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Individual- and Community- Level Associations With Healthcare Utilization Among a Health System, Emergency Department Population

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ABSTRACT

AIM: The primary aim of this study was to examine individual-level and community-level characteristics associated with ambulatory or primary care utilization, emergency department (ED) utilization, and ED charges among a sample of ED patients.

DESIGN AND SAMPLE: Data for this cross-sectional study were obtained from three distinct sources: (i) electronic medical records (EMR); (ii) billing records; and (iii) the 2013-2017 American Community Survey (ACS). The individual-level EMR and billing sample included all adults residing in Mecklenburg County, North Carolina who visited an Atrium Health ED in 2017. The ACS sample included population and demographic estimates from Mecklenburg County's 27 ZIP code tabulation areas (ZCTAs).

METHODS: The total number of billed ED visits and associated ED charges were primary outcomes in the study. The total number of billed visits to ambulatory or primary care (APC) was both an outcome and a covariate. Other individual-level covariates were: insurance coverage type, race, ethnicity, age, and gender. ZCTA-level covariates were: residential segregation, measured using the dissimilarity index, and living in a public health priority area (PHPA), defined as areas with disproportionately low educational attainment and high poverty. Mean regression (i.e. negative binomial, and linear regression) models were used to assess associations between healthcare utilization and residential segregation on average. Quantile regression models were used to assess the relationship between covariates and ED utilization (avoidable utilization, ED visit frequency, and ED Charges) at the 25^{th}, 50^{th}, 75^{th}, 95^{th}, and 99^{th} percentiles of the distributions.

RESULTS: Residential segregation was not associated with the average number of ED visits and was associated with the average number of APC visits during the study period. The relationships between residential segregation and not having any visits to APC in the past year, and average ED charges varied based on the race of the individual. There was heterogeneity in the association between APC utilization and avoidable ED scores by insurance type. Having Medicaid or Medicare insurance was positively associated with ED visits compared to those that were uninsured, at the 50^{th} and 75^{th} percentiles of the distribution. Medicaid and Medicare were positively associated with ED charges and having Private insurance was negatively associated with ED charges across all percentiles of the distribution. Visits to APC was positively and negatively associated with ED visit frequency, and living in a PHPA was positively and negatively associated with ED charges.

CONCLUSIONS: Residential segregation was associated with APC utilization and ED charges, but not with ED visits. The associations between APC utilization and avoidable ED utilization varied based on segments of the distribution and was significantly different among insurance stratum. The associations between APC visits and PHPA status with the outcomes of ED visits and ED charges varied by percentile of the distribution, and included relationships that were in qualitatively opposite directions. Modeling ED utilization outcomes using internal, distribution-based cut points described their relationships with independent variables more accurately than conventional methods that dichotomize the outcome or evaluate the average of the entire distribution.

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CHAPTER 1

INTRODUCTION

1.1 EMERGENCY DEPARTMENT UTILIZATION

The United States (U.S.) healthcare system experiences a disproportionate burden of Emergency Department (ED) utilization among a high-need, high-cost group of patients that reflects a small overall percentage of the population (LaCalle & Rabin, 2010; Martin, Stokes-Buzzelli, Peltzer-Jones, & Schultz, 2013). Up to 30% of all ED visits are directed towards 1-8% of the patient population identified as frequent ED utilizers (Jiang, Weiss, & Barrett, 2017; Hunt, Weber, Showstack, Colby, & Callaham, 2006; Fuda & Immekus, 2006). The risk of frequent utilization is higher among minority patients (Mandelberg et al., 2000; Saef et al., 2016; Agarwal et al., 2016), and individuals with social and economic risk factors such as poverty (Hunt et al., 2006) and homelessness (Mandelberg et al., 2000). Frequent utilization increases the overall financial burdens for individual patients, payers, and some healthcare providers. In 2010, the top 1% of patients ranked by healthcare expenditure accounted for ~20% of the total healthcare spending, with an average annual cost of almost $90,000 per person (Cohen, Uberoi, & Quality, 2013).

Additional individual- and system-level waste occurs when patients are treated in the ED for nonurgent or avoidable conditions, potentially resulting in poor quality of care and increased health disparities among vulnerable populations. Nonurgent or avoidable ED utilization (hereafter referred to as avoidable) occurs when individuals seek treatment in the ED that could have been delayed several hours to several days without increasing the likelihood of an adverse outcome, and/or a patient could have accessed other healthcare services such as primary care or urgent care for preventive treatment. Avoidable ED utilization is a waste of resources that lowers health system efficiency and raises cost (Enard & Ganelin, 2013). Charges in the ED are 320%-728% higher than charges for comparable treatment in primary care clinics, resulting in a potential savings of 69%-86% if avoidable care is shifted from the ED to primary care (McWilliams, Tapp, Barker, & Dulin, 2011). Approximately 13% to 27% of all ED visits in the US are avoidable, with an estimated annual cost of $4.4 billion (Weinick, Burns, & Mehrotra, 2010). Chronic avoidable ED utilization can result in poor quality of care due to overcrowding, increased wait time, and a lack of care continuity and follow-up (Moskop, Sklar, Geiderman, Schears, & Bookman, 2009; Khangura, Flodgren, Perera, Rowe, & Shepperd, 2012). Avoidable ED utilization occurs at higher rates among minority and Medicaid-insured patients and lower rates among Medicare-insured populations (McWilliams et al., 2011) and is a potential indicator of poor care management and inadequate access to primary care (Dowd et al., 2014).

Many efforts to reduce ED utilization are focused on reducing disparities in preventive healthcare access and shifting utilization to ambulatory care settings (Enard & Ganelin, 2013; Seaberg et al., 2017; Natale-Pereira, Enard, Nevarez, & Jones, 2011; Peart, Lewis, Brown, & Russell, 2018). Preventive healthcare is delivered in primary care and other ambulatory healthcare settings (Silverstein et al., 2008) and includes services such as cancer screenings, annual wellness exams, and vaccinations that can prevent and reduce the severity of many chronic diseases and health conditions (Shi, 2012).

