMONT	**6**	**8**	**8**	**10**	**8**	**9**	**8**	**8**	**7**
GREENMOUNT EAST	**3**	**9**	**10**	**9**	**10**	**10**	**10**	**10**	**10**
HAMILTON	**9**	**3**	**2**	**3**	**5**	**2**	**4**	**2**	**4**
HARBOR EAST/LITTLE ITALY	**1**	**5**	**6**	**6**	**6**	**3**	**4**	**6**	**6**
HARFORD/ECHODALE	**10**	**2**	**2**	**2**	**4**	**3**	**4**	**2**	**3**
HIGHLANDTOWN	**1**	**7**	**4**	**1**	**7**	**2**	**3**	**3**	**4**
HOWARD PARK/WEST ARLINGTON	**10**	**4**	**5**	**6**	**7**	**5**	**5**	**5**	**3**
INNER HARBOR/FEDERAL HILL	**1**	**1**	**2**	**2**	**1**	**1**	**2**	**2**	**1**
LAURAVILLE	**8**	**3**	**3**	**3**	**4**	**2**	**4**	**2**	**2**
LOCH RAVEN	**9**	**3**	**2**	**4**	**4**	**4**	**3**	**3**	**3**
MADISON/EAST END	**4**	**8**	**9**	**9**	**10**	**8**	**10**	**9**	**9**
MEDFIELD/HAMPDEN/ WOODBERRY/REMING TON	**6**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**
MIDTOWN	**2**	**2**	**6**	**2**	**2**	**4**	**2**	**3**	**2**
MIDWAY/COLDSTREA M	**4**	**8**	**9**	**10**	**10**	**7**	**10**	**10**	**9**
MORRELL PARK/VIOLETVILLE	**10**	**5**	**7**	**6**	**3**	**6**	**7**	**7**	**5**
MOUNT WASHINGTON/COLDSP RING	**9**	**1**	**1**	**1**	**2**	**1**	**1**	**1**	**1**
NORTH BALTIMORE/GUILFOR D/HOMELAND	**9**	**1**	**1**	**2**	**1**	**2**	**1**	**1**	**1**
NORTHWOOD	**8**	**3**	**2**	**4**	**6**	**3**	**5**	**3**	**3**
OLDTOWN/MIDDLE EAST	**2**	**9**	**8**	**4**	**10**	**9**	**6**	**8**	**8**

ORANGEVILLE/EAST HIGHLANDTOWN	3	6	3	4	6	5	5	5	6
PATTERSON PARK NORTH & EAST	4	4	6	3	9	2	3	4	6
PENN NORTH/RESERVOIR HILL	2	9	7	7	5	6	6	7	7
PIMLICO/ARLINGTON/ HILLTOP	6	10	7	9	8	6	7	9	9
POPPLETON/THE TERRACES/HOLLINS MARKET	5	10	10	9	7	10	8	9	9
SANDTOWN-WINCHESTER/HARLEM PARK	3	10	8	9	9	8	9	10	8
SOUTH BALTIMORE	3	2	1	1	1	1	1	1	2
SOUTHEASTERN	6	5	3	7	2	9	6	5	6
SOUTHERN PARK HEIGHTS	7	8	10	10	8	10	9	9	8
SOUTHWEST BALTIMORE	4	10	9	10	9	9	10	10	10
THE WAVERLIES	2	6	6	5	7	7	7	6	7
UPTON/DRUID HEIGHTS	2	9	10	8	7	10	9	10	10
WASHINGTON VILLAGE/PIGTOWN	1	9	9	8	10	3	4	8	8
WESTPORT/MOUNT WINANS/LAKELAND	5	7	7	7	6	5	9	7	4

*1 indicates most favorable conditions, 10 represents least favorable

Chapter 4: Manuscript 2

NEIGHBORHOOD MATTERS: THE IMPACT OF NEIGHBORHOOD AND INDIVIDUAL LEVEL SOCIAL FACTORS ON THE DISTRIBUTION OF MEDICAL SPENDING IN A MEDICAID POPULATION

ABSTRACT

Objective:

To assess whether a multidimensional index of neighborhood social and environmental factors is significantly associated with medical spending across the distribution, conditional on individual level covariates.

Data Source:

Individual level health and utilization data are drawn from a sample of Baltimore City residents insured by a large Medicaid Managed Care Organization during 2016. A neighborhood social risk variable stratified into three categories (high, medium, and low) was created using data from the Baltimore Neighborhood Indicators Alliance.

Study Design:

We examine differences in medical spending associated with our 3 neighborhood social and environmental resource groups by applying unadjusted and adjusted quantile regression models with and without adjustment for individual level factors such as demographics and presence of chronic conditions. We test for differences in spending by neighborhood group across the 30^{th} to 90^{th} quantiles of medical spending, and test for differences in the size of associations across the distribution. We also test sensitivity of results using two part models to control for skew of medical expenditures.

Principal Findings:

Individuals who live in neighborhoods with low social and environmental resources experience significantly higher health care spending across the distribution of medical spending then individuals in high social and environmental resource areas, even after

controlling for individual level characteristics known to be associated with medical spending. The size of this difference in medical spending is significantly larger at the highest quantiles 80th-90th quantiles compared to the lowest (30th-40th).

Conclusions

Low resource neighborhoods are associated with higher individual level medical spending than high resource neighborhoods across the distribution of medical spending. Findings of this study suggest that payer efforts to reduce spending and improve sustainability could benefit from focusing on underlying issues like social inequities, and partnerships across other sectors.

CHAPTER 4.1: INTRODUCTION

Rising medical spending is an ongoing challenge in the United States. A growing body of evidence demonstrates that poor health outcomes and high utilization of healthcare resources are affected by neighborhood level factors (area level education, income, etc.)[7,60,61], through exposure to educational and economic opportunities, stress, crime, environmental toxins such as lead and pollution, availability of healthy food options and areas to walk and exercise, which in turn impact health behaviors, health outcomes and healthcare spending[37,38]. Evidence for the role of neighborhoods in affecting both behavioral and clinical causes of illness is further supported by studies that link material deprivation (individual and neighborhood level) to conditions which typically require higher levels of patient self-management and engagement with the health system to manage properly, such as diabetes, cancer, and depression[60,62,63].

As evidence continues to mount that neighborhood deprivation is linked to poorer health outcomes and higher preventable utilization, payers are taking notice and experimenting with interventions to address the social determinants of health, in particular, for individuals who are already at the high end of the medical spending distribution[61,62,64]. For payers, finding ways to reduce healthcare spending by targeting factors that drive morbidity, inappropriate utilization and potentially avoidable spending has been difficult, in particular, because addressing the social determinants of health requires interventions that are preventive and address the complex neighborhood and individual level factors that lead to poor health and health behaviors [64,65]. However, despite a growing body of evidence associating neighborhood factors to healthcare utilization and spending, many limitations remain.[61,62]. First, little is known about how neighborhood factors are associated with healthcare spending across the distribution of medical spending. For example, it is possible that at lower levels of spending, neighborhoods that are more disadvantaged may have stronger associations with spending due to lack of preventive care and worse self-management measures through pathways such as lack of transportation to get to primary care or less availability of healthy food to control chronic conditions like diabetes or hypertension[63]. At the higher end of the spending distribution, more disadvantaged neighborhoods may contribute to excess spending through acute utilization caused by exacerbations of chronic conditions or higher readmission risk after hospitalization[60].

While there is evidence that neighborhoods play a role in whether individuals are high utilizers of healthcare resources, no studies to date have examined how neighborhood effects are associated with medical spending outcomes across the spending distribution.[61] Further, the majority of existing studies examine neighborhood factors in relation to disease-specific outcomes (such as cardiovascular disease or diabetes); few studies have examined outcomes that encompass multiple types of morbidity, utilization, or total medical spending[61,62]. Examining medical spending rather than utilization is important for capturing variation in intensity of care in addition to service use, and is of particular interest to payers who are interested investing in prevention to manage total cost of health care spending[66]. The purpose of this study is to shed light on the associations between neighborhood contexts and individual level medical spending outcomes across the distribution of healthcare spending to help inform the way resources are targeted to improve the value of care delivered to patients among a large publicly insured population in Baltimore, Maryland.

CHAPTER 4.2: METHODS

Data Sources

All individual level data was derived from Johns Hopkins HealthCare claims and enrollment files for years 2015- 2016. Neighborhood level data was drawn from the 2015 Baltimore Neighborhood Indicators Alliance Data (BNIA), an open source, publicly available dataset organized at the community statistical area (CSA) level. Neighborhood level data available for Baltimore City is measured at the Community Statistical Area level (CSA). Community Statistical Areas are small clusters of neighborhoods that align with Census Tracts, and reflect city planner understanding of resident and institution perceptions of the boundaries of the community. Each CSA defines a relatively demographically homogenous area for which data can be consistently measured over time[18]. Baltimore City is comprised by 55 CSA, each of which consist of 1-8 census tracts with populations ranging between 5,000 and 20,000 individuals[18].

Study Design and Participants

This cross-sectional study examines total medical spending in relation to neighborhood social and environmental risk across community statistical areas in a large Medicaid population in Baltimore, Maryland. Although data was available for several types of insured populations, this analysis focuses specifically on one Medicaid plan given that income is strongly associated with both where individuals live and health and utilization outcomes[35]. By limiting the sample to individuals who qualify for Medicaid in a single state, we ensure that participants are relatively homogeneous with respect to having income that falls below a poverty threshold that qualifies them for enrollment (138% of the Federal Poverty line for parents and adults, 259% of the poverty line for pregnant women)[67]. Further, because all participants are covered under the same health insurance plan, access to care and benefits are uniform. Because of our interest in examining small-area variation in neighborhoods, participant eligibility was further restricted to individuals residing in Baltimore City who live in close proximity to multiple health systems, which minimizes differences in geographic access to care.

Setting

This study was carried out in Baltimore City, Maryland. Baltimore has an ethnically and economically diverse population of about 600,000 individuals[49] and comprises distinct urban neighborhoods marked by variable cultures and backgrounds.

Neighborhood level data available for Baltimore City is measured at the Community Statistical Area level (CSA).

Participants

Eligibility for this study included individuals age 18-64, who were non-institutionalized and continuously enrolled in a Johns Hopkins HealthCare administered Medicaid health plan (Priority Partners) during calendar year 2016 without more than a 30 day gap in enrollment, and with a valid address in a Baltimore City neighborhood during the study period. Individual addresses were drawn from health plan enrollment data and geocoded in order to link addresses to the community statistical area in which they were located. Individuals with invalid addresses during the study period were excluded (N=5).

Conceptual Model and Variable Selection

The conceptual model used in this study to guide variable selection was an adapted version of the National Academies of Science, Engineering and Medicine's framework for social risk factors and their relationship to healthcare use, outcomes and medical spending (see Figure 2). This model depicts the complex ways in which social risk factors are related to clinical and behavioral risk, access, health care use, and ultimately, healthcare and resource outcomes through multiple pathways, in particular, through their relationship with morbidity. Variables for this study were selected to represent neighborhood and individual level factors (neighborhood scores and individual demographics) and a morbidity measure (count of chronic conditions). The dependent variable is a measure of payer medical spending.

Dependent Variables

The main dependent variable in this study is total medical spending by a Medicaid Managed Care plan for each individual, which was calculated from aggregating all non-pharmacy related health spending across a 12-month timeframe (2016). Medical spending and morbidity measures were calculated using the ACG System, a statistically valid, case-mix methodology that allows calculation of scores representing multimorbidity and describes and predicts a population's past, concurrent, or future healthcare utilization and spending[41]. Total medical spending included outpatient and ambulatory care spending (including labs), inpatient and emergency department spending. Spending for long term care and psychiatric-specific outpatient visits and inpatient stays were not available or included in this analysis as these services are reimbursed separately. Medical spending did not include patient out of pocket spending or claims that were denied by JHHC; total medical spending represents spending by the payer.

Independent Variables

Given strong evidence linking neighborhood effects to chronic disease, [35-38,62,63,68-70] we use count of chronic conditions from the ACG System as a measure of morbidity, as it represents a count of all conditions identified from the ACG system which are considered to be "an alteration in the structures or functions of the body that are likely to last longer than twelve months and are likely to have a negative impact on health or functional status (see Appendix 2.3 for list of conditions considered to be chronic). Neighborhood disadvantage affects the likelihood of developing chronic conditions as well as ability to manage them, as disadvantaged neighborhoods tend to be less walkable, have fewer healthy food options, and impose barriers to self management[63]. Higher counts of chronic conditions represent higher morbidity burden. A binary pregnancy variable was also identified using ACG system definitions.

Individual level age, gender, and geocoded address were derived from health plan enrollment data. Age was stratified into 3 bands (18-34, 35-54, 55+), gender was binary (female or male), and addresses were linked to the CSA in which they are located. Individual level race data was available from Medicaid Managed Care enrollment files, however 4,569 individuals had a race that was "not provided", and 64 were missing a race value, resulting in a total of 4, 633 individuals in PPMCO with missing race values. Therefore, the authors used multivariate logistic regression to impute missing race as "black" or "non-black" using the mi procedure in Stata[71]. After imputation, 16%-19% of the imputed samples were identified as non-black, and 81-84% were identified as black.

<u>Neighborhood Level Variables</u>

The Baltimore Neighborhood Social and Environmental Index (BNSEI) is a multidimensional index of neighborhood social and environmental risk factors that encompasses 137 measures from BNIA data using principal components analysis to create a final index score for each CSA (see Chapter 3 for details). The final BNSEI index represents 18 indicators from the following domains of social risk: Crime (2 indicators), Education (5 indicators) Employment and Workforce (3 indicators) Housing (4 indicators) Living Environment and Physical Conditions (1 indicators), and Income and Wealth (2 indicators). This study relies on the aggregate index, which was standardized and grouped by tertile, with a score of 1 representing the most favorable social and environmental conditions (high), and 3 representing the least favorable social and environmental conditions (low). Each individual was assigned to a BNSEI category of 1-3 based on the CSA of residence.

Study Sample

After removing 5 individuals without a valid address from the original dataset, the final sample contained 9,783 individuals living in 55 CSAs that were grouped by categories representing high (n= 2,564), medium (n=3,221), and low (n=3,998) values of the Baltimore Neighborhood Social and Environmental Index.

Statistical Analysis

To examine differences in the association between the levels of neighborhood social and environmental status across the distribution of medical spending, we first use descriptive statistics to examine study participants by category of neighborhood social and environmental resources. Next, we use unadjusted quantile regressions to examine how medical spending varies by neighborhood categories and quantiles of medical spending. We examine the significance of differences by neighborhood social and environmental resources for individuals with nonzero medical spending. Finally, we estimate the neighborhood effects on medical spending conditional on covariates including morbidity for individuals with medical spending greater than zero, and ran Wald tests to determine whether disparities in medical spending across quantiles were equivalent. To check the robustness of our models to other specifications, we conduct sensitivity analyses using two part generalized linear models to test that patterns between neighborhoods and medical spending hold when individuals with no medical spending are included in the estimation equations, by testing models with pregnancy, by testing an alternate measure of morbidity that captures acute and unstable chronic conditions, and by testing additional variables, including having a hospital in the neighborhood and racial diversity of the neighborhood.

Unadjusted Comparisons by Neighborhood Social and Environmental Index Category

Descriptive statistics were used to examine spending and characteristics of individuals across each of the three levels of the social and environmental resource index. Categorical variables were presented as numbers and percentages with chi square tests used to determine whether characteristics differed significantly across high, medium, and low social and environmental resource neighborhoods. Continuous variables were presented as means, and group differences were tested with ANOVA . The authors also calculated the probability of having any medical expenditure, overall and by neighborhood social and environmental resource level, using logistic regression and calculated the mean spending overall and by neighborhood level.

To examine the extent to which neighborhood index scores and medical spending vary along the medical expenditure distribution, unadjusted quantile regressions were used. Because medical spending distributions are often skewed by high numbers of zero spending, we restricted the sample to those who incurred nonzero healthcare spending and who did not have a pregnancy flag in the time period (N=8,096), and ran unadjusted quantile models at the 30th, 40th, 50th, 60th, 70th, 80th and 90th quantiles to test whether there were significant differences in medical spending at each quantile, comparing medium and low resource neighborhoods to the reference neighborhood (high social and environmental resources) .

Adjusted Quantile Regression Models

We first examine whether differences in spending by neighborhood would be attenuated when adjusted for individual factors (age, gender, individual level race, and chronic conditions). Wald tests were used to test the equivalence of the neighborhood coefficients across quantiles after running simultaneous quantile regression models. Select interaction terms were chosen based on evidence from health disparity literature, which included testing the interactions between race and neighborhood social and environmental resource level, and race and morbidity given the abundance of evidence on racial disparities in health and medical expenditure outcomes[72,73]. We also test an interaction between age and chronic condition count, since age is highly correlated with having additional chronic conditions.

Two additional variables were tested in the model to control for possible relationships between neighborhood social and environmental resources and spending: a racial index representing a measure of neighborhood segregation (the odds of choosing two people at random from the same neighborhood and having them each be a different race or ethnicity)[18] and whether a hospital was located in an individuals' neighborhood, which was used to control for any relationship between higher utilization related to close proximity to a hospital and emergency room. We test sensitivity of the results to models that include pregnancies given the strong evidence that pregnancy outcomes are influenced by neighborhood social factors, and also test results against the mean values using two part generalized linear models to account for skewness and zero mass in the data.

CHAPTER 4. 3: RESULTS

Descriptive Data

Table 4.1 summarizes the characteristics of the study sample in total and by neighborhood social and environmental resource level. No major differences in gender, age, or number of chronic conditions were observed across levels of neighborhood social and environmental resources. Across neighborhood types, significant differences were found in distribution of black versus non-black (p=0.00), with neighborhoods categorized as having medium and low social and environmental resources had incrementally higher percentages of black individuals as we move from high to low resource neighborhood categories. Mean medical spending was higher in neighborhoods with lower resources, although differences were only marginally significant at p=0.085.

Unadjusted Medical Spending

A total of 2,374 (24%) participants incurred no medical spending, indicating no use of insurer-reimbursed healthcare services and no spending to the payer. The probability of having non-zero medical spending was 87% among adults in our sample, and was similar across neighborhood social and environmental resources (see Table 4.2). Only individuals with nonzero medical spending (N=8,730) were included in subsequent analyses. In unadjusted quantile regression models, average medical spending was not significantly different across levels of neighborhood social and environmental resources (average of $5,410.39, $5,975.48, $6,578.35 for high, medium and low resource neighborhoods respectively, respectively). However, significant differences in medical spending was observed by neighborhood social and environmental resources across each quantile including the median. Medical spending was significantly higher across all quantiles for neighborhoods with lower social and environmental resources as compared with those living in neighborhoods with greater social and environmental resources. For example, individuals in low resource neighborhoods incurred additional spending of $209 relative to those in high resource neighborhoods at the 30% of spending; this difference was generally larger at higher levels of spending, and was nearly $4800 at the 90% of spending.

Fully Adjusted Models of Medical Spending

In models that adjust for chronic conditions and other covariates, medical spending was significantly higher for neighborhoods with low versus high social and environmental resources across all quantiles, although in comparing medium resource neighborhoods to high, results are only significant at the 30th, 40th and 60th quantiles (See Table 4.3). The magnitude of difference in medical spending for neighborhoods with the low social and environmental resources was significantly larger in magnitude at the 80th and 90th quantiles than the lower end of the spending distribution (30th- 50th). For example, when we test the size of the difference between high and low resource neighborhoods at the 30th quantile ($68.07) against the size of the difference at the 90th quantile ($695.20) we find that the magnitude of the difference is significantly different than zero. This indicates that the gap in medical spending becomes significantly wider across quantiles of medical spending.

Sensitivity Analyses

Neither racial diversity nor living in close proximity to a hospital were significantly associated with total medical spending, and these variables were dropped from the final models. When pregnancies are included from analyses adjusting for chronic conditions, all quantiles remained significant when comparing medical spending in the lowest resource to highest resource neighborhoods, and several quantiles showed significant difference in medical spending between the medium and high resource neighborhoods as well (0.3, 0.6) (See Appendix 4.1). However, when we run sensitivity analyses using a measure of major chronic and acute conditions, we find racial differences in the significance of our neighborhood variable. In race-stratified models that adjust for all control variables and major chronic and acute conditions, medical spending was higher for blacks living in neighborhoods with lower (versus higher) social and environmental resources at all quantiles except the 90^{th} . No significant difference in neighborhood social and environmental resources was observed for participants who were non-black (see Appendix 4.3-4.5).

Finally, in two part models that include individuals with zero spending, neighborhood social and environmental resource level is significantly associated with higher medical spending among individuals who incurred medical costs who live in low versus high resource neighborhoods, after adjusting for chronic conditions, (see Table 4.4). Further, average differences in medical spending by neighborhood social and environmental resources are not due to differences in engagement with the healthcare system as measured by having non-zero spending, but instead, significant differences in medical spending by neighborhood social and environmental resource level occur among individuals who have nonzero spending.