Individuals experiencing social, economic and environmental health risk factors are less likely to use preventive healthcare (Ross, Bernheim, Bradley, Teng, & Gallo, 2007) and are more likely to experience severe chronic disease that contributes to clustering of health risk (Cockerham, Hamby, & Oates, 2017). Access to preventive healthcare is impeded by financial barriers in the form of insurance, but can also include other expenses associated with health care utilization such as deductibles and copayments. National healthcare policy has made efforts to improve preventive healthcare access through the Affordable Care Act (ACA), that includes several requirements for private health insurance plans to cover certain preventive healthcare services, like mammograms, cholesterol screenings, and flu shots, without deductibles, copayments, and other cost sharing.

1.2 SOCIAL DETERMINANTS OF HEALTH & RESIDENTIAL SEGREGATION

Health disparities are a function of larger system-level inequities that impact healthcare access and utilization. Social determinants of health (SDoH), are defined by the World Health Organization as the conditions in which people are born, grow, live, work, and age that are shaped by the distribution of money, power and resources at global, national, and local levels (Secretary’s Advisory Committee on Health Promotion and Disease Prevention Objectives for 2020, 2010). Healthcare access is a recognized SDoH (McGibbon, Etowa, & McPherson, 2008) that impacts the availability and quality of medical care resulting in increased risk of disease severity and mortality among disadvantaged groups (Eachus, Chan, Pearson, Propper, & Smith, 1999; Weissman, Stern, Fielding, & Epstein, 1991; Sommers, Baicker, & Epstein, 2012). In addition to disparate health outcomes, SDoH also impact mortality rates. A meta-analysis of almost

50 studies found that over one-third of the annual total deaths in the U.S. are attributable to social and economic factors including residential segregation, income inequality, and low educational attainment (Galea, Tracy, Hoggatt, DiMaggio, & Karpati, 2011).

Racial residential segregation is a SDoH and a fundamental cause of racial disparities in health outcomes (Williams & Collins, 2001) that concentrates exposure to other social and economic risk factors. Residential segregation is associated with lower rates of health insurance coverage among Black residents (K. F. Anderson & Fullerton, 2012) and worse access to a usual source of care (Caldwell, Ford, Wallace, Wang, & Takahashi, 2017). Individuals living in neighborhoods with high racial and economic inequality have higher rates of preventable 30-day readmissions (H. F. Chen, Homan, Carlson, Popoola, & Radhakrishnan, 2017), preventable hospitalizations (Bocour & Tria, 2016), all-cause mortality (Warren Andersen et al., 2018), cancer-related mortality (Singh & Jemal, 2017), and heart, stroke, and cardiovascular disease-related mortality (Singh, Siahpush, Azuine, & Williams, 2015). The geographic concentration of poverty theory operationalizes the negative health effects of residential segregation as a function of the spatial concentration of poor minority populations in a geographic area (D. S. Massey & Denton, 1988).

1.3 COMMUNITY SETTING

The Charlotte-Mecklenburg county of North Carolina (NC) is a community with recognized health and economic disparities that are geographically concentrated. A widely cited study by Chetty and colleagues ranked Charlotte-Mecklenburg county 50th out of 50 major metropolitan cities for economic mobility, the odds of moving from the bottom 5% of the income distribution to the top 5% of the income distribution. In this study, areas with the highest odds of economic mobility had the lowest rates of segregation between Black and White residents (Chetty, Hendren, Kline, & Saez, 2014). According to the 2017-2018 Community Health Assessment, there are 1,054,835 residents in the county with 12.1% living in poverty and 11% lacking insurance. The county Health Department previously identified six public health priority areas (PHPAs) as ZIP code tabulation areas (ZCTAs) with disproportionately low educational attainment and high percent of the population living below the poverty threshold. Results from the 2017 Behavioral Risk Factor Surveillance System (BRFSS) showed that PHPAs had higher rates of major chronic health conditions, including high blood pressure (42.0% versus 30.1%), high cholesterol (36.3% versus 30.2%), diabetes (15.8% versus 9.6%), and cardiovascular disease (11.5% versus 7.5%) when compared to non-PHPAs in the county.

Charlotte-Mecklenburg county PHPAs are the focus of an innovative collaborative effort to address community health disparities and economic mobility, in part through improving access to and utilization of preventive healthcare. This partnership, the One Charlotte Health Alliance (OCHA), includes Atrium and Novant Health systems in addition to the Mecklenburg County Health Department (Cole, 2017). Atrium Health (formerly Carolinas HealthCare System), is the largest provider of both tertiary and quaternary care in the Carolinas as well as the Southeastern U.S. and is the third largest governmental non-profit healthcare system in the U.S. This dissertation examined healthcare utilization and associated charges among a sample of Atrium Health ED patients living in Mecklenburg county ZCTAs.

CHAPTER 2

LITERATURE REVIEW

2.1 PUBLIC HEALTH IMPLICATION

Emergency departments (EDs) serve as the primary safety net of the U.S. healthcare system. However, the EDs' function is to stabilize seriously ill or injured patients and meet the "last resort" routine care demands that are inaccessible from other parts of the healthcare system (Morganti et al., 2013). This role is reinforced legally through the Emergency Medical Treatment and Labor Act of 1986 that requires hospitals receiving Medicare reimbursements to offer emergency services regardless of a patient's ability to pay. EDs have experienced an increasing burden of care relative to the larger healthcare ecosystem. Between 1996 and 2010, the number of ED visits in U.S. increased by 44%, resulting in almost half of hospital-associated medical care, defined as ED visits, outpatient visits, and hospital admissions, now occurring in the ED (Marcozzi, Carr, Liferidge, Baehr, & Browne, 2018).

The ED safety net has expanded to serve an increasing proportion of medically underserved patients, particularly adults enrolled in Medicaid, with subsequent increases in the overall cost burden of ED utilization. ED utilization increased from 1997 to 2007 at a rate that was almost double what was expected from population growth (352.8 to 390.5 per 1000 persons) with the largest increase occurring among adults enrolled in Medicaid (693.9 to 947.2 visits per 1000 enrollees) (Tang, Stein, Hsia, Maselli, & Gonzales, 2010). In 2010, the national cost of ED utilization was $328.1 billion, representing 12.5% of

National Health Expenditure (Galarraga & Pines, 2016). Between 2010 and 2016, the nationally representative mean charges per ED visit increased by 56%, from $2,061 in 2010 to $3,516 in 2016 (Lane, Mallow, Hooker, & Hooker, 2019).

The position of the ED as the most accessible entry point into the healthcare system has made it an indicator of social disfunction within a community (E. S. Anderson, Hsieh, & Alter, 2016). Structural, economic, and social inequalities manifest as health disparities that are directly observable in the ED. Individuals living in neighborhoods with high racial inequality and income disparities are at an increased risk for preventable 30 day readmissions (H. F. Chen et al., 2017), preventable hospitalizations (Bocour & Tria, 2016), all-cause mortality (Warren Andersen et al., 2018), cancer mortality (Singh & Jemal, 2017), and heart, stroke and cardiovascular disease mortality (Singh et al., 2015). In the Jackson Heart Study, a significant association was observed between neighborhood social disadvantage and metabolic syndrome among a cohort of non-diabetic black women (prevalence ratio [PR]: 1.13, 95% confidence interval [CI]: 1.01 to 1.27) after controlling for the health behavior and socioeconomic status of individual respondents (Clark et al., 2013).

Intervention on SDoH through patient care at individual- and community- levels (i.e. Social Emergency Medicine; E. S. Anderson et al., 2016) is hindered by financial disincentives and a lack of evidence to inform interventions. The current policy of reimbursement through pay-for-performance models disincentivizes SDoH interventions (Roberts et al., 2018), and can ultimately exacerbate disparities in access and health outcomes. The legal mandate to serve all patients regardless of ability to pay makes EDs more vulnerable to market forces compared to other domains of the healthcare system.

Emergency departments serving higher proportions of minority and Medicaid patients are at a higher risk for closure (Hsia, Kellermann, & Shen, 2011; Hsia, Srebotnjak, Kanzaria, McCulloch, & Auerbach, 2012), which is associated with an increase in patient mortality (Liu, Srebotnjak, & Hsia, 2014) and may increase existing disparities in access to trauma care (Carr et al., 2017). The lack of evidence to inform SDoH interventions that reduce the cost and frequency of ED utilization has been highlighted in major review articles (LaCalle & Rabin, 2010; Soril, Leggett, Lorenzetti, Noseworthy, & Clement, 2015; Morgan, Chang, Alqatari, & Pines, 2013).

A comprehensive understanding of the characteristics associated with the frequency and cost of ED utilization is critical to inform patient care and community-based interventions in an era of increasing social burden on ED safety net systems. The following chapter will discuss the current literature, methodological standards, and limitations in following sections: i) Measurement of ED utilization ii) Cost of ED utilization iii) Insurance coverage and ED utilization iv) Ambulatory and primary care utilization, v) Individual- and Community- level covariates.

2.2 MEASUREMENT OF EMERGENCY DEPARTMENT UTILIZATION

Frequent Utilization

The measurement of frequent ED utilization is impaired by a lack of standardization and the use of dichotomized outcomes that reduces the comparability and sensitivity of evaluation. Frequent utilization is typically measured as a dichotomous (i.e. yes/no) outcome based on a predetermined threshold for the total number of visits in a calendar year. The threshold definition for frequent ED use is not standardized, making it difficult to compare results between studies (Pines et al., 2011). The most common definition is greater than 3 or more visits in a year (Hunt et al., 2006), but can range from 4 to 20 visits in a year (Fuda & Immekus, 2006; Blank et al., 2005; Mandelberg et al., 2000; Peppe, Mays, & Chang, 2007). Some studies use multiple thresholds, for example a study measuring ED utilization among Medicaid recipients in New York City defined frequent utilization as ≥ 3, ≥ 5, ≥ 8, and ≥ 10 ED visits in a calendar year (Billings & Raven, 2013). The use of common cut-point thresholds to define frequent ED utilization has been criticized as an oversimplification based on previous research showing that associated risk factors exist along a continuum without clear-cut breakpoints (Weber, 2012), and that frequent utilizers are a heterogeneous group (LaCalle & Rabin, 2010).

A range of analytic models have been used to assess ED utilization that vary based on how the outcome variable is operationalized. A majority of studies using a dichotomous outcome to assess frequent utilization apply a logistic regression model to predict the odds of frequent utilization while controlling for demographic and comorbid factors (Billings & Raven, 2013; Hudon, Courteau, Krieg, & Vanasse, 2017; Pines & Buford, 2006). When ED utilization is measured as a count or rate, the shape of the distribution influences the model selection. One study measured ED utilization at a population level as the annual ED visit rate for a census block (i.e. the total number of visits to the study ED from individuals in a given census block group divided by the total number of residents in that census block group). This study used a multivariate linear regression, with log-transformed ED utilization rates due to skewness in the distribution (Li, Grabowski, McCarthy, & Kelen, 2003). Another study used a Poisson regression model to determine the strongest predictors of ED utilization counts among a sample of patients with at least 6 visits during the 1-year study period (Milbrett & Halm, 2009).

Avoidable ED Utilization

Avoidable ED utilization can be measured using the New York University Emergency Department algorithm (NYU Algorithm), a validated classification system for ED visits using 9 distinct categories of probability (Ballard et al., 2010). The first 4 categories of the NYU Algorithm are used to classify the probability of an ED visit being: 1) non-emergent, 2) emergent, primary care treatable, 3) emergent, preventable or avoidable, and 4) emergent, not preventable or avoidable. In categories 1-4, a probability between 0 and 1 is estimated by the algorithm based on the primary diagnosis code for each ED visit. The sum total of all 1-4 categories equals 1. If the primary diagnosis code aligns with the category for injury, mental health, alcohol, drug-related diagnoses, or is unclassified, the remaining categories 5-9 will be populated as either a 0 or 1, and are treated as mutually exclusive probabilities. Therefore, ED visits for which the urgency is calculated (categories 1-4), exclude visits that are injury, mental health, alcohol, drug-related or are unclassified (categories 5-9).