CHAPTER 4. 4: DISCUSSION

This paper examines the effect of neighborhood social and environmental resources across the distribution of medical spending after controlling for individual and neighborhood factors. Using data from a single Medicaid Managed Care plan to control for income and insurance status, we find that individuals living in neighborhoods with fewer social and environmental resources have higher medical spending than their counterparts living in high resource neighborhoods across the spending distribution. Further, we find that the effects of low social and environmental resource neighborhoods on medical spending extend beyond associations with morbidity. We found fewer differences in medical spending when comparing medium to high resource neighborhoods, which may be explained by the smaller difference in disadvantage between these neighborhoods.

Consistent with literature on neighborhood disadvantage and health status, we find higher levels of morbidity (chronic and non-chronic) and higher medical spending in lower resource neighborhoods[62,63,69,74]. While other studies have suggested that individual level factors and morbidity may attenuate the neighborhood effects associated with health outcomes[75], we find that neighborhood effects persisted after controlling for income, insurance status, morbidity, gender, race and age when examining the distribution of medical spending (see Appendix 6.2 for more detailed analysis of associations between age and medical spending). Significantly higher medical spending persisted across all medical spending quantiles, even after adjusting for chronic conditions. The lack of a neighborhood effect across the whole distribution of medical spending is notable, given payers often target individuals only in the top 5-10% of the medical spending distribution for enrollment in programs that address social determinants[64].

Following the theory that the causal pathway through which neighborhoods affect medical spending is that neighborhood disadvantage creates more difficult conditions for individuals to self-manage chronic conditions[62,63,69], we expected that the association between lower versus higher social and environmental resource neighborhoods and higher spending would persist even after controlling for chronic condition count. The results of our study align with this hypothesis across all quantiles.

In sensitivity models including pregnancy, we see that the neighborhood social and environmental resource effect remains the same in the model, with higher medical spending across all quantiles when comparing the lowest resource neighborhoods to the highest resource neighborhoods. Further, in sensitivity analyses where we adjusted for acute and major chronic morbidity instead of chronic conditions alone, we found results varied significantly by race. The higher medical spending seen in the lower resource neighborhoods remained significant when comparing the lowest social and environmental resource neighborhoods to the highest for blacks at every quantile except the 90th in the spending distribution, although not for non-blacks. For non-black participants, low social and environmental resource neighborhoods were associated with higher medical spending before controlling for morbidity, but not after. Further research is needed to better understand how higher medical spending in lower social and environmental resource neighborhoods is linked to differences in utilization patterns by race and across neighborhoods (see Appendix 6.1 for additional analyses and discussion on this).

Another interesting finding was that neighborhoods were not associated with the likelihood of having zero versus nonzero medical expenditures: a measure which could be explained by either an unwillingness to engage with the healthcare delivery system for spending, access, or personal reasons, or could reflect good health and a lack of need for healthcare services[66]. All significant effects of neighborhoods from the two-part models were found among individuals who had utilized the health system, which may be due to the fact that everyone in the study sample had healthcare coverage under a single health plan with the same theoretical access to services. Future studies examining the pathways by which neighborhood social and environmental resources relate to higher medical spending are needed to determine what types of interventions could help target high medical spending for individuals in low resource neighborhoods.

Limitations

We recognize several limitations to the validity of this study. First, the study was cross sectional, and only represents a point in time, and therefore causality cannot be determined. The study only reflects data for individuals who are low income and living in Baltimore City, and we are unable to control for factors that may improve health, such as care management programs, neighborhood initiatives, public health programs, and other initiatives addressing neighborhood determinants during this time period. We also have no controls for social cohesion or community groups who may impact medical spending outcomes in different communities. Further, due to a large amount of missing race data, we imputed racial values, and this could have biased our results, in particular in our non-black population, which was relatively small in this study. Sensitivity analyses indicated that imputed data followed patterns detected when using non-imputed race data only, however the numbers of non-black participants was significantly smaller than black participants.

Additionally, we cannot measure how long individuals were living at the place of residence that was listed in enrollment files and therefore, it is possible that individuals within neighborhoods had moved elsewhere during the study period and therefore their spending may have no link to the neighborhood of study. Data related to long-term care and spending on inpatient and outpatient psychiatric services was unavailable, and this may impact spending patterns across neighborhoods, although we know that black and low income individuals tend to have higher need, but less use of such services[76]. Finally, we cannot control for mortality in this dataset, although individuals who die during the year are typically disenrolled from the health plan and therefore would not have met the eligibility criteria of our target population.

It is difficult to determine directionality of neighborhood associations with medical spending, as it is possible that sicker individuals move to more disadvantaged neighborhoods because of spending on illness rather than neighborhood factors producing worse health outcomes. However, controlling for income and access by focusing on a single Medicaid Managed Care enrolled population only, where all healthcare expenses are covered and there are no copayments that would serve as financial barriers to access, it is less likely that individuals moved to more disadvantaged neighborhoods because of the burden of their healthcare expenses, although still possible if high medical spending occurred prior to enrollment in Medicaid.

CHAPTER 4.5: CONCLUSION

This study examined the association between neighborhood social and environmental resources and the distribution of medical spending by a single insurer in Baltimore, Maryland, and found that low neighborhood social and environmental resources are linked to higher medical spending across the distribution of the dependent variable. While medical spending differences by neighborhood are relatively small, they are significant, and when multiplied across a large number of enrollees, they are considerable. Findings of this study suggest that payer efforts to reduce spending and improve sustainability could benefit from focusing on underlying issues like social inequities, and partnerships across other sectors[61]. Working with communities and other sectors to identify neighborhood factors that lead to higher medical spending across the risk spectrum could help payers move upstream to address the root causes of higher medical spending and health disparities, and ultimately, could help build more equitable and sustainable health systems.

CHAPTER 4 TABLES

Table 4.1: Summary Characteristics of Study population by level of Baltimore Neighborhood Social and Environmental Resources

		Neighborhood Social and Environmental Resource Category * N(%)			P value
	Overall Population	**High Resource**	**Medium Resource**	**Low Resource**	
Total Individuals	9,783	2,564 (26.2%)	3,221 (32.9%)	3,998 (40.9%)	
Gender					P<0.303
Male	3,710 (38.0%)	988 (38.5%)	1,212 (37.6%)	1,510 (37.8%)	
Female	6,073 (62.1%)	1,576(61.5%)	2,009 (62.4%)	2,488 (62.2%)	
Age					P<0.152
18-34	4,708 (48.1%)	1,289 (50.3%)	1,520 (47.2%)	1,899 (47.5%)	
35-54	3,601 (36.8%)	908 (35.4%)	1,211 (37.6%)	1,482 (37.1%)	
55+	1,474 (15.1%)	367 (14.3%)	490 (15.2%)	617 (15.4%)	
Race					P<0.00
Black	6,835 (69.9%)	1,489 (58.1%)	2,117 (65.7%)	3,229 (80.7%)	
Other	1,401 (14.3%)	585 (22.8%)	620 (19.2%)	196 (4.9%)	
Missing	1,547 (15.8%	490 (19.1%)	484 (15.0%)	573 (14.3%)	
Morbidity					
Chronic Condition Count (mean)	1.9	1.79	1.92	1.98	P<0.001
Pregnancy					P<0.21
Yes	644 (6.6%)	151 (5.9%)	213 (6.6%)	280 (7.0%)	
No	9139 (93.4%)	2,413 (94.1%)	3,008 (93.3%)	3,718 (93.0%)	
Medical Cost (Mean)	$5,428.03	$4,815.58	$5,366.42	$5,869.18	P<0.00

*BNSEI Category descriptions are 1. High Social and Environmental Score (higher resources, lower risks) 2. Medium social and environmental score (medium resources, medium risks) 3. Low Social and Environmental Score (Lower resources, higher risks)

Table 4.2: Unadjusted Differences in Medical Costs by Neighborhood Across Quantiles

	Probability of Any Medical Spending	Mean Medical Spending*	Spending at Each Quantile (US Dollars)**						
			.3	.4	.5	.6	.7	.8	.9
Medical Spending	0.869	5,428.03	792.74	1,244.30	1,869.78	2,874.55	4,512.91	8,093.04	17,383.51
High Resource Neighborhood	0.860	5,410.39	663.27	1,039.85	1,542.19	2,401.76	3,686.14	6,786.82	15,225.30
Medium Resource Neighborhood	0.872	5,975.48	804.22	1,282.29	1,888.6	2,921.49	4,618.18	8,437.72	16,929.97
Low Resource Neighborhood	0.873	6,578.35	872.34	1,382.11	2,076.91	3,152.78	4,969.15	9,015.42	20,000.06
Low Versus High Cost Difference	--	-1,167.96	209.07**	342.25***	534.73***	751.02***	1,283.01***	2,228.60***	4,774.76*
Medium Versus High Cost Difference	--	-565.09	140.95**	242.44***	346.42***	519.73***	932.04***	1650.92***	1704.67***

**Means calculated using medical costs that have been top coded to set all outliers above 2 standard deviations from the mean to the value of 2 SD above the mean ($48,894)*
***Only individuals with a cost>0 are included in the cost quantile calculations (N=8,740). Quantiles represent deciles of cost, for example, 0.3 corresponds to the 30th percentile of medical spending. Overall, there were 2,374 (24.3%) of individuals with no costs, with similar percentages of non-users across the three levels of the neighborhood resource variable.*

Table 4.3: Differences in Medical Spending Across Quantiles by Neighborhood Social and Environmental Resource Levels, Adjusted for Gender, Age, Race and Chronic Condition Count

	Quantile*						
N=8096	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Neighborhood Index							
High Resource Neighborhood	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Medium Resource Neighborhood	40.60	64.05*	33.25	66.75	36.96	-11.00	226.0
	(31.63)	(35.96)	(41.59)	(55.64)	(76.29)	(109.5)	(157.1)
Low Resource Neighborhood	68.07**	81.60**	94.08**	126.40**	119.30*+	252.10**+	695.20***+
	(32.49)	(33.87)	(44.68)	(59.17)	(71.54)	(122.1)	(201.7)
Gender							
Male	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Female	111.0***	151.3***	181.3***	177.3***	225.7***	102.4	-138.3
	(22.82)	(26.32)	(32.72)	(46.92)	(60.89)	(95.45)	(190.9)
Age							
Age 18-34	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Age 35-54	-126.2***	-134.9***	-163.4***	-213.1***	-268.9***	-317.7***	-590.8***
	(24.39)	(30.52)	(34.12)	(45.80)	(62.06)	(94.97)	(165.0)
Age 55+	-548.8***	-696.2***	-854.5***	-1,006***	-969.0***	-1,286***	-1,580***
	(93.53)	(129.4)	(189.9)	(252.1)	(201.9)	(147.5)	(229.8)
Race							
Non Black	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Black	5.708	-8.790	27.19	78.27	37.31	64.95	239.3
	(32.56)	(39.72)	(45.29)	(63.35)	(88.26)	(145.1)	(171.8)
Morbidity							
Chronic Condition Count	827.6***	1,109***	1,465***	2,006***	2,629***	3,722***	6,351***
	(23.34)	(35.33)	(44.46)	(63.71)	(72.97)	(134.9)	(319.3)
Constant	109.8***	191.7***	282.7***	373.0***	669.0***	1,184***	1,887***
	(37.27)	(40.39)	(49.96)	(65.09)	(101.0)	(151.9)	(284.9)

*All differences are in US Dollars, t-statistics in brackets *** p<0.01, ** p<0.05, * p<0.1
Observations=8,096 (pregnancies and individuals with zero medical spending excluded from models)
+ indicates difference in size of effect across quantiles is statistically different than the size of the difference at the 30th quantile.

Table 4.4: Two Part Models of the Neighborhood Social and Environmental Index and Medical Spending, Adjusted for Other Covariates

	Logit (Odds of Any Cost)	Regress (Log Costs+)
Neighborhood Social and Environmental Resource Index	**N=8,495**	**N=8,096**
High Resource	Ref	Ref
Medium Resource	0.0581	0.101***
	(0.0881)	(0.0357)
Low Resource	0.00261	0.143***
	(0.0874)	(0.0357)
Gender		
Male	Ref	Ref
Female	0.814***	0.120***
	(0.0681)	(0.0286)
Age		
18-34	Ref	Ref
35-54	-0.216***	0.0807**
	(0.0760)	(0.0319)
55+	-0.658***	-0.0824*
	(0.131)	(0.0421)
Race		
Non Black	Ref	Ref
Black	0.0883	0.0108
	(0.102)	(0.0395)
Morbidity		
Chronic Condition Count	2.684***	0.347***
	(0.176)	(0.00598)
Constant	0.397***	6.516***
	(0.108)	(0.0465)

+Logit models represent the odds of having any medical spending, and regression models represent the log of medical spending. T-statistics are in brackets.
*** p<0.01, ** p<0.05, * p<0.1. Pregnancies not included in these models.

Chapter 5: Manuscript 3

NEIGHBORHOOD MATTERS: ESTIMATING THE RELATIVE CONTRIBUTION OF NEIGHBORHOOD RISK DOMAINS TO MEDICAL SPENDING FOR A MEDICAID POPULATION IN BALTIMORE CITY

ABSTRACT

Introduction

A growing body of evidence suggests that health outcomes and utilization of health services are linked to both neighborhood factors and individual characteristics. However, limited information exists on the relationship between different constructs of neighborhood risk and medical spending. Considering which neighborhood domains should be considered in addition to individual factors for risk prediction and intervention purposes may help payers better target resources to improve health and reduce medical spending.

Methods

This cross sectional study includes 9,772 subjects across 52 neighborhoods in Baltimore, Maryland who were insured by single Medicaid Managed Care Organization in 2016. The relationship between medical spending and index scores for neighborhood domains of social risk including crime, education, housing, living environment, workforce and employment, income and wealth, and an overall index representing all domains are examined to determine which indies have a significant relationship to medical spending in adjusted and unadjusted two-part models of medical spending.

Results

All neighborhood domains were significantly associated with higher medical spending as neighborhood characteristics became less favorable in unadjusted two-part models, but no domains were significantly associated with likelihood of any medical spending. In

models that adjust for individual factors known to influence medical spending (age, race, gender, morbidity, and neighborhood segregation), the multidimensional neighborhood social and environmental resource index, the crime index, the housing index, and the employment and workforce index were all significantly associated with medical spending among individuals who had non-zero spending.

Conclusion:

There are significant relationships between neighborhood social risk domains and medical spending even after adjusting for multiple other individual level predictors of medical spending. The significant association between domains such as crime, housing, employment, and an index that includes multiple domains of neighborhood risk indicates a need for further research into the pathways by which neighborhood factors lead to higher medical spending. Future risk adjustment methodologies and intervention targeting by payers should consider the multidimensional nature of neighborhoods, and future research is needed to better elucidate the pathways by which neighborhood factors effect medical spending.

CHAPTER 5.1: INTRODUCTION

High medical spending continues to challenge the sustainability of the United States healthcare system. Studies indicate that individual level risk factors such as being black and having low socioeconomic status predict lower use of preventive services, higher use of emergency and hospital based services, and higher healthcare spending[44,60,72-74,77-81]. While patient level characteristics are well established as being associated with healthcare utilization, a growing body of evidence suggests that neighborhood level factors such as poverty, deprivation and segregation moderate the effect of individual level factors on health service utilization and medical spending[35,44,61,69,80,82-84]. The relationship between individual level factors and health utilization and spending is closely tied with neighborhood context[62,76,79,83,85,86].

Neighborhood context affects health through complex pathways that involve exposure to educational and economic opportunities, stress, availability of healthy food options and areas to walk and exercise, crime, tobacco and alcohol influences, and environmental toxins such as lead and pollution, which all in turn impact individual level health related behaviors, health outcomes, and associated medical spending[37,38] [37,38]. The literature on neighborhood association with medical spending has thus far been mostly limited to studies of how the use of neighborhood risk factors improves risk adjustment or payment models, and for targeting interventions to improve health and reduce costs, in particular, among high risk, high cost individuals[39,87-89]. In Massachusetts, for example, a neighborhood stress score made up of measures of low SES was added to individual level risk factors more commonly used in risk adjustment models, and is being used to risk adjust payments to providers for extra effort needed to manage the care of higher risk patients[88]. Other studies have found that neighborhood level factors are less useful for predicting utilization of services after adjusting for individual level factors and morbidity[84,89]. For example, one study examining the value of adding neighborhood level socioeconomic status to predictive models of health outcomes found that it did not contribute meaningfully to prediction of outcomes, although the authors acknowledged that the specific neighborhood socioeconomic measures used may not capture the full neighborhood effect on the outcome[89].

Currently there is a lack of strong evidence indicating which neighborhood constructs have the strongest associations to medical spending. Prior studies examining associations between neighborhood risk factors, utilization and cost outcomes have focused exclusively on composite measures of neighborhood social risk from census data (poverty, demographics, housing, and education attainment) [61,62]. However, specific dimensions of neighborhood environment such as physical environment, crime, and social resources are differentially associated with morbidity and utilization outcomes[34,62,90]. Therefore, understanding which domains of neighborhood risk are most highly associated with medical spending could inform improved risk adjustment methodology, encourage more uniform collection of neighborhood domains outside of just socioeconomic variables, and inform direction for further targeting of neighborhood investments, as well as research on the pathways by which neighborhood factors lead to worse health outcomes and higher medical spending.

Objectives

This study does not seek to explain causal pathways between neighborhood social risk factors, morbidity, and the medical spending. Instead, this study assesses associations among domains of neighborhood risk factors and medical spending. This study compares associations between medical spending and commonly used neighborhood measures (a summary neighborhood social and environmental resources index, a measure of segregation, and multiple indices representing domains such as income, housing, and education, in addition to indices representing less commonly studied domains (crime and living environment). This study adds to the current literature on neighborhood social risk and medical spending by comprehensively examining a diverse set of neighborhood domains that extend beyond common socioeconomic measures and by examining the association between each domain and medical spending in a Medicaid population in Baltimore, Maryland.

CHAPTER 5.2: METHODS

Data Sources

Individual level data was drawn from Johns Hopkins HealthCare claims and enrollment files for years 2015- 2016. Data on neighborhood risk factors were drawn from an open source, publicly available dataset called the Baltimore Neighborhood Indicators Alliance Data (BNIA). The BNIA data used in this study was measured at the community statistical area level, which represents small clusters of neighborhoods that align with Census Tracts, but also represent city planner and resident understanding of community boundaries. Each CSA defines a relatively demographically homogenous area for which data can be consistently measured over time[18]. This study was limited to 52 CSAs in which more than 10 adults were residents and also enrolled in the Johns Hopkins Medicaid Managed Care plan during 2016. Each CSA theoretically represents populations ranging between 5,000 and 20,000 individuals[18].

Study Design, Setting, and Participants

This cross sectional study examines neighborhood domains and their association with medical spending, utilizing claims data from a population of non-institutionalized adults age 16-64 who were continuously enrolled in a single Medicaid Managed Care plan in Baltimore, Maryland during calendar year 2016. Baltimore has an ethnically and economically diverse population of about 600,000 individuals[49] and comprises distinct urban neighborhoods marked by variable cultures and backgrounds.

By limiting our sample to only individuals with Medicaid, we effectively control for low income related to programmatic eligibility (138% of the Federal Poverty line for parents and adults, 259% of the poverty line for pregnant women), and ensure comparable access to Medicaid-funded services. Children were excluded given the differing pathways through which neighborhoods may affect child utilization and costs as compared to adults[39]. We further restrict the sample to only individuals with a valid address in a Baltimore City CSAs in order to link addresses to neighborhood domains of risk. Individual addresses were drawn from health plan enrollment data and geocoded to link addresses to the CSA in which they were located. In total, there were 9,772 study subjects.

Variables

The conceptual model used in this study to guide variable selection in this study was an adapted version of the National Academies of Science, Engineering and Medicine's framework for social risk factors and their relationship to healthcare use, outcomes and medical spending, which shows several pathways by which neighborhood factors may lead to higher medical spending (see Figure 2)[17]. The dependent variable in this study is total annual medical spending, representing the aggregate of all non-pharmacy related health spending from January 1 to December 31st, 2016. Spending data related to long-term care and psychiatric-specific outpatient visits and inpatient stays were not available or included in this analysis as these services are reimbursed separately in Maryland. Medical spending represented claims paid by the insurer alone, and did not reflect patient out of pocket spending or claims denied by the insurer. We top coded medical spending at $48,894 (replaced larger spending amounts with $48,894, which represented medical spending at two standard deviations above the mean) to prevent outliers from affecting the model. In separate analyses, we examined models where top coding was not enforced, and found that the significance of the neighborhood domain variables did not change.

A measure of morbidity was calculated using count of chronic conditions, using definitions from the ACG System, a validated case mix methodology that allows for calculation of scores representing multimorbidity[91]. Chronic condition count represents a count of high impact and chronic conditions likely to last more than 12 months with or without medical treatment (see Appendix 2.3 for list of conditions considered to be chronic)[91]. We choose to use chronic condition count over other measures of morbidity given chronic conditions are the most commonly used measure of morbidity in the literature on neighborhoods and health, and is also a common measure of morbidity used for risk adjustment purposes[62]. Pregnancy was flagged using definitions from the ACG System to identify a pregnancy at any time during 2016. Individual level age, gender, and geocoded address were derived from health plan enrollment data, and linked to CSAs. Race data was available; however 1,544 individuals were missing race values. Therefore, the authors used multivariate logistic regression to impute missing race as "black" or "non-black" using the mi procedure in Stata[71]. After imputation, 16%-19% of the imputed samples were identified as non-black, and 81-84% were identified as black.