Prior studies have measured ED visit avoidability using a dichotomized outcome, calculated as the sum of category 1-2 or 1-3 probabilities and scored as above or below a predetermined cut-off point (Coe et al., 2018). For example in one study, an ED visit was coded as non-emergent (i.e. avoidable) when the sum of category 1-2 probabilities was greater than 50% and emergent (i.e. non-avoidable) when the sum of category 3-4 probabilities was greater than 50% (Gandhi & Sabik, 2014). This method was cited as a solution for having a bounded, continuous outcome variable (i.e. a total probability between 0 and 1) and a distribution that violated the standard linear regression assumption of constant variance (Kieschnick & Mccullough, 2003). Studies have criticized this method of dichotomizing the total probability as arbitrary (Lines, Rosen, & Ash, 2017) and an unnecessary loss of sensitivity (W. Chen, Waters, & Chang, 2015) when the total probability itself can be modeled using appropriate regression methods. This dissertation used quantile regression, a method that is applicable to bounded, non-normal error distribution assumptions, to model the total probability of avoidable ED utilization as a continuous score.

2.3 COST OF EMERGENCY DEPARTMENT UTILIZATION

The cost of care delivered through the ED is high, relative to other parts of the healthcare system, and may be disproportionate among vulnerable populations. A total of $328.1 billion was spent on ED care in 2010, representing 12.5% of the National Health Expenditure (Galarraga & Pines, 2016). In 2016, the average individual-level cost of an outpatient ED visit was $1,917, a value that increased over 30% between 2012 and 2016 (Health Care Cost Institute, 2016). Similar healthcare services are more expensive in the ED compared to other areas of the healthcare system, with variable charges based on an individual's insurance status. Among a sample of Medicaid billing records, ED physicians had a higher overall markup ratio (4.4; 340% excess charges), defined as the charges submitted by the hospital divided by the Medicare allowable amount, when compared to internal medicine physicians (2.1; 110% excess charges) according to a study examining over 2,700 US hospitals. Results also showed that higher ED markup ratios were associated with hospitals serving a greater percentage of uninsured patients (median: 5.0; inter-quartile range: 3.5-6.7 for ≥ 20% uninsured)(Xu et al., 2017).

When individuals are utilizing the ED at a higher than typical rate (i.e. frequent users), and/or for nonurgent or preventable healthcare needs, the cost burden is exacerbated. In 2010, the top 1% of patients ranked by healthcare expenditure accounted for ~20% of the total healthcare spending, with an average annual cost of almost $90,000 per person (Cohen et al., 2013). Approximately 13% to 27% of all ED visits in the US are nonurgent or avoidable with an estimated annual cost of approximately $4.4 billion (Weinick et al., 2010). High-volume ED utilization may be an indicator of future utilization. Among a cohort of uninsured patients in Mecklenburg County, NC, baseline ED utilization rate and healthcare cost were the strongest predictors of future healthcare cost (Lubanski et al., 2017). These results indicate that high-cost and high-frequency utilizers in single-time point samples are a risk factor for future high cost ED utilization.

2.4 INSURANCE COVERAGE & UTILIZATION

Researchers have used natural experiments created by policy changes to determine the role of insurance coverage in healthcare utilization patterns. This work has primarily focused on the impact of new insurance programs like the Affordable Care Act (ACA) Medicaid Expansion. In a repeated cross-sectional study examining BRFSS data from 2010-2016, results showed improved healthcare access among low-income childless adults aged 19–64. Following Medicaid expansion the proportion of individuals with health insurance was 16.7% higher (95% CI: 0.067 to 0.140; $p < 0.001$), having a personal doctor was 3.9% higher (95% CI: 0.001 to 0.049; $p = 0.044$), and with cost as a barrier to medical care was 10.7% lower (95% CI: -0.058 to -0.014; $p = 0.002$) (Cawley, Soni, & Simon, 2018). Experts have argued that insurance coverage does significantly increase a patients' access to preventive healthcare and utilization of preventive services. However, the downstream impact of these benefits on ED utilization patterns: i) are manifest in a variety of ways among minorities, vulnerable populations, and previously uninsured populations; ii) may only be evident over an extended period of time (> 10 years); and iii) are attenuated by other confounding factors associated with socio-economic disadvantage (Sommers, Gawande, & Baicker, 2017).

Studies examining the impact of ACA Medicaid Expansion on ED utilization show mixed results, highlighting the complexity of the relationship. The Oregon experiment, a randomized controlled trial examining the impact of ACA Medicaid Expansion within the state, found an approximately 40% increase in ED use (Taubman, Allen, Wright, Baicker, & Finkelstein, 2014) that remained consistent over the 2 year study period (2008-2010)(Finkelstein, Taubman, Allen, Wright, & Baicker, 2016). A study examining 14 states with expansion and 11 states without expansion found that ED use per 1,000 persons increased by 2.5 visits more in expansion states than in non-expansion states after 2014 (Nikpay, Freedman, Levy, & Buchmueller, 2017). In contrast, a more recent study showed a significant 12% increase in access to primary care and a significant 6% reduction in likelihood of ED visits between 2014 and 2015 when comparing low-income adults in Kentucky and Arkansas (states with expansion) to low-income adults in Texas (a state without expansion)(Sommers, Blendon, Orav, & Epstein, 2016). In these studies, ED use was not measured as avoidable or primary care sensitive. Additionally, a study examining non-elderly adults in California found that post ACA implementation the odds of being a frequent ED user (≥ 4 visits per year) were reduced by 12% among patients who were Medicaid-insured prior to ACA and by nearly 50% among patients who were uninsured prior to ACA (McConville, Raven, Sabbagh, & Hsia, 2018).

Some studies examining the impact of state ACA Medicaid Expansion have attributed increases in ED utilization to a redistribution of the overall payer mix (i.e. shifting the non-insurance population into the Medicaid insurance population for analysis). A study examining 478 hospitals in 36 states during 2014 found that among expansion states, Medicaid-paid ED visits increased by 27.1%, uninsured visits decreased by 31.4%, and privately insured visits decreased by 6.7% (Pines et al., 2016). A population-level analysis of Illinois Public Use Micro Areas (PUMAs) using American Community Survey data found that between 2012 and 2015, the average monthly ED visits by the uninsured dropped by 42%, but increased by 42% among individuals with Medicaid and by 10% among those privately insured (Dresden et al., 2017). While the overall volume of ED utilization was not impacted in these studies, the results have important implications for the cost burden of healthcare. Shifting utilization from uninsured to Medicaid-insured populations could result in some individual-level cost savings and health-system level reimbursement.

Other, more comprehensive data sources have supported individual-level regression analysis of the relationship between insurance coverage and ED utilization. The state of Massachusetts implemented a state-sponsored universal health insurance plan in 2006, that was used as a model for the 2010 ACA. A cohort of 353,515 low-income adults receiving subsidized insurance coverage through the Massachusetts state insurance program was followed from 2004 to 2008. Results showed that the overall odds of using the ED during the study period decreased by 4% (odds ratio [OR]: 0.96; 95% CI: 0.94 to 0.98) when comparing pre-enrollment and post-enrollment periods. However, a significant qualitative interaction effect was observed based on the participant's pre-enrollment insurance status. Results showed that the odds of ED utilization were 12% higher among enrollees without insurance prior to enrollment (OR: 1.12; 95% CI: 1.10 to 1.25) and 18% lower among enrollees who transitioned from a health safety net program that payed for limited services prior to enrollment (OR: 0.82; 95% CI: 0.78 to 0.85) (McCarthy et al., 2014). Another cohort study using Massachusetts claims data found that having public insurance was associated with 150% more primary care sensitive ED use when compared to individuals with private insurance (Lines, Li, Mick, & Ash, 2019).

2.5 AMBULATORY & PRIMARY CARE UTILIZATION

Ambulatory or primary care is an access point for many preventive healthcare services such as cancer screenings, annual wellness exams, and vaccinations that can prevent and reduce the severity of many chronic diseases and health conditions (Shi, 2012). In contrast to the ED, ambulatory or primary care is a more efficient means of diagnosing and treating conditions before they reach a severity level requiring expensive procedures and hospitalization (Price, Freeman, Cleland, Kaplan, & Cerasoli, 2011; Starfield, Shi, & Macinko, 2005). Areas with higher concentrations of primary care physicians have lower mortality, fewer nonurgent hospitalizations (Chang, Stukel, Flood, & Goodman, 2011), and fewer ED visits (Kravet et al., 2008). A re-evaluation of the Oregon Health Experiment data highlighted primary care access and utilization as key factor for the successful implementation of insurance expansion programs (Heintzman, Gold, Bailey, & DeVoe, 2014).

The relationship between insurance coverage, ambulatory or primary care utilization, and ED utilization is not well understood. Two widely cited studies examining the impact of insurance coverage have either limited or no measurement of other healthcare utilization. First, a study found that newly insured individuals participating in the Oregon Health Experiment were more likely to visited the ED for nonurgent conditions compared to participants who were previously insured. Researchers did not evaluate other forms of healthcare utilization in this analysis (Taubman et al., 2014). Second, a study examining health outcomes associated with the Oregon Health Experiment assessed self-report primary care utilization, and found no significant associations with study outcomes (Baicker et al., 2013). A more objective measure of healthcare utilization, such as a review of medical records, would mitigate the recall and reporting bias associated with self-report data in future studies (Heintzman et al., 2014).

There is evidence to suggest that ambulatory or primary care utilization patterns may be different for individuals based on the frequency of ED utilization. Frequent utilization of the ED can be an indicator of chronic unmet health needs and influence heavy use of all levels of healthcare. A cross-sectional survey of 2 urban hospitals found that frequent ED users reported similar primary care access and twice as many primary care visits as non-frequent users, but were significantly less likely to report getting what they need from their primary care provider when compared to non-frequent users (76% vs. 93%) in the study population (Cunningham, Mautner, Ku, Scott, & LaNoue, 2017). A systematic review found that previous hospitalizations and high primary care use (> 3 visits per year) were associated with increased risk of frequent ED utilization among recipients of National Health Insurance coverage (Soril, Leggett, Lorenzetti, Noseworthy, & Clement, 2016). A 2017 study examining Medicaid claims data among a cohort of patients in The Boston Health Care for the Homeless program found that frequent utilization of the ED was associated with higher non-ED healthcare cost (Mitchell, León, Byrne, Lin, & Bharel, 2017). An analysis of the US National Health Interview Survey found that individuals with $\geq$ 10 outpatient visits in the past 12 months were more likely to be frequent ED users (OR: 11.4; 95% CI: 9.09 to 14.2)(Vinton, Capp, Rooks, Abbott, & Ginde, 2014), compared to those without any outpatient visits during the study period.

2.6 INDIVIDUAL- AND COMMUNITY- LEVEL COVARIATES

Individual-Level Covariates

Utilization of the ED is more common among minorities (Mandelberg et al., 2000; Saef et al., 2016; Agarwal et al., 2016), women (Milani, Crooke, Cottler, & Striley, 2016), and individuals experiencing poor mental health, poverty (Hunt et al., 2006), and homelessness (Mandelberg et al., 2000). One study found that demographic characteristics of frequent ED users included being a single parent, single or divorced marital status, high school education or less, with an annual income of less than $10,000 (Fuda & Immekus, 2006). According to the Medical Expenditure Panel Survey, frequent ED users are more likely to have at least one physical or mental chronic condition (84%) compared to non-frequent users (64%) of the ED (Peppe et al., 2007). A 2017 study examined data from the Massachusetts managed care network (i.e. a population with commercial insurance) predicted ED utilization as: any ED visit, total ED visits, and total primary care sensitive ED visits, or non-urgent ED utilization. Final models for all three outcomes found significant individual-level associations for age, gender, race, any prior ED visit in the last year, congestive heart failure, depression, and smoking (Lines et al., 2017).