Neighborhood domains were derived from 137 measures describing CSAs from BNIA data using principal components analysis. An overall index score referred to as the

Baltimore Neighborhood Social and Environmental Index (BNSEI) represents 18 indicators from the following domains of social risk: Crime (2 indicators), Education (5 indicators) Employment and Workforce (3 indicators) Housing (4 indicators) Living Environment and Physical Conditions (1 indicators), and Income and Wealth (2 indicators). Domain specific indices are used to compare associations with medical spending between domains as well as with comparisons to a summary index. These indices were calculated using principal components analysis to create an index score for each of the following neighborhood domains: Crime, Education, Housing, Living Environment and Physical Conditions, and Income and Wealth. Each index was converted into a z score with a mean of zero and standard deviation of 1 prior to use in regression models, with low scores indicated the most favorable conditions, and higher scores indicating less favorable conditions. For details on the creation of these indices, please refer to Chapter 3. See Appendix 3.1 for a list of variables that comprise each index.

Further, this study uses a measure of neighborhood segregation as a control variable in all fully adjusted models, given the strong evidence linking segregation to poor health outcomes and differences in utilization and spending patterns[76,79]. In this study, neighborhood segregation is represented by a dissimilarity index score, which measures the proportion of individuals of a given race that would have to change their area of residence to achieve even distribution on a scale from 0 to 100, with larger values indicating higher segregation. The dissimilarity index is well supported in the literature as a robust measure of segregation that captures multiple dimensions of segregation[43].

Statistical Analyses

Data were described using counts, percentages, and mean scores to compare demographics and average morbidity and cost across the population. We computed correlation matrices that included all neighborhood domain indices, a measure of racial segregation, and medical costs averaged across CSAs. Next, we estimated multilevel models with community specific terms and no covariates to determine the amount of clustering at the neighborhood level. The multilevel models showed a very low intra-cluster correlation coefficient (0.003) Model fit was assessed by comparing the fixed and random effects log likelihood and Akaike Information Criteria (AIC). Results of Hausman tests of fixed versus random effects showed the fixed effects model is appropriate at $p<0.05$ (see Appendix 2.8). Given the low ICC values and Hausman tests, we concluded that fixed effect two-part models are appropriate.

We then used two-part models to model our data, considering both individual and neighborhood factors at the same level, but using clustered, robust errors to account for the small amount of clustering within neighborhoods. Given our interest in the relationship between each neighborhood domain and medical spending, we run unadjusted models separately for each neighborhood domain and examine the significance of the domain score in each model. We use two-part models with logistic regression in the first part to predict any medical spending, and an ordinary least squares model with log transformed medical spending (to adjust for skew in medical spending data) in the second part to jointly test the neighborhood domain's relationship with likelihood of having any medical spending, as well as the amount of spending predicted by each neighborhood domain variable. Finally, we rerun the two-part models, adjusting for other factors known to influence medical spending (age, gender, morbidity, race, neighborhood segregation), excluding pregnancies.

Given high collinearity between neighborhood domains, as well as the fact that our neighborhood index variable captures the variation among the different neighborhood domains, we do not include all neighborhood domains within one model, and instead present them separately for comparison. Select interactions including chronic condition count and race, gender and race, and age and chronic condition count were chosen based theories of neighborhoods and health resource use and tested within each model. A significant interaction between age band and chronic condition count was included in all fully adjusted models (see Table 5. 4). Sensitivity analyses were conducted by running models with pregnancy included, with the neighborhood segregation excluded, with a measure of morbidity that included acute as well as unstable chronic conditions, and by using multilevel models to ensure significance and directionality of neighborhood effects were robust to other model specifications (See Appendices 5.10-5.12).

CHAPTER 5.3: RESULTS

Descriptive Data

Table 1 describes the demographics and average morbidity and medical spending for the sample. Overall, 69% of the population was black, 14.3% was non-black. The majority of the sample was age 18-34 (48.1%) and only 15% were 55 and older. The average chronic condition count for the population was 1.91, and the average medical spend per person was $5,428.03. Overall, 1,275 (13%) of individuals incurred no spending. Table 5.2

shows the mean, standard deviation, and rage of each neighborhood domain before it was transformed into a z score to show variation among the domains.

Correlations and Unadjusted Analyses

While there was variation in correlation magnitude among neighborhood domain indices (range: 0.41- 0.91), all correlations between neighborhood domains were significant at $p<0.05$ (see Table 3). The Living Environment Domain and measure of neighborhood segregation had the smallest correlations with other indices. The strongest correlation with average medical spending was Crime (0.48), followed by the overall Neighborhood Social and Environmental Resource Index (0.46), Housing (0.45), and Education (0.42). Employment (0.29) and the Income and Wealth (0.30) domains were least highly associated with neighborhood average medical spending. The Housing and Neighborhood Social and Environmental Resource Index domains had the highest correlation with neighborhood segregation (0.61, 0.56).

In unadjusted two-part models of individual medical spending, all neighborhood domains were significant predictors of higher medical spending among those with nonzero spending at $p<0.00$, but no neighborhood domains were significantly associated with likelihood of incurring any medical spending (Table 5.4).

Adjusted Analyses

In the first part of our two-part models predicting likelihood of any medical spending, after adjusting for age, gender, morbidity, race, neighborhood segregation, an interaction term for age and chronic conditions, and excluding pregnancy, we found that no neighborhood domains significantly predicted the likelihood of having any medical spending (Table 5. 4). Being female and each additional chronic condition count significantly increased odds of having any medical spending (see Appendices 5.3-5.9). For each age band, increased age significantly decreased likelihood of having any medical spending. Interaction terms for age and chronic conditions were not significant in part one of our models. For detailed analysis of this unexpected age effect, please see Appendix 6.2.

For the second part of our fully adjusted models on log medical spending that include only those with non-zero medical spending (N=8,497), associations between neighborhoods domains and medical spending remained significant for the overall Social and Environmental Resource Index, Crime, Housing, and Employment and Workforce. In our model adjusting for the overall Social and Environmental Resource Index, individual level covariates including being female, being older, and having higher morbidity were significantly associated with higher medical spending after accounting for neighborhood-level factors. Neighborhood segregation was not significant in this model. Interestingly, interactions between chronic condition count and age bands were significant in a negative direction, indicating that as individuals age, the cost per additional chronic condition decreases. For control variable coefficients from each of the other neighborhood domains models, please see Appendices 5.3-5.9.

Sensitivity Analyses

In sensitivity analyses, our findings were robust to other model specifications such as using multilevel models and including pregnancy (see Appendix 2.6 and 5.10 for results), however in models that included a morbidity adjustment for acute and chronic conditions instead of chronic conditions alone, we found that there were significant interactions between neighborhood domains and individual level race for the

Neighborhood Social and Environmental Resource Index, the Crime domain, the Education Domain, and the Employment and Workforce Domain (See Appendix 6.1 for further analysis). The Housing domain, the Income and Wealth Domain, and the Living Environment domain were not significant predictors of higher medical spending in these models. In sensitivity analyses that excluded neighborhood segregation in the fully adjusted models as a neighborhood control variable, all neighborhood domains were significant in part two of the two-part model, indicating that there was collinearity between neighborhood domains and our measure of segregation. See Appendix 5.11 for the tables of these results.

CHAPTER 5.4: DISCUSSION

Study findings support the use of domains commonly used to describe neighborhood socioeconomic status such as multidimensional indices, racial segregation, housing, and employment and workforce, but demonstrate the value of including additional measures such as crime in models of medical spending. Our findings reinforce the multidimensionality of neighborhood socioeconomic status and the varied associations with medical spending among individuals with non-zero medical spending, even after adjusting for individual level factors and morbidity. Study findings also point to the interrelationship between measures of neighborhood socioeconomic status and racial segregation. More specifically, we find that including the neighborhood segregation variable in our models attenuated the significance of associations between several domains of neighborhoods and medical spending. We also find that neighborhood domains may predict medical spending differently depending on the type of morbidity measure used (i.e. number of chronic conditions versus number of major acute and chronic conditions). Further, we found significant interactions between neighborhood domains and individual level race when we adjust for acute and major chronic illness, which requires further research to better understand. The fact that neighborhood variables significantly interact with race in associations with medical spending when adjusting for acute and major chronic illness, but not when adjusting for chronic condition count underscores the complexity of pathways between individual health and neighborhood context.

Interestingly, neighborhood measures of income and wealth, and education were not significant in fully adjusted models, which may be due in part to the large variation in incomes and education within neighborhoods in Baltimore City, where gentrification has led to mixed income levels and backgrounds even within resource poor neighborhoods. This may also be due in part to our narrowly defined sample that includes only individuals who are low income enough to qualify for Medicaid. The findings of this study align with other work showing a small but significant effect of neighborhood socioeconomic factors on utilization and cost outcomes, and point to the need to consider other domains as well, such as crime.[61,84,89].

Overall, we observe no significant associations between domains of neighborhood and likelihood of any use of medical services, however small but significant associations between medical spending and neighborhood domains were observed for individuals with non-zero medical spending. A challenge of this line of inquiry is that the relationship between neighborhood factors and higher medical spending is characterized through many different pathways. The conceptual framework that guided this study suggests three main pathways through which neighborhoods influence medical spending. The first is that neighborhoods create conditions that both cause and selectively co-locate sub-populations with higher morbidity and worse outcomes across the life course, the second is that neighborhood factors are often associated with insurance status as well as the physical location and availability of healthcare services in neighborhoods, and the third is that neighborhood factors influence health behaviors and care seeking behaviors that alter use of preventive services, increased emergency room and inpatient use, and increased morbidity.

In regards to the first pathway, we expected that adjusting for chronic conditions would account for a large amount of the variation in medical spending that we would expect across neighborhoods, given the theory that neighborhoods affect medical spending by creating conditions for multiple co-morbidities among residents that make medical episodes more complicated and costly[62]. To adjust for the second pathway, we controlled for individual level access and income by limiting our sample to individuals enrolled in Medicaid and living in a defined geography with physical availability of healthcare services, since research has shown that insurance status and individual income levels are responsible for a large amount of variation in access to preventive services, and also influence behaviors such as use of appropriate medical care, and medical spending outcomes[85]. While theories of segregation suggest that racial concentration in neighborhoods may influence health behaviors through social networks[43], we are unable to capture specific health behaviors such as smoking, substance abuse, and use of emergency services for non-emergent conditions, which may be part of the effect that our neighborhood variables capture in the significant association with medical spending.

After controlling for individual income and insurance access, adjusting for individual characteristics and neighborhood racial segregation, and adjusting for chronic morbidity, we found that several individual neighborhood domains remain significantly associated with medical spending, but not with the likelihood of non-zero medical spending. The significant interaction term (in all models adjusted for chronic condition count) between older age groups and lower medical spending per additional chronic condition as well as the decreased likelihood of having any cost by age may can be explained by newly diagnosed chronic conditions in younger age groups and higher likelihood of uncontrolled chronic conditions in younger age groups, and that older age groups tend to have higher numbers of chronic conditions which may reduce the overall average medical spend per chronic condition (see Appendix 6.2 for more detailed discussion and analysis of this).

In sensitivity analyses that adjusted for a morbidity measure inclusive of acute illness and injuries, neighborhood Housing was no longer significant in its association with spending, but Education became significant, and more interestingly, the effects of all significant neighborhood domains vary significantly by race. Further research is needed to better understand the mechanisms by which different domains of neighborhoods relate to higher medical spending, pathways by which neighborhood domains and medical spending may be differently associated with race through social networks or differences in utilization patterns related to neighborhood domains, and to better understand the implications of the choice of morbidity variables to be prioritized for risk adjustment and predictive model purposes. To date, most predictive models of medical spending ignore neighborhood level measures, given their generally small effect on predictive power[89].

More research would be needed to determine whether predictive models would be strengthened by inclusion of neighborhood variables with associations of a relatively small magnitude.

The fact that multiple domains of neighborhood social and economic resources remained significant as predictors of medical spending after controlling for individual level income, access, morbidity, age, gender, and race, and neighborhood segregation is yet another indicator of the need for payers to understand and address the community based approaches in efforts to better manage the care of enrolled populations. While payers and healthcare providers are key to improving health and medical spending outcomes for the health system, truly changing the trajectory of medical spending in the US will be dependent on the health sector partnering with other sectors and with communities to better understand how neighborhoods influence health outcomes and improving the conditions by which individuals become healthy or unhealthy[87,92].

Limitations

There are many limitations affecting the validity of this study. The study is cross sectional, and only represents one year of time, therefore, we cannot examine causality or persistence of relationships between neighborhoods and medical spending over time. Further, all data used in this study was from Baltimore City, and may not reflect patterns seen in other cities, or in particular, in less urban areas. All individuals in this study were insured by a single insurer, were low income, and were predominantly black, so results may not be generalizable to other populations and locations. Further, we imputed race data given high amount of missing data in this area, which may have biased our results, in particular, for the non-black population which was much smaller in size. Other limitations include our inability to control for length of time at residence, the possibility that individuals could have moved during the study period without updating their address, use of a predefined “neighborhood” definitions that could vary according to different individual’s perceptions of what neighborhood constitutes, and the lack of long term care and inpatient and outpatient psychiatry data available to calculate total medical spending. Finally, it is difficult to determine directionality of associations between neighborhoods and medical spending, since individuals who are sicker may have moved to lower resource areas due to the high costs of illness. Further research is needed to explore causal pathways and to use more robust methodology to elucidate the relationships between neighborhood factors and medical spending over time.

CHAPTER 5.5: CONCLUSIONS

In this study, we make two observations with policy implications. The first, is that while neighborhood measures commonly used in the literature (housing, racial segregation, employment and workforce, multidimensional indices describing neighborhoods), have significant associations with individual level medical spending, crime may also be important. Measures of housing, employment and workforce, segregation, and index measures of neighborhood SES are widely available from census data, however data on neighborhood crime may also be an important domain to capture and use on a wider scale. The second is that multiple neighborhood domains are significantly associated with medical spending even after adjusting for multiple individual level factors and morbidity, which indicates a need to further examine the usefulness of including neighborhood domain scores in predictive models of medical spending. Study findings speak to how neighborhood-level measures can be used to help improve value based contracts, for risk adjustment purposes, and to guide interventions that address neighborhood factors that are associated with disparities in health outcome.

CHAPTER 5: TABLES

Table 5.1: Individual Level Variables and Demographics of Sample Comprised of Johns Hopkins Medicaid Managed Care Enrollees Living in Baltimore City

	Overall Population (N, %)	
Total Individuals	9,772	100.0%
Gender		
Male	3,706	38.0%
Female	6,066	62.1%
Age		
18-34	4,703	48.1%
35-54	3,599	36.8%
55+	1,474	15.0%
Race		
Black	6,830	69.9%
Nonblack	1,398	14.3%
Missing	1,544	15.8%
Pregnancy		
Yes	644	6.6%
No	9128	93.4%
Chronic Condition Count (Mean)**	1.91	--
Number with No Medical Spend	1,275	13.0%
Average Individual Medical Spend*	$5,428.03	--

**Medical spending calculated in US dollars, with top coded outliers. Mean including original value of outliers is $6,729.77*

Table 5.2: Area Level Variables and Medical Spending in a Sample Comprised of Johns Hopkins Medicaid Managed Care Enrollees Living in Baltimore City

	Average	Std Deviation	Min	Max
Subjects per Community Statistical Area	188	166	13	668
Neighborhood Segregation Index Score	33.0	0.15	3.8	48.54
Composite Neighborhood Score	1.58	2.80	-6.22	5.30
Crime Domain Score	0.42	1.32	-1.37	3.69
Education Domain Score	0.79	1.31	-4.53	3.17
Housing Domain Score	1.01	1.85	-4.31	3.61
Income and Wealth Domain Score	0.53	1.17	-3.68	2.34
Living Environment Score	0.85	1.47	-1.94	4.28
Employment and Workforce Domain Score	0.83	1.27	-4.55	2.52
Average Community Statistical Area Medical Spending*	$5,420.82	$835.79	$2,967.22	$7,290.83

**Calculated with top coded outliers. Mean with original outliers included is $6,272.91*

Table 5.3: Correlations Between Neighborhood Domain Variables and Average Neighborhood Level Medical Spending*

	Avg. Medical Spend	Crime domain	Education Domain	Housing Domain	Living Environment Domain	Income and Wealth Domain	Employment Domain	BNSEI Index	Neighborhood Segregation Index
Avg. Medical Spend	1.00								
Crime Domain	0.48	1.00							
Education Domain	0.42	0.72	1.00						
Housing Domain	0.45	0.72	0.83	1.00					
Living Environment Domain	0.39	0.55	0.70	0.62	1.00				
Income and Wealth Domain	0.30	0.60	0.70	0.80	0.41	1.00			
Employment and Workforce Domain	0.29	0.64	0.78	0.84	0.64	0.80	1.00		
Baltimore Neighborhood Social and Environmental Index	0.46	0.85	0.92	0.91	0.72	0.82	0.88	1.00	
Neighborhood Segregation Index	0.21	0.46	0.42	0.61	0.49	0.53	0.52	0.56	1.00

**Pearson Correlation Coefficients were calculated for all domains, a measure of neighborhood segregation and average neighborhood level medical spending, and all correlations were significant at $p<0.05$. A total of 9,772 individuals across 52 different CSAs with minimum of 10 individuals per CSA and an average of 188 per CSA were included in this sample.*

Table 5.4: Two Part Models of Neighborhood Level Domain Indices: Comparison of Unadjusted and Fully Adjusted Models

	Logit (Odds of Any Cost) N= 9,772		**Regress (Log Medical Spending)** N = 8,497	
	Unadjusted[1]	**Adjusted[2]**	**Unadjusted[1]**	**Adjusted[2]**
Baltimore Neighborhood Social and Environmental Index	0.019 (0.033)	-0.041 (0.04)	0.100 (0.019)***	0.036 (0.02)*
Crime Domain	-0.017 (0.030)	-0.05 (0.04)	0.090 (0.018)***	0.039 (0.016)**
Education Domain	0.020 (0.030)	-0.044 (0.04)	0.084 (0.017)***	0.024 (0.02)
Housing Domain	0.038 (0.030)	-0.021 (0.04)	0.088 (0.017)***	0.038 (0.02)**
Income and Wealth Domain	0.036 (0.029)	0.002(0.04)	0.067 (0.000)***	0.011 (0.016)
Living Environment Domain	0.031 (0.030)	-0.034 (0.04)	0.064 (0.018)***	0.004 (0.02)
Employment and Workforce Domain	0.019 (0.029)	-0.036 (0.04)	0.072 (0.018)***	0.028 (0.02)*

[1]Scores for each neighborhood domain were calculated by running separate unadjusted models containing only individual level medical spending as the outcome and the neighborhood level variable as the single predictor per model. Each index contains a score for all 52 CSAs with greater than 10 individuals from our sample.

[2]Neighborhood domain coefficients and standard errors calculated by running each neighborhood domain separately in models adjusted for gender, age, chronic condition count, race, the neighborhood variable of interest, neighborhood segregation and an interaction term between age band and chronic condition count. Pregnancy was excluded. The values for each neighborhood domain score are specific to each separate neighborhood domain model. For Log likelihood values for each adjusted model please see Appendix 5.3-5.9.

Chapter 6: Conclusions

CHAPTER 6.1: SUMMARY OF PRINCIPAL FINDINGS

This study capitalized on a rich neighborhood level dataset available for neighborhoods in Baltimore, Maryland by creating summary measures of neighborhood social risks and using these indices to examine associations between neighborhood level social risk and individual level medical spending for individuals insured by a single large Medicaid Managed Care payer.

My first study built on existing literature detailing methods for building neighborhood level indices by including methods for creation of multiple indices representing neighborhood risk domains that can be combined into a single, multidimensional index. The single index can be used to represent multiple domains of neighborhood risk simultaneously without issues of collinearity, and the sub-indices can be used for neighborhood research that examines more specific domains of neighborhood risk. Further, the methods included options for incorporating community input into construction of indices to capitalize on community knowledge of risk factors. After construction of 6 social risk indices and a summary index, I found there was heterogeneity across neighborhoods and across domains within neighborhoods, and that the indices were correlated against health measures known to be influenced by neighborhood factors.

In the second study, I assessed whether the multidimensional neighborhood social and environmental resource index was associated with individual level medical spending, and whether this association varied across the distribution of medical spending. Using quantile regressions and controlling for individual level factors known to influence medical spending, I found that living in a low resource neighborhood was associated with being more expensive than living in a high resource neighborhood and that this relationship held across the entire distribution of medical spending. Further, I found that the size of the effect was significantly larger as medical spending reached higher levels. Results of this study support further research to delineate the pathways by which neighborhood social and environmental resources relate to medical spending. Further elucidation of the pathways by which neighborhoods are related to medical costs is the first step towards mobilizing partnerships between communities, public health agencies, and payers to address neighborhood factors tied to worse health outcomes and higher medical spending.