Racial Residential Segregation

The impact of residential segregation on population health is described by the geographic concentration of poverty theory as a function of the higher geographic concentration of the negative social and health effects of poverty (e.g. crime, education quality, housing quality, food deserts) among poor Black populations compared to the poor White populations (Douglas S. Massey, Gross, & Shibuya, 1994; Douglas S. Massey, 1990). There are five distinct axes of segregation used as metrics for the geographic concentration of poverty theory: evenness, exposure, concentration, centralization, and clustering (D. S. Massey & Denton, 1988) with up to 19 possible indexes of measurement (US Census Bureau, 2016). This dissertation focused on the axis of evenness, which compares the spatial distribution of majority and minority groups in a specified unit of a geographic area, as the most appropriate for the sample size of the project and as the most common axis used in comparable studies.

The following section discusses several ways to measure the axis of evenness, all of which produce an index score that ranges from 0 (complete integration) to 1 (complete segregation). First, the Gini coefficient is a measure of the mean absolute difference between minority proportions weighted across all pairs of larger and smaller units. Another measure is the information/entropy index, measured as the weighted difference from each smaller unit's entropy, from the larger unit's entropy. An advantage of the information/entropy index, is that it can measure differences between more than two groups simultaneously (D. S. Massey & Denton, 1988). The final and most common measure used by health researchers is the dissimilarity index (Kramer, M. R., & Hogue, 2009), which measures the weighted mean absolute deviation of a unit's minority population from the overall minority population in the larger unit. The dissimilarity index has an easy conceptual interpretation, the proportion of minority members that would have to change residence for each smaller unit to have the same proportions as the overall larger unit, which is considered a major advantage of the index compared to other options (D. S. Massey & Denton, 1988). A major disadvantage of the dissimilarity index is its insensitivity to the principal of transfers (Merschrod, 1981). The dissertation applied the dissimilarity index as a measure of residential segregation because of the i) comparability with other major studies examining the relationship between residential segregation and healthcare utilization ii) ease of conceptual interpretation and ability to deconstruct the formula into individual components and iii) focus on racial segregation, compared to ethnic segregation, had stronger validity over time and continuity with prior studies (Douglas S. Massey, 1996).

The harmful impact of residential segregation on health disparities is well supported in the literature. In a study assessing radical disparities in hypertension, Black respondents had 1.74 times higher odds of hypertension when compared to White respondents (95% CI: 2.32 to 3.25), and differences between races were significantly smaller in low-segregation communities compared to high segregation communities (p-interaction = 0.006) (Kershaw et al., 2011). Another study found that residential segregation was significantly associated with a lower probability of survival among Black men and women compared to their White counterparts using data from the 2009-2013 American Community Survey (Popescu, Duffy, Mendelsohn, & Escarce, 2018). In a meta-analysis, residential segregation was associated with an increased risk of pre-term birth (OR: 1.20; 95% CI: 1.05 to 1.37) when comparing residents of most segregated neighborhoods to least segregated neighborhoods (Mehra, Boyd, & Ickovics, 2017).

Residential segregation may impact health, in part, through disparities in healthcare access. Neighborhood-level racial integration (i.e. the inverse of segregation) is associated with an increased likelihood of black residents having a health-care visit in the past year (Gaskin, Price, Brandon, & Laveist, 2009). Another study found that residential segregation between Black and White populations is associated with a decrease in the likelihood of black residents having insurance, while controlling for educational, and economic differences between racial groups (K. F. Anderson & Fullerton, 2012). Residential segregation was associated with worse access to a usual source of care among rural Black respondents (OR: 0.90, 95% CI: 0.84 to 0.96) when examining nationally representative data from the Medical Expenditure Panel Survey (Caldwell et al., 2017).

Only a few studies have examined the relationship between residential segregation and healthcare utilization, with only two using theoretically-driven metrics. The racial composition of a neighborhood (i.e. 50% or more Black residents) is associated with higher rates of ED utilization (Li et al., 2003), and lower odds of an office-based physician visit (OR: 0.44; p = 0.001), outpatient department physician visit (OR: 0.57; p = 0.037) or a nurse, physician assistant, or midwife visit (OR: 0.45; p = 0.011) among Black residents compared to White residents (Gaskin, Dinwiddie, Chan, & McCleary, 2012a). One study found that increasing racial isolation at the county-level is associated with increased odds of asthma-related ED utilization among Medicaid-enrolled children with asthma (OR: 1.04; 95% CI: 1.01 to 1.08) (Baltrus et al., 2017).

Another study found a significant interaction effect between race and residential segregation among adults with end stage renal disease. For each one-unit increase in the dissimilarity index score of a county, the odds of ED readmission among the Black population increased by 0.8 units. This relationship was protective among the White population where increasing dissimilarity index scores were associated with lower odds of ED readmission (Thomas-Hawkins, Flynn, Zha, & Savage, 2019).

This dissertation focused on racial residential segregation defined as the geographic separation between Black and White populations. Other forms of residential segregation based on ethnicity can be measured, however, the health and social impacts of ethnic segregation may be protective in some ways that are conceptually distinct from racial segregation. Ethnic segregation is associated with a protective health effect for rates of obesity among Mexican-American women (Kershaw, Albrecht, & Carnethon, 2013), rates of depression among urban Latino populations in the US (Vega, Ang, Rodriguez, & Finch, 2011), and is not significantly associated with low-birth weight among Latino Americans (Walton, 2009). A 2018 study examining the impact of racial and ethnic segregation on self-rated health found that Black/White segregation increased the disparity in self-rated health by up to 25%. Results for White/Hispanic segregation showed that increasing levels of Hispanic centralization was associated with a decrease in the disparity in self-rated health (Yang, Zhao, & Song, 2017). Researchers suggest that residential segregation among ethnic groups could have protective effects for health because of increased exposure to social support and cultural preservation, absence of language barriers (Vega et al., 2011).

CHAPTER 3

METHODOLOGY

3.1 RESEARCH AIMS

This study aimed to evaluate individual-level and neighborhood-level factors associated with healthcare utilization among Atrium Health ED patients living in Charlotte-Mecklenburg county, North Carolina.

Aim 1: To: i) identify key demographic differences among ED patients living in public health priority areas (PHPAs), compared to the larger county (non-PHPAs) ii) explore the distributions of healthcare utilization and examine heterogeneity between PHPA and non-PHPAs; and iii) assess the extent to which residential segregation was associated with healthcare utilization.

Aim 2: To assess i) the relationship between visits to ambulatory or primary care (APC), type of insurance coverage, and avoidable ED utilization; and ii) the degree to which the relationship between APC visits and avoidable ED utilization varied by type of insurance coverage.

Aim 3: To examine frequent utilization and ED charges using internal-cut points based on percentiles of the distributions by i) identifying characteristics of the study population associated with the percentiles of ED visit frequency and ED charges and ii) plotting percentiles of utilization among select demographic groupings.

3.2 DATA SOURCES

Data for this study were obtained from three distinct sources: (i) Atrium Health Electronic Medical Record (EMR); (ii) Atrium Health billing records; and (iii) the US Census Bureau. Individual-level data were extracted from Cerner Millennium (Cerner Corporation, Kansas City KS) EMRs and billing records (Epic Systems Corporation, Verona WI) from all five Atrium Health EDs in Mecklenburg County (Main, Pineville, University, Mercy, and South Park). Records were identified for extraction by the ZIP code tabulation area (ZCTA) associated with the home address of the index visit (i.e. the first visit to the ED during the study period). ZCTAs are a generalized representation of the U.S. Postal Service ZIP code service areas, and are calculated as the most frequently occurring zip code in an area.

Data for the ZCTA estimates of demographic and population factors were downloaded from the American Community Survey (ACS), a population survey conducted annually by the U.S. Census Bureau. The 5-year (2013-2017) ACS estimates for all 27 Mecklenburg County ZCTAs were downloaded for this study. The 5-year estimates are more reliable, with a larger sample size and greater precision, compared to the 1-year estimates (United States Census Bureau, 2013).

3.3 DESIGN AND SAMPLE

The study design was a cross-sectional analysis during the project period of January 1st, 2017 to December 31st, 2017. The extracted EMR and billing datasets included a total of 101,810 patients, 18 years or older, who resided in a Charlotte-Mecklenburg county ZCTA and visited a Charlotte-Mecklenburg county Atrium Health ED during the project period. Patients that died during the study period were excluded to reduce measurement error, along with those with unknown gender and those with extreme and potentially miscoded ages, resulting in the Aim 1 analytic sample (n = 101,060).

Additional exclusions were made for Aim 2 (n = 70,870) and Aim 3 (n = 99,637) analytic samples. Approximately 1% of the study population was covered through insurance classified as "other", including governmental insurance benefits (e.g. Veterans Affairs) and other program-specific options that did not conceptually align with larger insurance categories. The sample size of individuals with "other" insurance was too small to produce regression model estimates as a stand-alone group, and was subsequently excluded from Aim 2 and Aim 3 samples. Individuals visiting the ED for injuries, mental health issues, alcohol and drug use related visits, or those that could not be classified by the NYU algorithm were excluded from the Aim 2 analytic sample. A flow chart depicting the final analytic sample selections was developed for each corresponding results chapter.

The research protocol was reviewed and approved by the Institutional Review Board (IRB) at Atrium Health and was exempt from IRB review by The University of South Carolina because of the use of de-identified secondary data.

3.4 MEASURES

Individual-Level Measures

<u>ED Visits:</u> The total number of ED visits was calculated as the total billed unique ED encounters during the study period by individual. ED encounters were linked to an individual by the unique patient ID number in the Atrium Health system.

ED Charges: The total associated charges for ED visits during the study period was calculated by individual. ED visits were identified in the Atrium Health Billing System using the unique encounter ID associated with each visit. Hospital charges represent the amount billed by the hospital and do not reflect the actual cost, out-of-pocket expenses, or reimbursement for the visit, which varies based on the type of insurance coverage. ED charges were rounded to the nearest dollar for descriptive analysis and not for regression models.

Avoidable ED Score: The score of avoidable ED utilization for each individual was calculated using the sum of NYU ED Algorithm probabilities (category 1-3) for all ED visits during the study period. To improve the interpretation of model estimates, the total score was multiplied by 100. In this context, an avoidable ED score value of 100 is equivalent to 1 ED visit that was deemed 100% avoidable, or 2 visits that were 60% avoidable and 40% avoidable during the study period.

Ambulatory or Primary Care Visits (APC): The total number of APC visits was measured as the total number of unique encounters to Atrium Health care facilities defined in the EMR system under the specialty categories of: Allergy, Cardiovascular, Dermatology, Endocrinology, Family Medicine, Internal Medicine, Primary Care Behavioral Health, Rheumatology, Sleep Medicine, Sports Medicine, Urgent Care; and the following OBGYN specialty categories: Generalist, and OBGYN. For Aim 1, APC visits was measured as a discrete count. For Aims 2 and 3, APC visits was categorized as: 0 visits, 1 visit, and > 1 visit for analysis.

Insurance Coverage: The primary source of payment indicated for the index visit in the study sample was used as a proxy for insurance coverage during the study period using the following categories: Medicaid, Medicare, private, other, or uninsured. Medicare included both Advantage (commercial) and non-Advantage (public) members. Private represented all commercial insurance categories. The other insurance category included governmental insurance benefits (e.g. Veterans Affairs). For the purpose of this study, patients indicating "self-pay" were recoded to represent the uninsured.