The third study contributes to the literature on neighborhood factors related to medical spending by examining which domains of neighborhood social risk are significantly associated with likelihood of use of any medical services, and which are associated with higher medical spending among those who engage with medical services. By running two part models separately for each neighborhood domain index created in Aim 1, and adjusting all models for individual level and neighborhood level factors including age, gender, race, morbidity, and segregation, I found that no neighborhood domain indices were significantly associated with likelihood of an individual having any medical spending, but domains of crime, housing, and employment and workforce, in addition to the overall social and environmental resource index, were significantly associated with medical spending about users of medical services. The results of this study contribute to the literature by showing significant associations between multiple domains of neighborhood social risk and medical spending, which confirms use of commonly used socioeconomic measures such as housing and employment and workforce indicators in studies relating neighborhood level factors to medical spending, but also suggests the need to consider crime as an important domain. Further, adding these domains to risk adjustment and predictive models could yield more accurate risk adjustment methods and improved targeting of resources for payers seeking new ways to manage health outcomes.

CHAPTER 6.2: STRENGTHS AND LIMITATIONS

Strengths

One of the main strengths of this research is that it capitalized on a rich set of neighborhood level data linked to individual level claims data to provide insight into the relationship between neighborhood social risk factors and medical spending; a relationship that has not been well explored in prior research. Establishing a link between lower resource neighborhoods and higher medical spending is crucial to financially justifying payer investment in community partnerships and in identifying strategies to address neighborhood level social risk factors that may relate to medical spending. In addition to justifying the importance of further knowledge of how neighborhood factors influence medical spending, the results of Aim 2 and 3 could be used to inform risk stratification and value based payment models, as well as to provide incentive for working with communities to better understand how neighborhood social risk factors influence health and spending outcomes across Baltimore City. While the social determinants of health are well recognized as influential to morbidity, this research filled an important gap by identifying the persistent association between neighborhood social and environmental resources across the distribution of medical spending for a Medicaid Managed Care Plan population, and by identifying which neighborhood social risk factors should be considered for use in risk adjustment, predictive models, and resource targeting purposes.

Limitations

The nature of this type of research means there are also limitations. First, combining available datasets means that quality and availability of data varies, and each dataset has a unique set of limitations. Smaller geographic areas, in particular, may have less reliable data, and issues of missing and/or inaccurate data are possible with each of the data sources. Further, data was limited to Baltimore City only, and only individuals who are insured by a Medicaid Managed Care plan, and therefore may not be generalizable to other individuals, insurance types, cities or locations, in particular, in rural areas or for individuals who are uninsured.

It is impossible to capture all of the types of variables that affect morbidity and medical spending, and therefore unmeasured factors could contribute to variation in medical spending that I was not able to capture in this research. Further, this type of research relies on showing associations, not causality, and therefore I cannot be certain that the factors measured in these models are what are driving medical spending. Temporality is also an issue in this research, as I was measuring all data across a fixed-point period of time, it is possible that the domains of neighborhood level social risk factors are not always measured before the outcomes I was measuring them against.

CHAPTER 6.3: POLICY IMPLICATIONS

Findings from these studies contribute several important policy implications. First, The Center for Medicaid and Medicare Services (CMS) is working nationally and across states to explore ways to reduce spending, improve health, and improve quality for health services for individuals insured by Medicaid and Medicare. Results of this study provide evidence for Medicaid to consider risk adjustment and alternative payment models that take neighborhood level measures and domains into account, and also indicate a need to further consider how investment in neighborhoods could lead to improved health outcomes and lower medical spending over time. Including neighborhood indices in risk adjustment and alternative payment models,, in particular, multidimensional indices that include multiple domains related to medical spending such as crime, housing, and employment and workforce, may allow payers to better stratify individuals by risk of becoming high cost, to more efficiently allocate resources such as care managers or community health workers to help address social determinants linked to health outcomes, and to intervene sooner to improve health outcomes and reduce medical spending.

Further, this research underscores the financial argument for payers to explore pathways by which community factors influence medical spending, and provides further incentive for payers to partner with communities to design interventions to help keep people healthy. Recent work across the US, including the Accountable Health Communities funded through federal government grants[1], state and local innovation initiatives aimed at moving upstream towards preventing individuals from becoming high risk and high cost in the first place[2,3], and specifically, efforts to manage the total cost of care in Maryland through creation of models which require a whole person approach to managing medical spending across care settings[4] are highlighting the increased importance of engaging with communities and non-health care sectors to build healthier communities. States such as Oregon, Illinois, Michigan and Maryland (among others), along with more local initiatives in places such as San Francisco, California and Hennepin County, Minnesota have developed innovative models designed to bring together healthcare delivery systems with other sectors to better coordinate services that relate to patient outcomes in order to achieve a shared vision of "population health" across geographic areas[5]. Evidence from this study showing associations between neighborhood crime, employment and workforce, housing, and multidimensional indices of neighborhood social and environmental factors and medical spending strengthens the argument for payers to partner across sectors to better understand pathways between neighborhood risk factors and medical spending.

Historically, health care dollars have been spent mostly on changing clinical factors such as healthcare access and quality and coordination of services. However evidence shows that clinical factors explain only 10-20% of morbidity.[6-11] While action taken to change the social determinants of health may take a longer time to show reward, ultimately, these actions may enhance sustainability of improvements over time[12]. Results from Aims 2 and 3 provide evidence that neighborhood level factors such as crime, housing, employment and workforce, and multidimensional neighborhood social and environmental resource measures are linked to medical spending, and suggest the need for policy makers to further prioritize exploration of interventions that address social risk factors in order to reduce medical spending and create a more sustainable US health system.

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Appendices

CHAPTER 2 APPENDICES

Appendix 2.1: NASEM Conceptual Framework Original Version

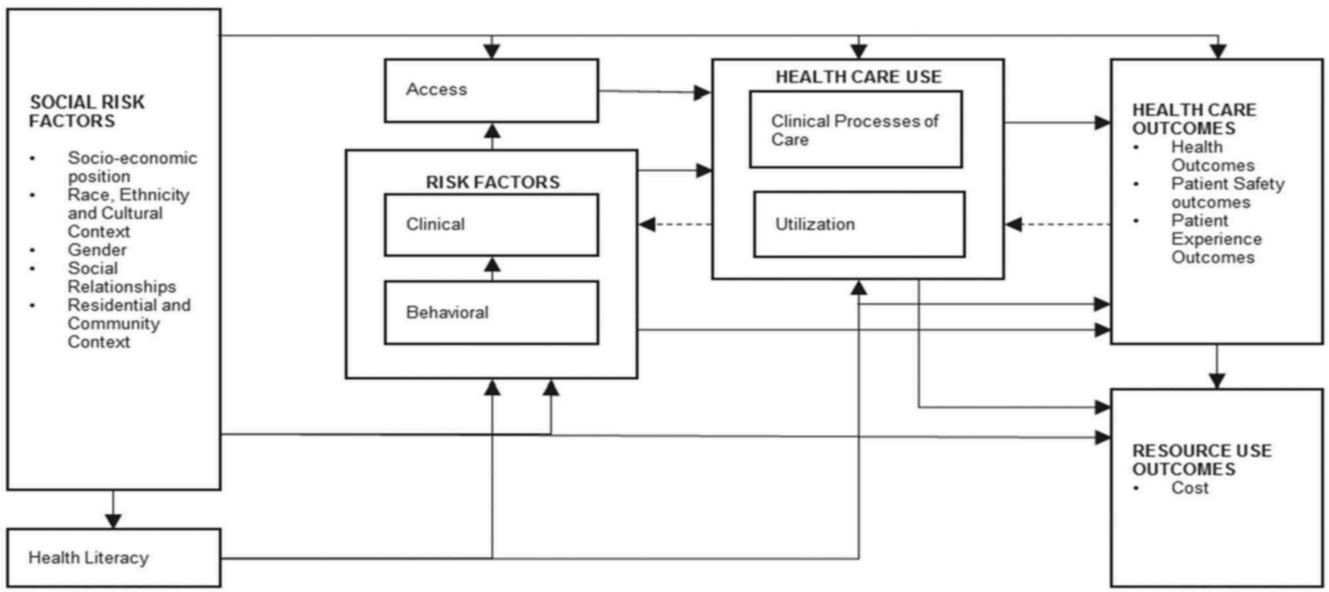

Figure 1. National Academy of Sciences, Engineering, and Medicine (NASEM) conceptual framework for social risk factors for healthcare use, outcomes, and cost.

Appendix 2.2: Full List of Baltimore Neighborhood Indicators Alliance (BNIA) Indicators and Data Sources[18]

CENSUS DEMOGRAPHICS	BNIA's Source
Average Household Size	**U.S. Bureau of the Census, American Community Survey**
Median Household Income	**American Community Survey**
Percent of Children Living Below the Poverty Line	**American Community Survey**
Percent of Family Households Living Below the Poverty Line	**American Community Survey**
Percent of Female-Headed Households with Children Under 18	**U.S. Bureau of the Census, American Community Survey**
Percent of Households Earning $25,000 to $40,000	**American Community Survey**
Percent of Households Earning $40,000 to $60,000	**American Community Survey**
Percent of Households Earning $60,000 to $75,000	**American Community Survey**
Percent of Households Earning Less than $25,000	**American Community Survey**
Percent of Households Earning More than $75,000	**American Community Survey**
Percent of Households with Children Under 18	**U.S. Bureau of the Census, American Community Survey**
Percent of Population Under 5 years old	**U.S. Bureau of the Census, American Community Survey**
Percent of Population 18-24 years old	**U.S. Bureau of the Census, American Community Survey**
Percent of Population 25-64 years old	**U.S. Bureau of the Census, American Community Survey**
Percent of Population 5-17 years old	**U.S. Bureau of the Census, American Community Survey**
Percent of Population 65 years and over	**U.S. Bureau of the Census, American Community Survey**
Percent of Residents - All Other Races (Hawaiian/ Pacific Islander, Alaskan/ Native American Other Race) (Non-Hispanic)	**U.S. Bureau of the Census, American Community Survey**
Percent of Residents - Asian (Non-Hispanic)	**U.S. Bureau of the Census, American Community Survey**
Percent of Residents - Black/African-American (Non-Hispanic)	**U.S. Bureau of the Census, American Community Survey**
Percent of Residents - Hispanic	**U.S. Bureau of the Census, American Community Survey**
Percent of Residents - Two or More Races (Non-Hispanic)	**U.S. Bureau of the Census, American Community Survey**
Percent of Residents - White/Caucasian (Non-Hispanic)	**U.S. Bureau of the Census, American Community Survey**
Racial Diversity Index	**U.S. Bureau of the Census,**

	American Community Survey
Total Female Population	**U.S. Bureau of the Census**
Total Male Population	**U.S. Bureau of the Census**
Total Number of Households	**U.S. Bureau of the Census, American Community Survey**
Total Population	**U.S. Bureau of the Census**
CHILDREN AND FAMILY HEALTH	
Average Healthy Food Availability Index	**Johns Hopkins University, Center for a Livable Future**
Fast Food Outlet Density (per 1,000 Residents)	**Johns Hopkins University, Center for a Livable Future**
Infant Mortality	**Baltimore City Health Department**
Life Expectancy	**Baltimore City Health Department**
Liquor Outlet density (per 1,000 Residents)	**Baltimore City Liquor Board**
Mortality by Age (1-14 years old)	**Baltimore City Health Department**
Mortality by Age (15-24 years old)	**Baltimore City Health Department**
Mortality by Age (25-44 years old)	**Baltimore City Health Department**
Mortality by Age (45-64 years old)	**Baltimore City Health Department**
Mortality by Age (65-84 years old)	**Baltimore City Health Department**
Mortality by Age (85 and over)	**Baltimore City Health Department**
Number of Children (aged 0-6) Tested for Elevated Blood Lead Levels	**Maryland Department of the Environment, Lead Poisoning Prevention Program**
Percent of Babies Born with a Satisfactory Birth Weight	**Maryland Department of Vital Statistics**
Percent of Births Delivered at Term (37-42 Weeks)	**Maryland Department of Vital Statistics**
Percent of Births Where the Mother Received Early Prenatal Care (First Trimester)	**Maryland Department of Vital Statistics**
Percent of Children (aged 0-6) with Elevated Blood Lead Levels	**Maryland Department of the Environment, Lead Poisoning Prevention Program**
Percent of Families Receiving TANF	**Maryland Department of Human Resources**
Teen Pregnancy Rate per 1,000 Females (aged 15-	**Maryland Department of Vital**

19)	**Statistics**
CRIME AND SAFETY	
Domestic Violence Calls for Service per 1,000 Residents	**Baltimore City Police Department**
Juvenile Arrest Rate for Drug-Related Offenses per 1,000 Juveniles	**Baltimore City Police Department**
Juvenile Arrest Rate for Violent Offenses per 1,000 Juveniles	**Baltimore City Police Department**
Juvenile Arrest Rate per 1,000 Juveniles	**Baltimore City Police Department**
Number of Arrests per 1,000 residents	**Baltimore City Police Department**
Number of Automobile Accident Calls for Service per 1,000 Residents	**Baltimore City Police Department**
Number of Common Assault Calls for Service per 1,000 Residents	**Baltimore City Police Department**
Number of Gun-Related Homicides per 1,000 Residents	**Baltimore City Police Department**
Number of Narcotics Calls for Service per 1,000 Residents	**Baltimore City Police Department**
Number of Shootings per 1,000 Residents	**Baltimore City Police Department**
Part 1 Crime Rate per 1,000 Residents	**Baltimore City Police Department**
Property Crime Rate per 1,000 Residents	**Baltimore City Police Department**
Violent Crime Rate per 1,000 Residents	**Baltimore City Police Department**
HOUSING AND COMMUNITY DEVELOPMENT	
Affordability Index - Mortgage	**American Community Survey**
Affordability Index - Rent	**American Community Survey**
Median Number of Days on the Market	**RBIntel, Inc.**
Median Price of Homes Sold	**First American Real Estate Solutions**
Number of Demolition Permits per 1,000 Residential Properties	**Baltimore City Department of Housing**
Number of Historic Tax Credits per 1,000 Residential Units	**Baltimore City Department of Finance**
Number of Homeowners Tax Credits per 1,000 Residential Units	**Baltimore City Department of Finance**
Number of Homes Sold	**First American Real Estate Solutions**

Number of Homestead Tax Credits per 1,000 Residential Units	**Baltimore City Department of Finance**
Number of New Construction Permits per 1,000 Residential Properties	**Baltimore City Department of Housing**
Percent Residential Properties that do Not Receive Mail	**U.S. Postal Service, U.S. Department of Housing and Urban Development**
Percentage of Housing Units that are Owner-Occupied	**Maryland Property View**
Percentage of Properties Under Mortgage Foreclosure	**Baltimore City Circuit Court**
Percentage of Properties with Rehabilitation Permits Exceeding $5,000	**Baltimore City Department of Housing**
Percentage of Residential Properties that are Vacant and Abandoned	**Baltimore City Department of Housing**
Percentage of Residential Properties with Housing Violations (Excluding Vacants)	**Baltimore City Department of Housing**
Percentage of Residential Sales for Cash	**RBIntel, Inc.**
Percentage of Residential Sales in Foreclosure (REO)	**RBIntel, Inc.**
Percentage of Residential Tax Lien Sales	**BidBaltimore**
Percentage of Vacant Properties Owned by Baltimore City	**Baltimore City Department of Housing**
Rate of Housing Vouchers per 1,000 Rental Units	**Picture of Subsidized Housing, HUD**
Total Number of Residential Properties	**Maryland Property View**
WORKFORCE AND ECONOMIC DEVELOPMENT	
Neighborhood Businesses per 1,000 residents (NAICS Sectors)	**InfoUSA**
Number of Banks and Bank Branches per 1,000 Residents	**Federal Deposit Insurance Corporation**
Number of Businesses by Selected Neighborhood Industry (NAICS Sectors)	**InfoUSA**
Number of Businesses with Under 50 Employees	**InfoUSA**
Number of Total Jobs Filled by Employees	**U.S. Census Bureau, Longitudinal Employer-Household Dynamics**
Percent Population (25 years and over) with a Bachelor's Degree or Above	**American Community Survey**
Percent Population (25 years and over) With High School Diploma and Some College or Associates Degree	**American Community Survey**

Percent Population (25 years and over) With Less Than a High School Diploma or GED	**American Community Survey**
Percent Population 16-64 Employed	**American Community Survey**
Percent Population 16-64 Not in Labor Force	**American Community Survey**
Percent Population 16-64 Unemployed and Looking for Work	**American Community Survey**
Percent of Businesses that are 1 year old or less	**InfoUSA**
Percent of Businesses that are 2 years old or less	**InfoUSA**
Percent of Businesses that are 4 years old or less	**InfoUSA**
Percent of Commercial Properties with Rehab Permits Above $5,000	**Baltimore City Department of Housing**
Percent of Employed Residents Who Work Outside the City	**U.S. Census Bureau, Longitudinal Employer-Household Dynamics**
Total Number of Businesses	**InfoUSA**
Total Number of Commercial Properties	**Maryland Property View**
Total Number of Employees	**InfoUSA**
Total number of Employees by Selected Neighborhood Industry (NAICS Sectors)	**InfoUSA**
Unemployment Rate	**American Community Survey**
SUSTAINABILITY	
Median Daily Water Consumption	**Baltimore City Department of Public Works**
Number of Community Managed Open Spaces	**Baltimore Neighborhood Indicators Alliance - Jacob France Institute**
Number of Miles of Bike Lanes	**Department of Transportation**
Number of Trees of Planted	**TreeBaltimore**
Percent of Area Covered by Trees	**University of Vermont Spatial Analysis Lab**
Percent of Employed Population with Travel Time to Work of 0-14 Minutes	**American Community Survey**
Percent of Employed Population with Travel Time to Work of 15-29 Minutes	**American Community Survey**
Percent of Employed Population with Travel Time to Work of 30-44 Minutes	**American Community Survey**
Percent of Employed Population with Travel Time to Work of 45 Minutes and Over	**American Community Survey**
Percent of Homes Weatherized	**Maryland Department of Housing and Community Development**

Percent of Households with No Vehicles Available	**American Community Survey**
Percent of Population (Over the age of 18) Who are Registered to Vote	**Baltimore City Board of Elections**
Percent of Population that Carpool to Work	**American Community Survey**
Percent of Population that Drove Alone to Work	**American Community Survey**
Percent of Population that Uses Public Transportation to Get to Work	**American Community Survey**
Percent of Population that Walks to Work	**American Community Survey**
Percent of Population Using Other Means to Commute to Work (Taxi, Motorcycle, Bicycle, Other)	**American Community Survey**
Percent of Residences Heated by Electricity	**American Community Survey**
Percent of Residences Heated by Utility Gas	**American Community Survey**
Percent Population (Over the age of 18) Who Voted in the General Election	**Baltimore City Board of Elections**
Rate of Clogged Storm Drain Reports per 1,000 Residents	**Baltimore City CitiStat**
Rate of Dirty Streets and Alleys Reports per 1,000 Residents	**Baltimore City CitiStat**
Walk Score	**Walk Score**
EDUCATION AND YOUTH	
High School Completion Rate	**Baltimore City Public Schools**
High School Dropout/Withdrawl Rate	**Baltimore City Public Schools**
Kindergarten School Readiness	**Baltimore City Public Schools**
Number of Students Ever Attended 1st - 5th Grade	**Baltimore City Public Schools**
Number of Students Ever Attended 6th - 8th Grade	**Baltimore City Public Schools**
Number of Students Ever Attended 9th - 12th Grade	**Baltimore City Public Schools**
Number of Students Officially Enrolled in 1st - 5th Grade	**Baltimore City Public Schools**
Number of Students Officially Enrolled in 6th - 8th Grade	**Baltimore City Public Schools**
Number of Students Officially Enrolled in 9th - 12th Grade	**Baltimore City Public Schools**
Percent of 1st-5th Grade Students that are Chronically Absent (Missing at least 20 days)	**Baltimore City Public Schools**
Percent of 6th-8th Grade Students that are Chronically Absent (Missing at least 20 days)	**Baltimore City Public Schools**
Percent of 9th-12th Grade Students that are Chronically Absent (Missing at least 20 days)	**Baltimore City Public Schools**
Percent of Students Switching Schools within School Year	**Baltimore City Public Schools**

Percent of Students that are African American (non-Hispanic)	**Baltimore City Public Schools**
Percent of Students that are Hispanic	**Baltimore City Public Schools**
Percent of Students that are White (non-Hispanic)	**Baltimore City Public Schools**
Percentage of 3rd Grade Students Passing MSA Math	**Baltimore City Public Schools**
Percentage of 3rd Grade Students Passing MSA Reading	**Baltimore City Public Schools**
Percentage of 3rd Grade Students who met or exceeded PARCC Math	**Baltimore City Public Schools**
Percentage of 3rd Grade Students who met or exceeded PARCC Reading	**Baltimore City Public Schools**
Percentage of 5th Grade Students Passing MSA Math	**Baltimore City Public Schools**
Percentage of 5th Grade Students Passing MSA Reading	**Baltimore City Public Schools**
Percentage of 5th Grade Students who met or exceeded PARCC Math	**Baltimore City Public Schools**
Percentage of 5th Grade Students who met or exceeded PARCC Reading	**Baltimore City Public Schools**
Percentage of 8th Grade Students Passing MSA Math	**Baltimore City Public Schools**
Percentage of 8th Grade Students Passing MSA Reading	**Baltimore City Public Schools**
Percentage of 8th Grade Students who met or exceeded PARCC Math	**Baltimore City Public Schools**
Percentage of 8th Grade Students who met or exceeded PARCC Reading	**Baltimore City Public Schools**
Percentage of Population aged 16-19 in School and/or Employed	**American Community Survey**
Percentage of Students Enrolled in Special Education Programs	**Baltimore City Public Schools**
Percentage of Students Passing H.S.A. Algebra	**Baltimore City Public Schools**
Percentage of Students Passing H.S.A. Biology	**Baltimore City Public Schools**
Percentage of Students Passing H.S.A. English	**Baltimore City Public Schools**
Percentage of Students Passing H.S.A. Government	**Baltimore City Public Schools**
Percentage of Students Receiving Free or Reduced Meals	**Baltimore City Public Schools**
Percentage of Students Suspended or Expelled During School Year	**Baltimore City Public Schools**
ARTS AND CULTURE	
Number of Businesses that are Arts-Related per 1,000 residents	**InfoUSA**

Number of Employees in the Creative Economy	**InfoUSA**
Number of Event Permits Requested per 1,000 Residents	**ENVISTA, with permission from the Baltimore City Department of Transportation**
Number of Persons with Library Cards per 1,000 Residents	**Enoch Pratt Free Library**
Number of Public Murals	**Baltimore Office of Promotion and Arts**
Public Art per 1,000 Residents	**Baltimore Office of Promotion and Arts**
Rate of Businesses in the Creative Economy per 1,000 residents	**InfoUSA**
Total Employment in Arts-Related Businesses	**InfoUSA**

Appendix 2.3: Diagnosis Clusters Included in Chronic Condition Count Variable from the ACG System

Expanded Diagnosis Clusters					
Acute hepatitis	Cardiovascular signs and symptoms	Disorders of lipid metabolism	Inflammatory bowel disease	Musculoskeletal disorders, other	Rheumatoid arthritis
Acute leukemia	Cataract, aphakia	Disorders of Newborn Period	Inherited metabolic disorders	Nephritis, nephrosis	Schizophrenia and affective psychosis
Acute lower respiratory tract infection	Central nervous system infections	Disorders of the immune system	Irritable bowel syndrome	Neurologic disorders, other	Seizure disorder
Acute myocardial infarction	Cerebral palsy	Eating disorder	Ischemic heart disease (excluding acute myocardial infarction)	Neurologic signs and symptoms	Short stature
Acute renal failure	Cerebrovascular disease	Emphysema, chronic bronchitis,	Kyphoscoliosis	Newborn Status, Complicated	Sleep apnea
Acute sprains and strains	Chromosomal anomalies	COPD	Lactose intolerance	Obesity	Sickle cell disease
Adjustment disorder	Chronic cystic disease of the breast	Endometriosis	Low back pain	Organic brain syndrome	Skin keratoses
Administrative concerns and non-specific laboratory abnormalities	Chronic liver disease	ESRD	Low impact malignant neoplasms	Osteoporosis	Spinal cord injury/disorders
Adverse events from medical/surgical procedures	Chronic pancreatitis	Eye, other disorders	Malignant neoplasms of the skin	Other endocrine disorders	Strabismus, amblyopia
Age-related macular degeneration	Chronic renal failure	Failure to thrive	Malignant neoplasms, bladder	Other hemolytic anemias	Substance use
Anxiety, neuroses	Chronic respiratory failure	Fluid/electrolyte disturbances	Malignant neoplasms, breast	Other skin disorders	Thrombophlebitis
Aplastic anemia	Chronic ulcer of the skin	Gastrointestinal signs and symptoms	Malignant neoplasms, cervix, uterus	Paralytic syndromes, other	Tracheostomy
Arthropathy	Cleft lip and palate	Gastrointestinal/Hepatic disorders, other	Malignant neoplasms, colorectal	Parkinson's disease	Transplant status
Asthma, w/o status asthmaticus	Congenital anomalies of limbs, hands, and feet	Generalized atherosclerosis	Malignant neoplasms, esophagus	Peripheral neuropathy, neuritis	Type 1 diabetes
Asthma, with status asthmaticus	Congenital heart disease	Genito-urinary disorders, other	Malignant neoplasms, kidney	Peripheral vascular disease	Type 2 diabetes
Attention deficit disorder	Congestive heart	Glaucoma	Malignant neoplasms,	Personality disorders	Vesicoureteral reflux

	failure		liver and biliary tract		
Autism Spectrum Disorder	Cystic fibrosis	Gout	Malignant neoplasms, lung	Prostatic hypertrophy	
Autoimmune and connective tissue diseases	Deafness, hearing loss	Hematologic disorders, other	Malignant neoplasms, lymphomas	Psychological disorders of childhood	
Benign and unspecified neoplasm	Deep vein thrombosis	Hemophilia, coagulation disorder	Malignant neoplasms, ovary	Psychosexual	
Bipolar disorder	Degenerative joint disease	High impact malignant neoplasms	Malignant neoplasms, pancreas	Psych-physiologic and somatoform disorders	
Blindness	Dementia	HIV, AIDS	Malignant neoplasms, prostate	Pulmonary embolism	
Cardiac arrhythmia	Delirium	Hypertension, w/o major complications	Malignant neoplasms, stomach	Quadriplegia and paraplegia	
Cardiac valve disorders	Depression	Hypertension, with major complications	Migraines	Renal disorders, other	
Cardiomyopathy	Developmental disorder	Hypothyroidism	Multiple sclerosis	Respiratory disorders, other	
Cardiovascular disorders, other	Diabetic retinopathy	Impulse control	Muscular dystrophy	Retinal disorders (excluding diabetic retinopathy)	

Appendix 2.4: List of Major ADGs and Definitions from ACG System

Name of Major ADG*	Definition**
Time Limited: Major	High-severity acute non-infectious medical conditions requiring specialty care
Time-Limited: Major-Primary Infections	High-severity acute medical/infectious conditions requiring specialty care
Likely to Recur: Progressive	High-severity recurrent non-infectious conditions requiring specialty care
Chronic Medical: Unstable	High-severity chronic non-infectious conditions likely requiring specialty care
Chronic Specialty: Unstable-Orthopedic	High-severity chronic anatomic/musculoskeletal conditions requiring orthopedic specialty care
Injuries/Adverse Effects: Major	High-severity acute injuries requiring specialty care
Psychosocial: Recurrent or Persistent, Unstable	High-severity chronic or recurrent psychosocial conditions requiring mental health care
Malignancy	High-severity chronic conditions with neoplastic etiology and likely requiring oncology care

*Major ADGs are mutually exclusive so that an individual is not assigned more than one category for the same diagnosis.
**Definitions from ACG Technical Manual Version 11[91]

Appendix 2. 5: Summary Statistics of Sample Population by Race

	Overall Population		Black		Nonblack		Missing	
	Number	*Percent*	*Number*	*Percent*	*Number*	*Percent*	*Number*	*Percent*
Total Individuals	9,783	100.0%	6,830	69.9%	1,398	14.3%	1,544	15.8%
Gender								
Male	3,710	38.0%	2,550	37.3%	581	41.6%	575	37.2%
Female	6,073	62.1%	4,280	62.7%	817	58.4%	969	62.8%
Age								
18-34	4,708	48.1%	3,385	49.6%	550	39.3%	768	49.7%
35-54	3,601	36.8%	2,431	35.6%	619	44.3%	549	35.6%
55+	1,474	15.1%	1,014	14.8%	229	16.4%	227	14.7%
Pregnancy								
Yes	644	6.6%	470	6.9%	73	5.2%	101	6.5%
No	9139	93.4%	6,360	93.1%	1,325	94.8%	1,443	93.5%
Major ADG Count (Mean)**	0.89	-	0.88	-	1.1	-	0.81	-
Chronic Condition Count (Mean)	1.9	-	1.9	-	2.3	-	1.6	-
Number with No Medical Spend	1,275	13.0%	869	12.7%	194	13.9%	212	13.7%
Average Medical Spend	$5,428.03	-	$5,553.70	-	$5,516.71	-	$4,791.87	-

Appendix 2.6: Results from Multilevel Model Regressing Baltimore Neighborhood Social and Environmental Index and Other Covariates on Log Medical Spending [1]

Control Variables	Coefficient (Log Spending)	Standard Error
N=7,853		
Neighborhood Domain Variable		
Neighborhood Social and Environmental Resource Index	0.0384*	(0.0221)
Gender		
Male	Ref	Ref
Female	0.120***	(0.0280)
Race		
Non Black	Ref	
Black	0.0112	(0.0433)
Age		
18-34	Ref	Ref
35-54	0.177***	(0.0376)
55+	0.233***	(0.0573)
Morbidity		
Chronic Condition Count	0.474***	(0.0121)
Area Level Control Variable		
Neighborhood Segregation Index	0.00205	(0.00141)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref
Chronic Condition Count x 35-54	-0.111***	(0.0141)
Chronic Condition Count x 55+	-0.164***	(0.0151)
Constant	6.411***	(0.0596)
Random Effects Coefficient	0.0670**	0.020
Log Likelihood	-10599.99	--
AIC	21223.98	--

*** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses

[1] Multilevel model run using xtmixed command with log medical spending for individuals with nonzero medical spending. Model was adjusted for age, gender, race, morbidity, neighborhood segregation, and interaction of age and morbidity, clustered at the CSA level. Pregnancies were excluded.

Appendix 2.7: Results from Fixed Effect Model Regressing Baltimore Neighborhood Social and Environmental Index and Other Covariates on Log Medical Spending[1]

Control Variables	Coefficient (Log Medical Spending)	Standard Error
N=7,853		
Neighborhood Domain Variable		
Neighborhood Social and Environmental Resource Index	0.0361**	(0.0179)
Gender		
Male	Ref	Ref
Female	0.119***	(0.0280)
Race		
Non Black	Ref	
Black	0.0171	(0.0419)
Age		
18-34	Ref	Ref
35-54	0.178***	(0.0377)
55+	0.232***	(0.0574)
Morbidity		
Chronic Condition Count	0.475***	(0.0121)
Area Level Control Variable		
Neighborhood Segregation Index	0.00146	(0.00115)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref
Chronic Condition Count x 35-54	-0.112***	(0.0141)
Chronic Condition Count x 55+	-0.164***	(0.0151)
Constant	6.424***	(0.0521)
Log Likelihood	-10601.79	--
AIC	21223.57	--

**** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses

[1] Fixed Effects Model run using regress command with log medical spending for individuals with nonzero medical spending. Model was adjusted for age, gender, race, morbidity, neighborhood segregation, and interaction of age and morbidity. Pregnancies were excluded.

Appendix 2.8: Hausman Test of Fixed Versus Random Effects, with Random Effects Clustered at CSA Level[1]

Control Variables*	Fixed Effects	Random Effects	Difference	SE
	N=7,853			
Gender				
Male	Ref	Ref	Ref	Ref
Female	.3300757	.3259028	.0041729	.0031828
Race				
Non Black	Ref			
Black	-.0079543	.0298125	-.0377667	.0210151
Age				
18-34	Ref	Ref		
35-54	-.0720719	-.0671518	-.00492	.0028305
55+	-.0217337	-.0236034	.0018697	.0038544
Morbidity				
Chronic Condition Count	.4688123	.4699044	-.0010921	.0007466
Interactions: Chronic Conditions and Age Band				
Chronic Condition Count x 18-34	Ref	Ref	Ref	Ref
Chronic Condition Count x 35-54	-.1132483	-.114885	.0016367	.0009184
Chronic Condition Count x 55+	-.1640318	-.1650854	.0010536	.0009991
Hausman Test: Ho: difference in coefficients is not systematic	**Chi2= 834 p>chi2=0.3032**			

1 RE and FE models run using log medical spending for individuals with nonzero medical spending. Models were adjusted for age, gender, race, morbidity, neighborhood segregation, and interaction of age and morbidity. Pregnancies were excluded.

CHAPTER 3 APPENDICES

Appendix 3.1: Full set of Indicators, Domains, and Indicators Remaining at Each Step of Domain and Index Creation Process

Measures	Original Domain	New Domain	Indicators Remaining after Reduction of Redundant Indicators	Loadings on Domain Specific Scores*	Final List of Indicators used to Calculate Baltimore Neighborhood Social and Environmental Resource Index*
Part 1 Crime Rate per 1,000 Residents	Crime	Crime	x	0.352	0.242
Violent Crime Rate per 1,000 Residents	Crime	Crime			
Property Crime Rate per 1,000 Residents	Crime	Crime			
Juvenile Arrest Rate per 1,000 Juveniles	Crime	Crime			
Juvenile Arrest Rate for Violent Offenses per 1,000 Juveniles	Crime	Crime			
Juvenile Arrest Rate for Drug-Related Offenses per 1,000 Juveniles	Crime	Crime	x	0.439	
Number of Shootings per 1,000 Residents	Crime	Crime	x	0.507	
Number of Gun-Related Homicides per 1,000 Residents	Crime	Crime	x	0.394	
Number of Common Assault Calls for Service per 1,000 Residents	Crime	Crime			
Number of Narcotics Calls for Service per 1,000 Residents	Crime	Crime	x	0.521	0.206
Number of Automobile Accident Calls for Service per 1,000 Residents	Crime	Crime			
Number of Adult Arrests per 1,000 Residents (Over the age of 18)	Crime	Crime			
Percent of Population Under 5 years old	Demographics	Demographics			
Percent of Population 5-17 years old	Demographics	Demographics			
Percent of Population 18-24 years old	Demographics	Demographics			
Percent of Population 25-64 Years Old	Demographics	Demographics			

Percent of Population 65 years and over	Demographics	Demographics			
Total Number of Households	Demographics	Demographics			
Percent of Female-Headed Households with Children Under 18	Demographics	Demographics			
Percent of Households with Children Under 18	Demographics	Demographics			
Average Household Size	Demographics	Demographics			
Percent of Residents - Black/African-American	Demographics	Demographics			
Percent of Residents - White/Caucasian	Demographics	Demographics			
Percent of Residents - Asian	Demographics	Demographics			
Percent of Residents - Two or More Races	Demographics	Demographics			
Percent of Residents - All Other Races (Hawaiian/ Pacific Islander, Alaskan/ Native American Other Race)	Demographics	Demographics			
Percent of Residents - Hispanic	Demographics	Demographics			
Racial Diversity Index	Demographics	Demographics			
Number of Students Ever Attended 1st - 5th Grade	Education	Education			
Number of Students Ever Attended 6th - 8th Grade	Education	Education	x	0.037	
Number of Students Ever Attended 9th - 12th Grade	Education	Education			
Percent of Students that are African American	Education	Education			
Percent of Students that are White (non-Hispanic)	Education	Education			
Percent of Students that are Hispanic	Education	Education	x	-0.047	
Percent of 1st-5th Grade Students that are Chronically Absent (Missing at least 20 days)	Education	Education	x	0.412	
Percent of 6th-8th Grade Students that are Chronically Absent (Missing at least 20 days)	Education	Education	x	0.361	0.211

Percent of 9th-12th Grade Students that are Chronically Absent (Missing at least 20 days)	Education	Education	x	0.436	0.249
High School Dropout/Withdrawal Rate	Education	Education	x	0.199	
High School Completion Rate	Education	Education	x	-0.267	
Percent of Students Switching Schools within School Year	Education	Education	x	0.403	0.272
Percentage of Population aged 16-19 in School and/or Employed	Education	Education	x	-0.268	
Number of Students Officially Enrolled in 1st - 5th Grade	Education	Education			
Number of Students Officially Enrolled in 6th - 8th Grade	Education	Education			
Number of Students Officially Enrolled in 9th - 12th Grade	Education	Education			
Percentage of 3rd Grade Students who met or exceeded PARCC Math	Education	Education	x	-0.402	-0.242
Percentage of 3rd Grade Students who met or exceeded PARCC Reading	Education	Education			
Percentage of 5th Grade Students who met or exceeded PARCC Math	Education	Education			
Percentage of 5th Grade Students who met or exceeded PARCC Reading	Education	Education			
Percentage of 8th Grade Students who met or exceeded PARCC Math	Education	Education			
Percentage of 8th Grade Students who met or exceeded PARCC Reading	Education	Education			
Percent Population 16-64 Employed	Workforce	Employment and Workforce			
Percent Population 16-64 Unemployed and Looking for Work	Workforce	Employment and Workforce			
Percent Population 16-64 Not in Labor Force	Workforce	Employment and Workforce			
Unemployment Rate	Workforce	Employment and Workforce	x	0.511	0.253

Percent Population (25 years and over) With Less Than a High School Diploma or GED	Workforce	Employment and Workforce	x	0.453	0.251
Percent Population (25 years and over) With High School Diploma and Some College or Associates Degree	Workforce	Employment and Workforce	x	0.485	0.206
Percent Population (25 years and over) with a Bachelor's Degree or Above	Workforce	Employment and Workforce			
Total Number of Commercial Properties	Workforce	Employment and Workforce	x	-0.081	
Percent of Commercial Properties with Rehab Permits Above $5,000	Workforce	Employment and Workforce	x	-0.408	
Total Number of Businesses	Workforce	Employment and Workforce	x	-0.108	
Number of Businesses with Under 50 Employees	Workforce	Employment and Workforce			
Number of Banks and Bank Branches per 1,000 Residents	Workforce	Employment and Workforce	x	-0.0323	
Percent of Businesses that are 1 year old or less	Workforce	Employment and Workforce	x	-0.095	
Percent of Businesses that are 2 years old or less	Workforce	Employment and Workforce			
Percent of Businesses that are 4 years old or less	Workforce	Employment and Workforce			
Number of Businesses by Selected Neighborhood Industry (NAICS Sectors)	Workforce	Employment and Workforce			
Neighborhood Businesses per 1,000 residents (NAICS Sectors)	Workforce	Employment and Workforce			
Total number of Employees by Selected Neighborhood Industry (NAICS Sectors)	Workforce	Employment and Workforce			
Teen Birth Rate per 1,000 Females (aged 15-19)	Health	Health			
Percent of Births Delivered at Term (37-42 Weeks)	Health	Health			
Percent of Babies	Health	Health			

Born with a Satisfactory Birth Weight					
Percent of Births Where the Mother Received Early Prenatal Care (First Trimester)	Health	Health			
Number of Children (aged 0-6) Tested for Elevated Blood Lead Levels	Health	Health			
Percent of Children (aged 0-6) with Elevated Blood Lead Levels	Health	Health			
Life Expectancy	Health	Health			
Infant Mortality	Health	Health			
Mortality by Age (1-14 years old)	Health	Health			
Mortality by Age (15-24 years old)	Health	Health			
Mortality by Age (25-44 years old)	Health	Health			
Mortality by Age (45-64 years old)	Health	Health			
Mortality by Age (65-84 years old)	Health	Health			
Mortality by Age (85 and over)	Health	Health			
Median Price of Homes Sold	Housing	Housing			
Median Number of Days on the Market	Housing	Housing	1	0.255	
Number of Homes Sold	Housing	Housing	1	-0.038	
Percentage of Properties that are Owner-Occupied	Housing	Housing	1	-0.243	-0.228
Percentage of Properties Under Mortgage Foreclosure	Housing	Housing	1	0.227	
Percentage of Residential Properties that are Vacant and Abandoned	Housing	Housing			
Percentage of Properties with Rehabilitation Permits Exceeding $5,000	Housing	Housing	1	-0.3611	-0.120
Total Number of Residential Properties	Housing	Housing			
Percentage of Residential Sales for Cash	Housing	Housing			
Percentage of Residential Sales in Foreclosure (REO)	Housing	Housing	1	0.257	
Percentage of	Housing	Housing	1	0.367	0.242

Residential Tax Lien Sales					
Number of Demolition Permits per 1,000 Residential Properties	Housing	Housing	1	0.161	
Number of New Construction Permits per 1,000 Residential Properties	Housing	Housing	1	-0.168	
Affordability Index - Mortgage	Housing	Housing	1	0.310	
Affordability Index - Rent	Housing	Housing	1	0.367	0.200
Number of Historic Tax Credits per 1,000 Residential Units	Housing	Housing	1	-0.228	
Number of Homestead Tax Credits per 1,000 Residential Units	Housing	Housing	1	-0.243	-0.204
Number of Homeowner's Tax Credits per 1,000 Residential Units	Housing	Housing	1	0.001	
Percent Residential Properties that do not Receive Mail	Housing	Housing			
Rate of Housing Vouchers per 1,000 Rental Units	Housing	Housing	1	0.310	
Median Household Income	Demographics	Income and Wealth			
Percent of Households Earning Less than $25,000	Demographics	Income and Wealth	1	0.498	0.275
Percent of Households Earning $25,000 to $40,000	Demographics	Income and Wealth	1	0.537	
Percent of Households Earning $40,000 to $60,000	Demographics	Income and Wealth	1	0.278	
Percent of Households Earning $60,000 to $75,000	Demographics	Income and Wealth			
Percent of Households Earning More than $75,000	Demographics	Income and Wealth	1	-0.622	-0.271
Percent of Family Households Living Below the Poverty Line	Demographics	Income and Wealth			
Percent of Children Living Below the Poverty Line	Demographics	Income and Wealth			
Rate of Dirty Streets and Alleys Reports per 1,000 Residents	Sustainability	Living Environment and Physical Conditions	1	0.457	
Rate of Clogged Storm Drain Reports per 1,000 Residents	Sustainability	Living Environment and Physical	1	0.135	

		Conditions			
Percent of Population that Drove Alone to Work	Sustainability	Living Environment and Physical Conditions			
Percent of Population that Carpool to Work	Sustainability	Living Environment and Physical Conditions	1	-0.131	
Percent of Population that Uses Public Transportation to Get to Work	Sustainability	Living Environment and Physical Conditions	1	0.511	
Percent of Population that Walks to Work	Sustainability	Living Environment and Physical Conditions	1	0.136	
Percent of Employed Population with Travel Time to Work of 0-14 Minutes	Sustainability	Living Environment and Physical Conditions			
Percent of Employed Population with Travel Time to Work of 15-29 Minutes	Sustainability	Living Environment and Physical Conditions			
Percent of Employed Population with Travel Time to Work of 30-44 Minutes	Sustainability	Living Environment and Physical Conditions			
Percent of Employed Population with Travel Time to Work of 45 Minutes and Over	Sustainability	Living Environment and Physical Conditions	1	0.453	0.220
Number of Community Managed Open Spaces	Sustainability	Living Environment and Physical Conditions	1	0.126	
Percent of Residences Heated by Utility Gas	Sustainability	Living Environment and Physical Conditions	1	-0.093	
Percent of Residences Heated by Electricity	Sustainability	Living Environment and Physical Conditions			
Percent of Households with No Vehicles Available	Sustainability	Living Environment and Physical Conditions			
Percent of Residential Properties Weatherized	Sustainability	Living Environment and Physical Conditions	1	0.497	
Number of Trees of Planted	Sustainability	Living Environment and Physical Conditions			
Number of Persons with Library Cards	Arts	Social Resources	x	0.339	

per 1,000 Residents					
Number of Event Permits Requested per 1,000 Residents	Arts	Social Resources	x	0.543	
Public Art per 1,000 Residents	Arts	Social Resources	x	0.490	
Number of Businesses that are Arts-Related per 1,000 residents	Arts	Social Resources			
Total Employment in Arts-Related Businesses	Arts	Social Resources	x	0.227	
Rate of Businesses in the Creative Economy per 1,000 residents	Arts	Social Resources			
Number of Employees in the Creative Economy	Arts	Social Resources			
Number of Public Murals	Arts	Social Resources			
Percent of Families Receiving TANF	Health	Social Resources	x	0.095	
Liquor Outlet density (per 1,000 Residents)	Health	Social Resources	x	0.524	
Average Healthy Food Availability Index	Health	Social Resources	x	0.127	
Total	8 Domains	8 Domains	58	31	18

**Indicates loading value on first component*

CHAPTER 4 APPENDICES

Appendix 4.1: Fully Adjusted Quantile Regression Models of Medical Spending with Pregnancies Included*

	Quantile*						
N=8,740	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Neighborhood Index							
High Resource Neighborhood	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Medium Resource Neighborhood	57.66* [1.712]	72.45** [2.076]	39.51 [0.913]	87.20* [1.645]	70.80 [0.950]	-21.07 [-0.182]	202.75 [1.313]
Low Resource Neighborhood	85.54** [2.425]	94.28*** [3.056]	104.44** [2.382]	152.76*** [2.625]	153.64** [2.047]	286.82** [2.276]	694.39*** [3.069]
Gender							
Male	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Female	110.54*** [4.702]	152.28*** [5.326]	178.01*** [5.089]	177.31*** [3.679]	226.78*** [3.680]	103.69 [1.045]	-121.37 [-0.635]
Age							
Age 18-34	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Age 35-54	-147.68*** [-6.100]	-159.82*** [-6.008]	-176.76*** [-5.540]	-229.88*** [-4.946]	-279.38*** [-4.405]	-349.97*** [-3.573]	-595.76*** [-3.471]
Age 55+	-614.66*** [-6.146]	-756.68*** [-6.050]	-933.34*** [-4.962]	-1,099.31*** [-4.731]	-971.81*** [-5.168]	-1,315.44*** [-9.458]	-1,565.43*** [-6.874]
Race							
Non Black	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Black	-4.08 [-0.111]	-5.09 [-0.129]	22.38 [0.498]	76.60 [1.215]	48.05 [0.542]	115.57 [0.859]	248.81 [1.367]
Morbidity							
Chronic Condition Count	847.77*** [33.316]	1,136.72*** [31.556]	1,496.84*** [29.802]	2,034.30*** [29.348]	2,658.44*** [35.762]	3,765.96*** [26.882]	6,382.08*** [21.105]
Pregnancy	5,368.78*** [12.928]	7,606.49*** [10.243]	9,960.18*** [18.247]	11,758.41*** [19.379]	13,663.82*** [27.574]	15,543.98*** [21.640]	17,623.62*** [18.837]
Constant	102.51** [2.501]	180.02*** [4.241]	280.55*** [5.846]	356.32*** [5.449]	625.75*** [6.792]	1,130.75*** [8.180]	1,868.31*** [6.889]

*Numbers reflect US dollars. Models include all individuals with medical spending greater than 0, adjusted for BNSEI, gender, race, chronic condition count, and pregnancy. t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

Appendix 4.2: Fully Adjusted Two Part Models of Medical Spending with Pregnancies Included*

	Logit (Odds of Any Spending)	Regress (Log Spending)
Neighborhood Social and Environmental Resource Index	**N=9,139**	**N=8,740**
High Resource	Ref	Ref
Medium Resource	0.0633 (0.0879)	0.0932*** (0.0359)
Low Resource	0.0114 (0.0873)	0.141*** (0.0360)
Gender		
Male	Ref	Ref
Female	0.811*** (0.0680)	0.113*** (0.0288)
Age		
18-34	Ref	Ref
35-54	-0.214*** (0.0759)	0.0598* (0.0320)
55+	-0.670*** (0.130)	-0.123*** (0.0424)
Neighborhood Social and Environmental Resource Index		
High Resource	Ref	Ref
Medium Resource	0.0633 (0.0879)	0.0932*** (0.0359)
Low Resource	0.0114 (0.0873)	0.141*** (0.0360)
Race		
Non Black	Ref	Ref
Black	0.0818 (0.101)	0.0119 (0.0398)
Morbidity		
Chronic Condition Count	2.688*** (0.176)	0.366*** (0.00584)
Pregnancy[1]	--	1.90*** (0.0418)
Constant	0.396*** (0.107)	6.513*** (0.0468)

t-statistics in brackets *** p<0.01, ** p<0.05, * p<0.1
*Incudes all individuals, adjusted for BNSEI, gender, race, chronic condition count, and pregnancy.

Appendix 4.3: Fully Adjusted Quantile Regression Tables with Major ADG Morbidity Adjustment, Including Both Races

	Quantiles*						
VARIABLES	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Female	257.99*** [11.449]	366.91*** [14.097]	473.08*** [13.791]	617.95*** [14.089]	721.37*** [11.764]	914.49*** [9.162]	1,362.87*** [8.073]
Age 35-54	7.18 [0.284]	8.75 [0.311]	51.33 [1.422]	96.44** [2.107]	173.66** [2.032]	341.00*** [3.436]	756.67*** [3.556]
Age 55+	50.63 [1.027]	111.03 [1.537]	147.19* [1.667]	206.50* [1.882]	145.04 [1.080]	458.46* [1.761]	997.94*** [2.672]
Black	69.79* [1.937]	54.41 [1.485]	107.60** [2.338]	129.82** [2.258]	191.91** [2.430]	396.80*** [3.241]	652.00*** [3.223]
Medium Resource Neighborhood	64.12** [2.082]	39.53 [1.199]	26.54 [0.577]	0.32 [0.006]	12.09 [0.172]	-57.25 [-0.483]	-208.99 [-0.995]
Low Resource Neighborhood	91.23*** [2.864]	82.23** [2.381]	52.43 [1.216]	43.90 [0.744]	130.32 [1.411]	119.21 [0.898]	44.51 [0.200]
Major ADG Count	1,485.27*** [31.134]	1,962.79*** [29.345]	2,665.43*** [27.013]	3,605.64*** [21.679]	5,203.75*** [28.102]	7,616.66*** [27.405]	12,865.70*** [20.813]
Pregnancy	5,193.22*** [12.505]	7,358.62*** [13.432]	9,741.04*** [19.204]	11,750.61*** [24.779]	13,493.06*** [25.713]	14,723.72*** [23.100]	16,557.05*** [20.567]
Constant	6.64 [0.167]	97.32*** [2.617]	152.29*** [2.825]	241.61*** [3.934]	358.27*** [4.871]	555.17*** [5.104]	1,011.28*** [5.811]
Observations	8,740						
*Adjusted for gender, age, BNSEI, Major ADG count and pregnancy. All numbers are US Dollars. t-statistics in brackets *** p<0.01, ** p<0.05, * p<0.1							

Appendix 4.4 Fully Adjusted Quantile Regression Tables with Major ADG Adjustment, Split by Black and Non-Black Race

	Quantiles*						
VARIABLES	**.3**	**.4**	**.5**	**.6**	**.7**	**.8**	**.9**
Black Only							
Medium resource neighborhood	64.15* (36.67)	43.05 (40.25)	80.08 (52.47)	85.30 (53.02)	127.3 (85.45)	129.5 (126.3)	99.04 (236.8)
Low Resource Neighborhood	90.80*** (34.48)	90.99** (35.83)	81.51* (44.36)	95.72* (54.30)	205.7** (91.45)	257.1* (133.7)	338.7 (249.2)
Female	266.5*** (25.99)	388.3*** (28.72)	494.2*** (40.39)	655.1*** (43.97)	771.3*** (69.17)	983.7*** (99.97)	1,452*** (194.7)
Age 35-54	4.874 (30.60)	-2.935 (35.74)	46.02 (51.63)	102.8* (54.68)	168.6* (94.61)	335.3*** (128.6)	911.5*** (271.3)
Age 55+	-15.52 (61.57)	27.19 (78.78)	104.2 (120.9)	267.4** (128.4)	164.7 (147.3)	342.2 (303.9)	485.1 (473.1)
Pregnancy	5,065*** (512.1)	7,389*** (660.8)	9,836*** (594.3)	11,637*** (599.2)	13,858*** (668.9)	15,145*** (726.7)	16,895*** (904.9)
Major ADG Count	1,516*** (48.48)	1,950*** (72.83)	2,656*** (113.9)	3,589*** (176.4)	5,168*** (221.7)	7,919*** (322.1)	13,596*** (1,012)
Constant	71.91** (29.69)	145.6*** (26.15)	227.4*** (36.35)	301.3*** (41.48)	449.0*** (66.75)	756.5*** (100.7)	1,342*** (167.2)

Non Black Only

Medium resource neighborhood	14.59 (70.88)	-6.590 (78.91)	-73.76 (86.68)	-246.7** (111.3)	-291.7* (150.9)	-541.6** (220.5)	-859.5 (588.8)
Low Resource Neighborhood	104.1 (102.8)	32.03 (125.4)	-88.60 (145.6)	-210.8 (258.5)	-218.6 (291.2)	-525.3 (352.8)	-712.5 (694.0)
Female	212.7*** (69.53)	276.7*** (73.55)	382.2*** (83.37)	414.0*** (92.21)	470.1*** (135.5)	692.5*** (217.1)	1,180*** (426.1)
Age 35-54	35.22 (75.16)	0.944 (76.48)	57.26 (78.57)	105.1 (90.14)	203.5 (142.0)	324.1 (218.0)	185.7 (459.1)
Age 55+	210.7* (110.4)	308.7** (128.6)	200.8 (140.0)	44.09 (170.9)	149.0 (376.3)	1,058* (581.3)	1,050 (826.7)
pregnancy	5,382*** (1,353)	7,046*** (1,532)	8,669*** (1,520)	11,599*** (1,983)	11,598*** (1,285)	12,331*** (1,420)	13,445*** (3,184)
Major ADG Count	1,406*** (113.3)	2,000*** (132.1)	2,730*** (190.3)	3,738*** (328.8)	5,369*** (478.7)	6,800*** (472.6)	11,124*** (1,125)
Constant	25.87 (71.92)	133.9** (66.29)	249.7*** (80.91)	484.1*** (106.3)	638.3*** (139.4)	1,049*** (204.7)	1,948*** (603.2)

***All numbers reflect US dollars. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1**
+ indicates a statistically significant difference in size of effect across quantiles
N=8,740

Appendix 4.5: ADG Adjusted Two Part Model Results Stratified by Race and Including Pregnancy

	Logit (Odds of Any Spending)	Regress (Log Spending)
BLACK ONLY		
MEDIUM RESOURCE NEIGHBORHOOD	0.0273 (0.103)	0.0902** (0.0415)
LOW RESOURCE NEIGHBORHOOD	-0.0437 (0.0939)	0.106*** (0.0387)
FEMALE	1.018*** (0.0748)	0.378*** (0.0324)
35-54	0.0481 (0.0816)	0.146*** (0.0350)
55+	-0.0796 (0.130)	0.204*** (0.0458)
MAJOR ADG COUNT	3.747*** (0.309)	0.736*** (0.0117)
PREGNANCY		1.807*** (0.0534)
CONSTANT	0.553*** (0.0904)	6.350*** (0.0412)
NON BLACK ONLY		
MEDIUM RESOURCE NEIGHBORHOOD	-0.0387 (0.182)	-0.0315 (0.0681)
LOW RESOURCE NEIGHBORHOOD	0.00918 (0.264)	-0.103 (0.0993)
FEMALE	0.975*** (0.173)	0.278*** (0.0675)
35-54	0.233 (0.173)	0.212*** (0.0772)
55+	0.623** (0.292)	0.378*** (0.0984)
MAJOR ADG COUNT	3.090*** (0.463)	0.725*** (0.0209)
PREGNANCY		1.788*** (0.133)
CONSTANT	0.319* (0.168)	6.354*** (0.0771)

ROBUST STANDARD ERRORS IN PARENTHESES
***** P<0.01, ** P<0.05, * P<0.1**

Appendix 4.6: Quantile Regression with Chronic Condition Morbidity Adjustement Interacted with Age

	Quantiles*						
VARIABLES	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Female	210.1***	298.4***	349.2***	465.3***	636.5***	786.6***	841.8***
	(25.92)	(31.77)	(44.15)	(57.46)	(88.37)	(120.9)	(264.6)
Age 35-54	-211.4***	-277.0***	-336.3***	-424.6***	-626.2***	-1,018***	-2,023***
	(31.18)	(37.20)	(44.36)	(53.20)	(69.98)	(129.5)	(475.0)
Age 55+	-838.3***	-919.0***	-1,132***	-1,201***	-1,518***	-1,821***	-2,880***
	(157.3)	(141.4)	(243.6)	(319.5)	(201.1)	(173.9)	(509.3)
Black	-16.14	-10.12	31.98	71.64	81.26	107.2	238.1
	(37.52)	(40.39)	(55.05)	(83.87)	(97.79)	(122.9)	(277.1)
Medium Resource Neighborhood	64.24*	68.58*	59.70	40.47	71.64	193.1	452.2
	(35.13)	(40.83)	(47.99)	(66.90)	(92.87)	(119.9)	(282.1)
Low Resource Neighborhood	96.04***	108.3***	145.6***	142.2**	230.6***	456.1***	981.7***
	(31.33)	(37.60)	(51.77)	(67.17)	(88.50)	(132.6)	(365.5)
Chronic Condition Count	840.1***	1,212***	1,669***	2,328***	3,454***	5,016***	10,894***
	(49.34)	(65.90)	(104.5)	(144.2)	(210.4)	(427.4)	(1,844)
Age 35-54 and Chronic Condition Count	22.36	-23.95	-90.54	-250.2	-717.5***	-967.3*	-4,294**
	(56.46)	(89.19)	(125.7)	(164.7)	(246.2)	(504.6)	(1,880)
Age 55+ and Chronic Condition Count	61.09	-53.48	-170.8	-340.3	-779.6***	-1,424***	-5,107**
	(78.47)	(82.78)	(140.2)	(217.6)	(264.4)	(477.1)	(2,030)
Constant	130.9***	206.7***	298.0***	449.7***	729.5***	1,258***	2,682***
	(42.16)	(43.09)	(65.08)	(88.63)	(105.7)	(162.0)	(483.9)
Observations	8,740						

* All numbers are US Dollars. t-statistics in brackets *** p<0.01, ** p<0.05, * p<0.1 Adjusted for gender, age, BNSEI, Chronic Condition Count, Race. Excludes pregnancy

CHAPTER 5 APPENDICES

Appendix 5.1: Indicators Included in Each Neighborhood Domain

Domain	Measures Used to Calculate Each Domain	Indicator Also Included in Overall Social and Environmental Index Score
Crime	Part 1 Crime Rate per 1,000 Residents	x
Crime	Juvenile Arrest Rate for Drug-Related Offenses per 1,000 Juveniles	
Crime	Number of Shootings per 1,000 Residents	
Crime	Number of Gun-Related Homicides per 1,000 Residents	
Crime	Number of Narcotics Calls for Service per 1,000 Residents	x
Education	Number of Students Ever Attended 6th - 8th Grade	
Education	Percent of Students that are Hispanic	
Education	Percent of 1st-5th Grade Students that are Chronically Absent (Missing at least 20 days)	
Education	Percent of 6th-8th Grade Students that are Chronically Absent (Missing at least 20 days)	x
Education	Percent of 9th-12th Grade Students that are Chronically Absent (Missing at least 20 days)	x
Education	High School Dropout/Withdrawal Rate	
Education	High School Completion Rate	
Education	Percent of Students Switching Schools within School Year	x
Education	Percentage of Population aged 16-19 in School and/or Employed	

Education	Percentage of 3rd Grade Students who met or exceeded PARCC Math	x
Employment and Workforce	Unemployment Rate	x
Employment and Workforce	Percent Population (25 years and over) With Less Than a High School Diploma or GED	x
Employment and Workforce	Percent Population (25 years and over) With High School Diploma and Some College or Associates Degree	x
Employment and Workforce	Total Number of Commercial Properties	
Employment and Workforce	Percent of Commercial Properties with Rehab Permits Above $5,000	
Employment and Workforce	Total Number of Businesses	
Employment and Workforce	Number of Banks and Bank Branches per 1,000 Residents	
Employment and Workforce	Percent of Businesses that are 1 year old or less	
Housing	Median Number of Days on the Market	
Housing	Number of Homes Sold	
Housing	Percentage of Properties that are Owner-Occupied	x
Housing	Percentage of Properties Under Mortgage Foreclosure	
Housing	Percentage of Residential Properties that are Vacant and Abandoned	
Housing	Percentage of Properties with Rehabilitation Permits Exceeding $5,000	x
Housing	Percentage of Residential Sales in Foreclosure (REO)	
Housing	Percentage of Residential Tax Lien Sales	x
Housing	Number of Demolition Permits per 1,000 Residential Properties	
Housing	Number of New Construction Permits per 1,000 Residential Properties	
Housing	Affordability Index - Mortgage	
Housing	Affordability Index - Rent	x
Housing	Number of Historic Tax Credits per 1,000 Residential Units	
Housing	Number of Homestead Tax Credits per 1,000 Residential Units	x
Housing	Number of Homeowner's Tax Credits per 1,000 Residential Units	
Housing	Rate of Housing Vouchers per 1,000 Rental Units	
Income and Wealth	Percent of Households Earning Less than $25,000	x
Income and Wealth	Percent of Households Earning $25,000 to $40,000	
Income and Wealth	Percent of Households Earning $40,000 to $60,000	

Income and Wealth	Percent of Households Earning More than $75,000	x
Living Environment and Physical Conditions	Rate of Dirty Streets and Alleys Reports per 1,000 Residents	
Living Environment and Physical Conditions	Rate of Clogged Storm Drain Reports per 1,000 Residents	
Living Environment and Physical Conditions	Percent of Population that Carpool to Work	
Living Environment and Physical Conditions	Percent of Population that Uses Public Transportation to Get to Work	
Living Environment and Physical Conditions	Percent of Population that Walks to Work	
Living Environment and Physical Conditions	Percent of Employed Population with Travel Time to Work of 45 Minutes and Over	x
Living Environment and Physical Conditions	Number of Community Managed Open Spaces	
Living Environment and Physical Conditions	Percent of Residences Heated by Utility Gas	
Living Environment and Physical Conditions	Percent of Residential Properties Weatherized	

Appendix 5.2. Two Part Model of Medical Spending and Neighborhood Social and Environmental Resource Index with Interaction between Chronic Conditions and Race

Control Variables*	Logit (Odds of Any Medical Spending)	Regress (Log Medical Spending)
	N=9,128	N= 7,853
Neighborhood Domain Variable		
Neighborhood Social and Environmental Resource Index	-0.0424 (0.0438)	0.0400** (0.0183)
Gender		
Male	Ref	Ref

Female	0.814*** (0.0682)	0.120*** (0.0286)
Race		
Non Black	Ref	Ref
Black	0.0891 (0.112)	0.0193 (0.0557)
Age		
18-34	Ref	Ref
35-54	-0.212*** (0.0760)	0.0821** (0.0320)
55+	-0.657*** (0.130)	-0.0800* (0.0421)
Morbidity		
Chronic Condition Count	2.536*** (0.520)	0.354*** (0.0141)
Area Level Control Variable		
Neighborhood Segregation Index	0.000757 (0.00288)	0.00146 (0.00116)
Interactions: Chronic Conditions and Race		
Chronic Condition Count x Non Black	Ref	Ref
Chronic Condition Count x Black	0.182 (0.549)	-0.00879 (0.0152)
Constant	0.401*** (0.122)	6.542*** (0.0603)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Calculated using model that adjusts for gender, age, chronic condition count, race, segregation, the BNSEI Index, and interaction term between chronic conditions and race. Pregnancies were excluded.

Appendix 5.3: Control Variable Coefficients and Standard Errors for Models Run with Baltimore Neighborhood Social and Environmental Index

Control Variables*	Logit (Odds of Any Spending)	Regress (Log Spending)
Log likelihood = -12,736.32	N=9,128	N= 7,853
Neighborhood Domain Variable		
Neighborhood Social and Environmental Resource Index	-0.0415 (0.0438)	0.0357* (0.0183)
Gender		
Male	Ref	Ref
Female	0.815*** (0.0681)	0.126*** (0.0283)
Race		
Non Black	Ref	Ref
Black	0.0984 (0.106)	0.00971 (0.0414)
Age		
18-34	Ref	Ref
35-54	-0.175** (0.0787)	0.187*** (0.0416)
55+	-0.658*** (0.141)	0.260*** (0.0589)
Morbidity		
Chronic Condition Count	3.026*** (0.394)	0.447*** (0.0156)
Area Level Control Variable		
Neighborhood Segregation Index	0.000765 (0.00289)	0.00159 (0.00115)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref

Chronic Condition Count x 35-54	-0.644 (0.443)	-0.101*** (0.0179)
Chronic Condition Count x 55+	-0.240 (0.579)	-0.153*** (0.0179)
Constant	0.381*** (0.118)	6.441*** (0.0518)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Calculated using model that adjusts for gender, age, chronic condition count, race, segregation, the BNSEI Index, and interaction term between age band and chronic conditions. Pregnancies were excluded.

Appendix 5.4: Control Variable Coefficients and Standard Errors for Models Run with Crime Domain*

Control Variables*	Logit (Odds of Any Spending)	Regress (Log Spending)
Log likelihood = -12734.52	N=9,128	N= 7,853
Neighborhood Domain Variable		
Crime Index	-0.0523 (0.0374)	0.0389** (0.0157)
Gender		
Male	Ref	Ref
Female	0.813*** (0.0681)	0.127*** (0.0283)
Race		
Non Black	Ref	Ref
Black	0.0966 (0.106)	0.0123 (0.0412)
Age		
18-34	Ref	Ref
35-54	-0.173** (0.0788)	0.186*** (0.0416)

55+	-0.657*** (0.141)	0.260*** (0.0589)
Morbidity		
Chronic Condition Count	3.026*** (0.394)	0.447*** (0.0156)
Area Level Control Variable		
Neighborhood Segregation Index	0.000977 (0.00275)	0.00160 (0.00109)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref
Chronic Condition Count x 35-54	-0.646 (0.443)	-0.101*** (0.0179)
Chronic Condition Count x 55+	-0.240 (0.579)	-0.153*** (0.0179)
Constant	0.365*** (0.117)	6.449*** (0.0514)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using model that adjusts for gender, age, chronic condition count, race, segregation, the Crime Index, and interaction term between age band and chronic conditions. Pregnancies were excluded.

Appendix 5.5: Control Variable Coefficients and Standard Errors for Models Run with Education Domain*

Control Variables*	Logit (Odds of Any Spending)	Regress (Log Spending)
Log likelihood = -12736.27	N=9,128	N= 7,853
Neighborhood Domain Variable		
Education Index	-0.0435 (0.0368)	0.0242 (0.0152)
Gender		
Male	Ref	Ref

Female	0.816*** (0.0681)	0.125*** (0.0283)
Race		
Non Black	Ref	Ref
Black	0.109 (0.115)	-0.0103 (0.0447)
Age		
18-34	Ref	Ref
35-54	-0.174** (0.0787)	0.187*** (0.0416)
55+	-0.658*** (0.141)	0.261*** (0.0589)
Morbidity		
Chronic Condition Count	3.026*** (0.394)	0.447*** (0.0155)
Area Level Control Variable		
Neighborhood Segregation Index	0.000555 (0.00269)	0.00213** (0.00107)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref
Chronic Condition Count x 35-54	-0.643 (0.443)	-0.101*** (0.0179)
Chronic Condition Count x 55+	-0.238 (0.579)	-0.153*** (0.0179)
Constant	0.372*** (0.118)	6.433*** (0.052)

Robust standard errors in parentheses
***p<0.01, ** p<0.05, * p<0.1
*Calculated using model that adjusts for gender, age, chronic condition count, race, segregation, the Education Index, and interaction term between age band and chronic conditions. Pregnancies were excluded.

Table 5.6: Control Variable Coefficients and Standard Errors for Models Run with Housing Domain*

Control Variables*	Logit (Odds of Any Spending)	Regress (Log Spending)
Log likelihood = -12736.48	N=9,128	N= 7,853
Neighborhood Domain Variable		
Housing Domain	-0.0213 (0.0427)	0.0382** (0.0173)
Gender		
Male	Ref	Ref
Female	0.815*** (0.0681)	0.126*** (0.0283)
Race		
Non Black	Ref	Ref
Black	0.0946 (0.107)	0.00729 (0.0414)
Age		
18-34	Ref	Ref
35-54	-0.176** (0.0787)	0.187*** (0.0416)
55+	-0.659*** (0.141)	0.261*** (0.0589)
Morbidity		
Chronic Condition Count	3.027*** (0.394)	0.447*** (0.0155)
Area Level Control Variable		
Neighborhood Segregation Index	0.000245 (0.00299)	0.00125 (0.00121)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref

Chronic Condition Count x 35-54	-0.646 (0.443)	-0.101*** (0.0179)
Chronic Condition Count x 55+	-0.242 (0.579)	-0.153*** (0.0179)
Constant	0.390*** (0.128)	6.464*** (0.0554)

*Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using model that adjusts for gender, age, chronic condition count, race, segregation, the Housing Index, and interaction term between age band and chronic conditions. Pregnancies were excluded.

Table 5.7: Control Variable Coefficients and Standard Errors for Models run with Living Environment Domain*

Control Variables*	Logit (Any Cost)	Regress (Log Costs)
-12737.63	N=9,128	N= 7,853
Neighborhood Domain Variable		
Living Environment Index	-0.0342 (0.0388)	0.00454 (0.0159)
Gender		
Male	Ref	Ref
Female	0.817*** (0.0682)	0.126*** (0.0283)
Race		
Non Black	Ref	Ref
Black	0.0987 (0.107)	0.0166 (0.0416)
Age		
18-34	Ref	Ref
35-54	-0.644 (0.443)	-0.101*** (0.0179)
55+	-0.238 (0.580)	-0.154*** (0.0179)

Morbidity		
Chronic Condition Count	3.027*** (0.394)	0.447*** (0.0155)
Area Level Control Variable		
Neighborhood Segregation Index	0.000475 (0.00278)	0.00261** (0.00111)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref
Chronic Condition Count x 35-54	-0.644 (0.443)	-0.101*** (0.0179)
Chronic Condition Count x 55+	-0.238 (0.580)	-0.154*** (0.0179)
Constant	0.378*** (0.122)	6.410*** (0.0528)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using model that adjusts for gender, age, chronic condition count, race, segregation, the Living Environment Index, and interaction term between age band and chronic conditions. Pregnancies were excluded.

Table 5.8: Control Variable Coefficients and Standard Errors for Models run with Income and Wealth Domain*

Control Variables*	Logit (Any Cost)	Regress (Log Costs)
Log likelihood = -12737.89	N=9,128	N= 7,853
Neighborhood Domain Variable		
Income and Wealth Domain	-0.00213 (0.0393)	0.0114 (0.0163)
Gender		
Male	Ref	Ref

Female	0.815*** (0.0681)	0.126*** (0.0283)
Race		
Non Black	Ref	Ref
Black	0.0888 (0.106)	0.0158 (0.0412)
Age		
18-34	Ref	Ref
35-54	-0.177** (0.0786)	0.188*** (0.0416)
55+	-0.660*** (0.141)	0.262*** (0.0589)
Morbidity		
Chronic Condition Count	3.027*** (0.395)	0.447*** (0.0155)
Area Level Control Variable		
Neighborhood Segregation Index	-0.000494 (0.00284)	0.00236** (0.00114)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref
Chronic Condition Count x 35-54	-0.646 (0.443)	-0.101*** (0.0179)
Chronic Condition Count x 55+	-0.242 (0.579)	-0.154*** (0.0179)
Constant	0.420*** (0.121)	6.419*** (0.0526)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using model that adjusts for gender, age, chronic condition count, race, segregation, the Income and Wealth Index, and interaction term between age band and chronic conditions. Pregnancies were excluded.

Appendix 5.9: Control Variable Coefficients and Standard Errors for Models Run with Employment and Workforce Domain*

Control Variables*	Logit (Odds of Any Spending)	Regress (Log Spending)
Log likelihood = -12737.26	N=9,128	N= 7,853
Neighborhood Domain Variable		
Employment and Workforce	-0.0359 (0.0391)	0.0275* (0.0160)
Gender		
Male	Ref	Ref
Female	0.816*** (0.0681)	0.125*** (0.0283)
Race		
Non Black	Ref	Ref
Black	0.0985 (0.106)	0.0117 (0.0413)
Age		
18-34	Ref	Ref
35-54	-0.176** (0.0787)	0.187*** (0.0416)
55+	-0.659*** (0.141)	0.261*** (0.0589)
Morbidity		
Chronic Condition Count	3.026*** (0.394)	0.447*** (0.0155)
Area Level Control Variable		
Neighborhood Segregation Index	0.000567 (0.00281)	0.00184 (0.00113)
Interactions: Chronic Conditions and Age Band		
Chronic Condition Count x 18-34	Ref	Ref

Chronic Condition Count x 35-54	-0.644 (0.442)	-0.101*** (0.0179)
Chronic Condition Count x 55+	-0.241 (0.579)	-0.153*** (0.0179)
Constant	0.376*** (0.121)	6.441*** (0.0529)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using model that adjusts for gender, age, chronic condition count, race, segregation, the Employment and Workforce Index, and interaction term between age band and chronic conditions. Pregnancies were excluded.

Appendix 5.10: Chronic Condition Adjusted Two Part Models of Neighborhood Level Variables : Comparison of Unadjusted and Fully Adjusted Models with Pregnancies included

	Logit (Odds of Any Medical Spending N= 9,772		**Regress (Log Medical Spending)** N = 8,497	
	Unadjusted[1]	**Adjusted[2]**	**Unadjusted[1]**	**Adjusted[2]**
BNSEI Index	0.019 (0.033)	-0.033 (0.05)	0.100 (0.019)***	0.033 (0.02)*
Crime Domain	-0.017 (0.030)	-0.046 (0.04)	0.090 (0.018)***	0.037 (0.015)**
Education Domain	0.020 (0.030)	-0.041 (0.04)	0.084 (0.017)***	-0.021 (0.02)
Housing Domain	0.038 (0.030)	-0.006 (0.05)	0.088 (0.017)***	0.038 (0.02)**
Income and Wealth Domain	0.036 (0.029)	0.016 (0.05)	0.067 (0.000)***	0.001 (0.017)
Living Environment	0.031 (0.030)	-0.027 (0.04)	0.064 (0.018)***	0.002(0.02)
Employment and Workforce Domain	0.019 (0.029)	-0.030 (0.05)	0.072 (0.018)***	0.015(0.02)

[1]Scores for each neighborhood domain were calculated by running separate unadjusted models containing only individual level medical spending as the outcome and the neighborhood level variable as the single predictor per model. Each index contains a score for all 52 CSAs with greater than 10 individuals from our sample.

[2]Neighborhood domain coefficients and standard errors calculated by running each neighborhood domain separately in models adjusted for gender, age, chronic condition count, race, pregnancy, the neighborhood variable of interest, neighborhood segregation and an interaction term between ageband and chronic condition count. The values for each neighborhood domain score are specific to each separate neighborhood domain model.

Appendix 5.11: Coefficients for Neighborhood Domains from Two Part Adjusted* Models Adjusted for Chronic Conditions, Without Segregation Variable

	Logit (Odds of Any Medical Spending) N= 9,772	Regress (Log Medical Spending) N = 8,497
BNSEI Index	-0.036 (0.038)	0.053 (0.015)***
Crime Domain	-0.047(0.034)	0.051(0.013)***
Education Domain	-0.041(0.034)	0.042(0.014)***
Housing Domain	-0.020(0.036)	0.052(0.014)***
Income and Wealth Domain	-0.006(0.035)	0.029(0.014)**
Living Environment	-0.032 (0.035)	0.026 (0.014)*
Employment and Workforce Domain	-0.033(0.035)	0.039(0.013)***
*** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses		

*Neighborhood domain coefficients and standard errors calculated by running each neighborhood domain separately in models adjusted for gender, age, chronic condition count, race, pregnancy, the neighborhood variable of interest and an interaction term between ageband and chronic condition count. The values for each neighborhood domain score are specific to each separate neighborhood domain model. Segregation was excluded in these models.

Appendix 5.12: Major ADG Adjusted Models of Domain Scores, Race, and Interaction with Pregnancy Included

Area Level Variables, Individual level Race, and Interaction Terms **	Logit (Odds of Any Spending)	Regress (Log Spending)
Domain		
BNSEI Index	-0.118 (0.10)	-0.074 (0.04)**
Individual Level Race		
Non Black	Ref	Ref
Black	0.170 (0.11)	0.093 (0.04)**
Interaction: Race and Neighborhood Domain		
Black x BNSEI Index	0.043 (0.10)	0.093 (0.04)**

Domain		
Crime Domain	-0.152 (0.10)	-0.079 (0.04)**
Individual Level Race		
Non Black	Ref	Ref
Black	0.181 (0.12)	0.111 (0.04)***
Interaction: Race and Neighborhood Domain		
Black x Crime Index	0.053 (0.10)	0.091 (0.04)**
Domain		
Education Domain	-0.144 (0.08)*	-0.078 (0.03)***
Individual Level Race		
Non Black	Ref	Ref
Black	0.213 (0.12)*	0.119 (0.043)***
Interaction: Race and Neighborhood Domain		
Black x Education Index	0.098 (0.08)	0.098 (0.03)**
Domain		
Housing Domain	-0.085(0.09	-0.033(0.04)
Individual Level Race		
Non Black	Ref	Ref
Black	0.202 (0.12)	0.111 (0.04)**
Interaction: Race and Neighborhood Domain		
Black x Housing Index	0.061 (0.97)	0.058 (0.036)
Domain		
Income and Wealth Domain	-0.011 (0.08)	-0.013 (0.03)
Individual Level Race		
Non Black	Ref	Ref
Black	0.177 (0.12)	-0.013 (0.03)
Neighborhood Level Control Variable		
Black x Income and Wealth Index	0.013 (0.09)	0.017 (0.03)

Domain		
Living Environment	-0.121 (0.12)	-0.061 (0.04)
Individual Level Race		
Non Black	Ref	Ref
Black	0.234 (0.12)**	0.115 (0.045)**
Interaction: Race and Neighborhood Domain		
Black x Living Environment Index	0.123 (0.12)	0.071 (0.04)
Domain		
Employment and Workforce Domain	-0.046 (0.08)	-0.044 (0.03)
Individual Level Race		
Non Black	Ref	Ref
Black	0.156 (0.12)	0.109 (0.04)**
Interaction: Race and Neighborhood Domain		
Black x Employment and Workforce Domain	-0.010 (0.09)	0.065 (0.03)*
*** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses		

** Neighborhood level variables, race, and interaction terms calculated by running each neighborhood domain separately in models adjusted for gender, age, pregnancy, major ADG count, race, the neighborhood variable of interest, percent African American and an interaction term between neighborhood and race. The values for race, percent African American, each neighborhood score and the interaction term are specific to each separate neighborhood domain model.

Appendix 5.13: Two Part models with Neighborhood Variables Split into 3 Categories instead of Full Index, Adjusted for Chronic Conditions, age, race, and gender

	Logit (Odds of Any Spending)	Regress (Log Spending)
BNSEI Index	Ref	Ref
2	0.058(0.088)	0.107(0.034)***
3	0.003(0.087	0.147(0.339)***
Crime Domain	Ref	Ref
2	-0.019 (0.0832)	0.092(0.031)***
3	-0.065(0.085)	0.109(0.033)***
Education Domain	Ref	Ref
2	-0.030(0.084)	0.146(0.032)***
3	-0.043(0.085)	0.095(0.032)***
Housing Domain	Ref	Ref
2	-0.024(0.083)	0.087(0.032)***
3	-0.0178(0.087)	0.101(0.029)***
Income and Wealth Domain	Ref	Ref
2	-0.101(0.083)	0.044(0.032)
3	-0.037(0.084)	0.083(0.032)***
Living Environment	Ref	Ref
2	-0.149(0.086)*	0.136(0.033)***
3	-0.135(0.089)	0.106(0.034)***
Employment and Workforce Domain	Ref	Ref
2	-0.055(0.087)	0.074(0.033)**
3	-0.074(0.085)	0.070(0.033)**
Segregation	Ref	Ref
2	-0.081(0.089)	0.007(0.034)
3	-0.012(0.089)	0.102(0.034)***

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses
** Neighborhood level variables, race, and interaction terms calculated by running each neighborhood domain separately in models adjusted for gender, age, pregnancy, major ADG count, race, the neighborhood variable of interest, segregation and an interaction term between neighborhood and race. The values for race, segregation, each neighborhood score and the interaction term are specific to each separate neighborhood domain model

APPENDIX 6: ADDITIONAL SENSITIVITY ANALYSIS DETAILS AND DISCUSSION

One finding from Aim 2 and 3 models that was counterintuitive to what I would have expected was the finding that when I control for chronic condition count, age groups appeared to get less expensive as individuals got older. Typically, the literature suggests the opposite: that as individuals age, their medical spending increases. Our findings in both the quantile regression models (Aim 2) and Two part models (Aim 3) indicate a significant interaction between age bands and chronic condition count in models of medical spending. However, when we do not control for chronic conditions, or when we control for major ADG count instead, this effect completely disappears, and older age bands are both more expensive and more likely to have any expense than younger age bands, as we would expect (see Appendix 4.3-4.5). Given the pattern of older age bands were associated with lower medical spending only when controlling for chronic condition count, I had two hypotheses about why this pattern was occurring. One was that there was a diminishing medical spending return on each additional chronic condition, and that older individuals had a higher number of chronic conditions, so medical spending per additional chronic condition would be lower for them versus younger individuals who have fewer chronic conditions. The second was that younger individuals with chronic conditions are likely to be newly diagnosed and have conditions that are less controlled than older age groups, who have had more time to learn how to manage their conditions and likely have been seeing doctors more regularly to control these conditions.

In order to test these hypotheses, I first created a descriptive table comparing age bands by average cost, costs when chronic conditions were equal to zero, and utilization data stratified by chronic condition band. I also tested whether or not the effect of increasing age on decreased medical spending after controlling for chronic condition count was gender specific, and found that the effect persisted when models were stratified by gender.

To test the first hypothesis, I examined the mean number of chronic condition by age group, as well as the average cost of having one more chronic condition per age group, and found that the oldest age group, on average had 4.01 chronic conditions, the 35-55 age group had an average of 2.35, and the youngest group had an average of 0.83. The proportion of individuals in the oldest age group without any chronic conditions was very small (6%) as compared to the youngest age group, where 64% of individuals had zero chronic conditions. Because of this, medical spending comparisons per additional chronic condition are occurring among only 36% of the youngest age group who have at least one chronic condition and are likely sicker than peers their age, and 94% of the oldest age group (see Appendix 6.1). Further, we see that on average, medical spending associated with having one more chronic condition in the youngest age group is higher than the middle or oldest age group, even after controlling for gender and race and excluding pregnancies ($2,612.31, $2,476.85, $2,364.49 respectively). These results suggest that older age groups have higher numbers of chronic conditions and therefore lower average cost per chronic condition, so the effect we see of lower medical spending as age bands increase is an effect of diminishing returns for additional chronic conditions for which older age groups have significantly more. The fact that among individuals with zero chronic conditions, the youngest age band still appears to have a higher average medical spend can be explained by the fact that only 6% of the oldest age group falls into this category, and individuals who are 55+ with zero chronic conditions are likely to be unusually healthy compared to their peers, or non-users of the health system and therefore diagnoses have yet to be captured for them.

The second hypothesis is that individual who are younger that already have chronic conditions are more likely to be newly diagnosed and less likely to have them under control. While I do not have a way to know if an individual is newly diagnosed, individuals with conditions that are out of control are more likely to have ED visits and hospitalizations than those who are not, so I examine utilization by age band and by number of chronic conditions. Further, I would expect that older age groups have more management visits to control their conditions, and management visits are low in cost to the payer and increase the likelihood that an individual can manage conditions and stay out of the hospital. In Appendix Table 6.1, we find that among individuals with at least one chronic condition, younger age groups have higher average numbers of hospitalizations, and lower average numbers of management visits than older age groups, which supports my hypothesis that younger groups may not have chronic conditions under control, resulting in higher cost utilization patterns. Further, among individuals with zero chronic conditions, I find that the oldest age group has higher average hospitalization count, as I would expect (older individuals typically have higher utilization), which suggests that the higher hospitalization rate among younger individuals with at least one chronic condition may be related specifically to chronic conditions.

When we adjust for Major ADG count, which includes unstable chronic conditions, injuries, infections, and other acute conditions (see Appendix 2.4 for more details), the age effect of older having significantly higher medical spending returns to the expected pattern, with average cost of additional ADGs being highest for the oldest age group, and the average number of ADGs also being highest for the oldest age group (see Appendix Table 6.1).

There is one additional explanation for why older age groups would have lower medical spending as chronic conditions increased, and that is that as individuals get older and have more chronic conditions, they are more likely to be assigned care managers to help manage conditions, and are also more likely to receive support from the government for supports such as social services and supplemental income, which would also help them better manage conditions. Individuals who are older and have severe chronic conditions are also more likely to qualify for dual eligibility in the state of Maryland, which means they would receive coverage as a dual eligible and therefore not be in our Priority Partners dataset, making the older age group seem artificially lower cost than if we had included dual eligible in the dataset. Further analyses by ICD code should be done to further explain these findings.

Appendix 6.1: Analysis of Morbidity and Spending by Age Bands Using Chronic Conditions, ADGs and Utilization

Age Bands *	18-34	35-55	55+	P Value
Mean Cost	2,687.27	5,806.54	8,398.23	0.000
Average cost if chronic condition count=0	941.63	842.42	578.39	0.005
Number and proportion with zero chronic conditions	2,552 (63.9%)	1,193 (29.9%)	246 (6.2%)	0.00
Average cost of having one more chronic condition, adjusting for gender and race	2,612.31	2,476.85	2,364.49	0.000
Average number of Chronic Conditions	0.83	2.35	4.01	0.000

Average Inpatient count if chronic conditions=0	0.006	0.006	0.015	0.422
Average Inpatient count if chronic conditions=1	0.030	0.021	0.019	0.29
Average Inpatient count if chronic conditions=2	0.071	0.068	0.012	0.03
Average inpatient count if chronic conditions==3	0.16	0.096	0.097	0.06
Average inpatient count if chronic conditions>=4	1.06	0.56	0.48	0.00
Management Visit Count if chronic condition count=0	1.66	1.56	1.7	0.321
Management Visit Count if chronic condition count=1	2.49	3.49	3.59	0.00
Management Visit Count if chronic condition count=2	3.89	4.95	5.06	0.00
Management Visit Count if chronic condition count=3	5.13	5.90	5.96	0.00
Management Visit Count if chronic condition count=4+	7.60	9.88	10.18	0.00
Emergency Visit Count if chronic condition count=0	0.69	0.56	0.25	0.00
Emergency Visit Count if chronic condition count=1	1.39	1.05	0.80	0.00
Emergency Visit Count if chronic condition count=2	2.19	1.19	0.62	0.00
Emergency Visit Count if chronic condition count=3	2.63	1.40	0.67	0.00
Emergency Visit Count if chronic condition count=4+	4.31	2.53	2.08	0.00
Average cost if ADGs = 0	965.97	1,429.87	1,288.89	0.000
Average cost of having one more adg, adjusting for gender and race	4,822.39	4,841.45	5,050.33	0.000
Average number of Major ADGs	0.48	1.09	1.68	0.000

*pregnancy excluded from all models in this table
*correlation between ADG count and Chronic Condition Count = .74
*correlation between ADG count and medical spending is 0.62
*correlation between Chronic Condition Count and medical spending is 0.64

Appendix 6.2 Interactions between Race and ADG Variables in Both Quantile and Two Part Models

In sensitivity analyses that include major ADGs as a measure of morbidity in quantile models as well as in two part models, I found that there was a significant interaction between race and significant measures of neighborhood social risk (see Appendix 5.12). I also found that the direction of associations between neighborhood factors and medical spending are different for blacks as compared to non-blacks. Interestingly, I found that for non-blacks, there appears to be a significant neighborhood effect predicting less medical spending as the neighborhood domains of Crime and Education get worse, however for blacks, the effect is the opposite and in the expected direction, with significantly higher medical spending.

There are several possible explanations for why non-black individuals may have a significant association between lower resource neighborhoods and lower medical spending. The first is that the sample of non-blacks was largely imputed, and relatively small compared to the black population, and therefore could be biased. However, the pattern persists when using only non-imputed data, so the imputation is unlikely to be a factor.

A second possible explanation is that some of the medical spending differences in lower resource neighborhoods as compared to higher resource neighborhoods were due to a percentage of mental health related medical spending incurred through visits to psychiatrists or other specialty mental health providers that would not be included in our medical spending data. This hypothesis is supported through both literature review and through additional analyses detailed below.

Evidence from the literature on neighborhoods and mental health suggests that as neighborhood resources worsen, psychosocial problems increase[8]. Appendix Table 6.2 shows that the likelihood of having a psychosocial diagnosis for nonblack population significantly increases as neighborhoods get worse. Further, literature demonstrates that there are differences in patterns of utilization of specialty mental health services observed in blacks versus non blacks[8], and it is possible that non-black patients are more likely to seek mental health services from specialists[7]; spending which would be absent from our data. This is further corroborated by analyses showing that being nonblack is significantly associated with fewer outpatient visits, and a higher likelihood of having mental health conditions under control as indicated by a diagnosis of "psychosocial stable" than blacks (see Appendix Table 6.3 and 6.4), which could indicate that non-blacks are using outpatient care for psychosocial services that is not accounted for in claims data due to the mental health carve out in Maryland.

In order to make sure that lower outpatient visit counts among non-blacks are not just due to less use of services, I compare black versus nonblack counts of management visits, and find that non-blacks have higher counts of visits related to management of conditions than blacks (Appendix 6.5). Together, these findings corroborate what has been found in the literature: that non-blacks may be more likely to seek preventive services, including mental health services, and therefore as psychosocial conditions become more prevalent as neighborhood circumstances get worse, they may be more likely to seek specialty mental health care: spending that would not be captured in our data. More research would be needed to further explain these associations.

Appendix 6.2: Odds of Having a Psychosocial Diagnosis using Logistic Regression models that control for Race, Age, Neighborhood Social and Environmental Index, Major ADG Count, and Neighborhoods Segregation

Variable	Coefficient (SE)
	N=9,772
Neighborhood Domain Variable	
Neighborhood Social and Environmental Index	0.351*** (0.0711)
Gender	
Male	Ref
Female	-0.621*** (0.0579)
Race	
Non Black	Ref
Black	-0.478*** (0.0804)
Age	
18-34	Ref
35-54	0.969*** (0.0664)
55+	1.114*** (0.0803)
Interaction BNSEI and Race	
BNSEI Index x black	-0.190** (0.0841)
Area Level Control Variable	
Neighborhood Segregation Index	-0.000226 (0.00252)
Constant	-1.401*** (0.101)

*Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using model of binary psychosocial diagnosis from ACG system that adjusts for gender, age, race, segregation, and interaction term between neighborhood index and race. Pregnancies were excluded.

Appendix 6.3: Poisson Regression of Outpatient Visit Count, adjusted for Race, Age, Neighborhood Social and Environmental Index, Major ADG Count, and

Variable	Coefficient (SE)
	N=9,772
Neighborhood Domain Variable	
Neighborhood Social and Environmental Index	-0.0107** (0.00444)
Gender	
Male	Ref
Female	0.462*** (0.00710)
Race	
Non Black	Ref
Black	0.0644*** (0.0188)
Age	
18-34	Ref
35-54	0.160*** (0.00778)
55+	0.356*** (0.00928)
Morbidity	
Major ADG Count	0.331*** (0.00189)
Area Level Control Variable	
Neighborhood Segregation Index	0.000880*** (0.000303)
Constant	1.342*** (0.0160)

*Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using model of outpatient visit count that adjusts for gender, age, major ADG count, race, segregation, and the neighborhood BNSEI index. Pregnancies were excluded.

Table 6.4: Odds of Having a Psychosocial Diagnosis Considered "Stable" using Logistic Regression models that control for Race, Age, Neighborhood Social and Environmental Index, Major ADG Count, and Neighborhoods Segregation

Variable	Coefficient (SE)
	N=9,772
Neighborhood Domain Variable	
Neighborhood Social and Environmental Index	-0.0417 (0.0373)
Gender	
Male	Ref
Female	0.211*** (0.0600)
Race	
Non Black	Ref
Black	-0.376*** (0.0794)
Age	
18-34	Ref
35-54	0.0194 (0.0651)
55+	-0.167* (0.0866)
Morbidity	
Major ADG Count	0.711*** (0.0217)
Area Level Control Variable	
Neighborhood Segregation Index	0.00104 (0.00238)

Constant	-2.141*** (0.103)

*Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using stable psychosocial condition as defined by ACG as binary outcome. Logistic model adjusts for gender, age, Major ADG Count, race, segregation, and the BNSEI Index. Pregnancies were excluded.

Appendix 6.5 Poisson Regression of Management Visit Counts, Adjusting for Race, Age, Neighborhood Social and Environmental Index, Major ADG Count, and Neighborhood Segregation

Variable	Coefficient (SE)
	N=9,772
Neighborhood Domain Variable	
Neighborhood Social and Environmental Index	-0.00854 (0.00675)
Gender	
Male	Ref
Female	0.407*** (0.0109)
Race	
Non Black	Ref
Black	-0.0558*** (0.0212)
Age	
18-34	Ref
35-54	0.326*** (0.0122)
55+	0.514*** (0.0145)
Morbidity	
Major ADG Count	0.313*** (0.00292)
Area Level Control Variable	
Neighborhood Segregation Index	-0.00184*** (0.000439)
Constant	0.607*** (0.0211)

*Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
*Calculated using model of management visits (outpatient and ambulatory visits for the purposes of routine care as defined by ACG system) that adjusts for gender, age, Major ADG Count, race, segregation, and the BNSEI Index. Pregnancies were excluded.

CURRICULUM VITAE

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Born in Minneapolis, MN on 12/05/1984

EDUCATION AND CERTIFICATIONS

Johns Hopkins Bloomberg School of Public Health — Baltimore, MD
PhD Candidate in Health Policy and Management — August 2014- Present
GPA: 3.9

Johns Hopkins Bloomberg School of Public Health — Baltimore, MD
Masters in Public Health — May 2010- 2012
Concentration in Health Systems and Policy
Certificate in Global Health
GPA: 3.9

National Board of Public Health Examiners
National Certification in Public Health — Received May 2012

The Ohio State University, Honors Program — Columbus, OH
Bachelor of Science in Psychology, Bachelor of the Arts in Strategic Communication
June 2008
Business Minor

EXPERIENCE

Johns Hopkins HealthCare LLC — Baltimore, MD
Director, Population Health Innovation and Transformation — 11/17-present

- Oversee, design, and implement population health programs for domestic and international clients seeking to improve the health of their populations
- Global speaker and consultant promoting population health innovations to reduce cost and improve health, strategies for addressing the social determinants of health, and sustainability in health systems
- Develops customized population health solutions to meet existing and emerging population health needs in response to state and federal healthcare transformation efforts and grant opportunities
- Serves as integration point between JHHC population health, analytics, business operations and population health IT development to jointly innovate for new solutions to population health challenges
- Promotes work of JHHC Innovations domestically and internationally through webinars, conferences, manuscripts, consulting, and teaching opportunities
- Serves as subject matter expert for population health analytics, including monitoring and evaluation of population health programs and integration of new initiatives with a state health information exchange

Interim Director, Community Health Partnership of Baltimore — 3/17-10/17

- Oversaw operations for 6.7 million dollar grant from state to change health outcomes and cost for Medicare beneficiaries in 19 zip code region of Baltimore City

- Led analytic strategy for grant, including complex reporting structure for 6 interventions to improve patient outcomes across 6 different partner hospitals with different data systems
- Redesigned intervention structures and workflows, and created new elements of programs to meet the evolving needs of the partnership
- Built on existing relationships with community-based organizations to ensure partnerships were mutually beneficial and partnership outcomes were maximized

Senior Program Administrator, Population Health Programs 10/16-3/17

- Created population health strategies and consulted on program design for new solutions to improving health and reducing costs for domestic and international population health contracts
- Worked with Johns Hopkins International to promote and implement population health consulting services internationally
- In partnership with the Johns Hopkins Center for Population Health IT, worked to create system wide framework for population health metrics that aligns commonly measured public health, population health, primary care, and quality measures

Senior Research Associate for International and Domestic Population Health 1/14-10/16

Research Associate 10/11-12/13

Research Coordinator 01/09-10/11

World Health Organization

Geneva, Switzerland

Health Systems Alliance 6/16-8/16, Ongoing

- Serve as a WHO Subject Matter Expert on the topic of community engagement on temporary assignments as needed
- Led Health Systems Alliance team to review literature on and create frameworks for development of community platforms for health
- Served as lead author for book chapter for the Disease Control Priorities 3rd Edition, Chapter 20 on Community Platforms for Health (Published in 2017)
- Developed white paper for distribution to WHO leadership on the need for public health strengthening to achieve the Sustainable Development Goals and subsequent book chapter on the same subject (currently in press as a book chapter in forthcoming book on achieving the vision of Alma Ata)

Jhpiego Baltimore, MD and Gaborone, Botswana

1/12-6/14

- Worked in collaboration with Botswana Ministry of Health Officials, CDC Botswana representatives, USAID representatives, HLSP representatives, and other health partners in Botswana and Mozambique to strengthen public health as part of a JHU/Jhpiego team aiming to strengthen health system performance through an emphasis on performance of essential public health functions.
- Developed tool kit for public health practice assessment now being used in the Middle East and Africa

HONORS AND AWARDS

Invited Speaker for Health Events Worldwide, including the following clients: 2017-2019

- Ministry of Health, Santiago Chile
- Regional Health Office of the NIH, London, UK
- World Health Organization’s EMRO Office, Cairo, Egypt
- Keynote Speaker for Top 20 Hospitals Conference, Madrid, Spain

- Fundacio Santa Fe De Bogota: Partner's Forum, Bogota, Colombia

Invited presenter and panelist for domestic healthcare conferences including: 2016-2019

- American Health Insurance Plans (AHIP)
- Inovalon Client Congress
- RISE Nashville
- Johns Hopkins ACG System International Conference

Invited Reviewer for:

- *Transforming Complex Care (TCC) National Advisory Committee*, a Robert Wood Johnson Foundation funded grant for refining and spreading effective care models
- *Community Management of Medication Complexity (CMMC) Advisory Committee*, a CHCS funded grant national initiative aimed at identifying community-based strategies to improve medication-related outcomes among low-income populations

Charles D Flagle Fund Award 2017-2018

- Awarded scholarship for dissertation work in health services research

Marilyn Bergner Award 2016-2017

- Awarded scholarship for dissertation work in health services research.

Awarded the Agency for Healthcare Research and Quality Training Grant 2014-2020

- Full tuition support and stipend during doctoral program at Johns Hopkins Bloomberg School of Public Health

Delta Omega Honor Society 2012

- Awarded to the top 10% of graduating students from the Johns Hopkins School of Public Health based on grades, experiences, and contributions to public health.

<u>OTHER RELEVANT EXPERIENCE AND SKILLS</u>

- **Guest Lecturer, Johns Hopkins Bloomberg School of Public Health-** Regularly invited to teach courses on population health management and the social determinants of health by various professors at JHSPH; courses include Managed Care Organizations, Executive Leadership Courses, and Population Health Courses for Masters level and above students

- **Invited Member of the Center for Health Care Strategies Innovation Lab –** For the past 5 years, invited to and participated in multiple yearly CHCS Innovation Lab meetings with invited representatives from 15+ selected innovative healthcare organizations across the US with to promote best practice in caring for high risk, high need Medicaid and Medicare patients. Goal is to use innovative population health approaches that go beyond traditional health care to address needs and change care for these patients.

- **Foreign Language Skills** – Conversational Spanish

- **Computer Skills** – Microsoft Office, Microsoft Word, Excel, PowerPoint, Visio, Access, STATA

- **Travel Experience –** Argentina, Austria, Australia, Bahrain, Bermuda, Bolivia, Bosnia and Herzegovina, Botswana, Cambodia, Chile, Colombia, Costa Rica, Croatia, Czech Republic, Egypt, Fiji, France, Israel, Hungary, Italy, Laos, Kuwait, Mexico, Mongolia, Montenegro, Morocco, Mozambique, Nepal, New Zealand, Oman, Peru, Saudi Arabia, Slovakia, Spain, South Africa, Switzerland, Thailand, United Arab Emirates, United Kingdom, Uruguay, Zimbabwe

<u>PUBLICATIONS</u>

- **Sherry, MK,** Bishai, DB, Ghaffar, A. *Chapter 20: Community Platforms for Health.* In Gelband, H., P. Jha, R.

Sankaranarayanan, and S. Horton, (EDs) Disease Control Priorities, Third Edition: Volume 9. Washington, DC: World Bank. Publication forthcoming, 2017.

- **Sherry, MK,** Wolff, JL, Ballreich, J; DuGoff, E; Davis, K; Anderson, G. Bridging the Silos of Service Delivery for High-Needs High-Cost Patients. *Journal of Population Health Management.* Accepted for publication December 2016.
- **Sherry, MK;** Mossallam, M; Mulligan, M; Hyder, AA; Bishai, D. Rates of intentionally caused and road crash deaths of US citizens abroad. *Journal of Injury Prevention*, Published Online First: 3 December 2913. doi:10.1136/injuryprev-2013-040923
- **Sherry, MK,** Ongoing Data Monitoring. In Sylvia, M and Terhaar, M (EDs.); Clinical Analytics and Data Management for the DNP. New York, Springer Publishing Company. April 2014.
- Bishai, D; Xu, J; and **Sherry, MK.** Strengthening the efferent arm in public health. *Am J Public Health*, 106(7):1196-7
- Bishai, D; **Sherry, MK**; Pereira; Chicumbe, S; Mbofana, F; Boores, A; Smith, M; Nhambi, L; Borse, N. Development and Usefulness of a District Health Systems Tool for Performance Improvement in Essential Public Health Functions in Botswana and Mozambique. Journal of Public Health Management and Practice. 2016 Nov-Dec;22(6):586-96
- Marsteller, J, Huizinga, M; Cooper, L; **Sherry, M.** Statistical Process Control – Possible Uses to Monitor and Evaluation Patient Centered Medical Home Models. Poster presented at the Academy Health Annual Research Meeting, Baltimore, MD, June 24, 2013.
- Ross-Friend C, Schuster A**, Sherry, MK.** Case Management for People Living with HIV/AIDS. *Care Management.* 2011,17:12-17.
- George H, **Sherry MK,** Sylvia, M. *Johns Hopkins USFHP Screening Algorithm for Care Management Interventions.* Poster presented at the Military Health Services Conference, National Harbor, MD, January 17th, 2011.
- Murphy S, **Sherry MK,** Teves M. *Something for Everyone: Addressing the Health Services Gap for Low Risk Military Beneficiaries Using HRAs and Health Coaching*. Poster presented at the Military Health Services Conference, National Harbor, MD, January 17th, 2011.
- Raffel M, Goldberg D, **Sherry MK,** Kritzler B, Feeser, S. *Improving Quality and Access to Medical Care for Johns Hopkins US Family Health Plan Members: Patient Centered Medical Home Pilot.* Poster Presented at the Military Health Services Conference in National Harbor, MD, January 17, 2011.
- **Sherry MK,** Castro HK, Vigil I. *Promoting Activation Among USFHP Beneficiaries Enrolled in Care Management.* Poster presented at the Military Health Services Conference in National Harbor, MD, January 24, 2011