PHPA Status: The Mecklenburg County Public Health Department identified the following six ZCTAs, with disproportionately low educational attainment and high proportion of the population living below the poverty threshold, as public health priority areas (PHPAs): 28217, 28208, 28216, 28206, 28205, and 28212. A binary variable (PHPA versus non-PHPA) was coded to indicate the PHPA status of each patient's home address ZCTA.

Participant Characteristics: Gender was measured as a categorical variable (male or female). Race (White, Black, and other or unknown) and Ethnicity (Hispanic or Latino and non-Hispanic or Latino) were measured as separate categorical variables. Age was measured as a continuous variable for descriptive and regression models.

ZCTA -Level Measures

Dissimilarity Index: The dissimilarity index (Cutler, Glaeser, & Vigdor, 1999) was used to measure residential segregation of Black and non-Black residents by ZCTA, relative to the larger county. In this context, dissimilarity represents the evenness of a population as the percentage of a race group that would have to change residence for each ZCTA to have the same proportions as the larger county. The dissimilarity index compares the relative proportion of Black residents in each ZCTA (i.e. number of Black residents in a ZCTA divided by the total number in the county) to the relative proportion of non-Black residents using the formula:

$$Dissimilarity\ Index = \frac{1}{2}\sum_{i=1}^{N} \left| \frac{B_i}{B_{total}} - \frac{B_i^c}{B_{total}^c} \right|$$

in which *B* is the number of Black residents in ZCTA i, and B_{total} is the number of Black residents in the county as a whole, B_i^c is number of non-Black residents in ZCTA i, and $B_{total}^c$is the number of non-Black residents in the county as a whole. The dissimilarity index ranges between 0 and 1 in which a value ≥ 0.6 indicate high, 0.3 to 0.6 indicates moderate, and ≤ 0.3 indicates low dissimilarities.

Dissimilarity Percentage: The dissimilarity index formula was adapted to measure the contribution of each ZCTA to the overall dissimilarity index score. The dissimilarity percentage was calculated as the difference between the relative proportions of Black and non-Black Residents for each ZCTA multiplied by 100 according to the formula:

$$Dissimilarity\ percentage = \left(\frac{B_i}{B_{total}} - \frac{B_i^c}{B_{total}^c}\right) * 100$$

in which *B* is the number of Black residents in ZCTA i, and B_{total} is the number of Black residents in the county as a whole, B_i^c is number of non-Black residents in ZCTA i, and $B_{total}^c$is the number of non-Black residents in the county as a whole. Patient ZCTAs in the individual-level sample were scored with dissimilarity percentage values calculated from the ZCTA-level sample.

3.5 ANALYTIC PLAN

Aim 1 Individual-Level Models

Demographic differences by PHPA status were assessed using a frequency table and a modified Poisson regression model with robust variance estimation to predict the prevalence ratio of PHPA status among insurance coverage and race groups, adjusting for gender, age, and ethnicity. Living in a PHPA was not a rare occurrence in the study population, therefore the odds ratio would overestimate the prevalence ratio (Barros & Hirakata, 2003). The use of robust standard errors accounted for violation of the Poisson distributional assumptions for a binary outcome (Zou, 2004). The distribution of healthcare utilization measures (APC visits, ED visits, and ED Charges) was evaluated by calculating the average values (i.e. mid-percentiles) for the 5^{th}, 25^{th}, 50^{th}, 75^{th}, 95^{th}, and 99^{th} percentiles of each measure.

The associations between dissimilarity percentage and APC visit and ED visit outcomes were assessed using negative binomial models to account for overdispersion (Rodriguez, 2013). Zero-truncated negative binomial models were used to model total ED visits to account for the absence of zero responses. Data were collected from ED EMRs, and therefore all patients in the sample had a minimum of 1 ED visit. A zero-inflated negative binomial model was used to predict APC visits due to excessive zero responses (Zeileis, Kleiber, & Jackman, 2008). The association between dissimilarity percentage and ED charges was assessed using a linear regression model. Standard errors were estimated using block bootstrapping by ZCTA with 100 replications to account for correlation between patients. All models were adjusted for insurance type, gender, age, race, and ethnicity. To evaluate the extent to which race impacts the relationship between residential segregation and healthcare utilization metrics, an interaction term between dissimilarity percentage and race was included in the models. Interaction terms that were significant at the 5% level were included in the final models; non-significant interaction terms were excluded.

The residual deviance was used to perform a goodness of fit test on all Poisson regression models. If the residual difference between the current model and the maximum deviance of the ideal model where the predicted values are identical to the observed is small (i.e. the goodness-of-fit chi-squared test is not statistically significant), the model fits reasonably well. For negative binomial models, the significance of the overdispersion parameter was tested using Poisson regression models for comparison.

Aim 1 ZCTA-Level Models

The proportion of ACS demographic estimates was calculated for PHPA and non-PHPA ZCTAs to validate the selection criteria designated by the county health department. The relationship between residential segregation and PHPA status was evaluated using a modified univariate Poisson regression model with robust standard errors to predict PHPA status given the dissimilarity percentage of a ZCTA. Residential segregation was visualized as the dissimilarity percentage of each ZCTA using R package mapview (Appelhans, Detsch, Reudenbach, & Woellauer, 2018).

Aim 2 and 3 Quantile Regression Models

The study populations were assessed using descriptive statistics. The distribution of the outcome measures, avoidable ED score (Aim 2), ED visits (Aim 3), and ED charges (Aim 3) was evaluated using box plots, histograms, and unconditional quantile-based location, scale, and shape measures. Quantile Regression (QR) models were used to evaluate the relationship between predictors and outcomes at the 25^{th}, 50^{th}, 75^{th}, 95^{th} and 99^{th} percentiles of the outcome distribution. QR can be applied to both discrete, hospital admission counts (Congdon, 2017; Winkelmann, 2006) and continuous, healthcare cost (Fliss, Weinstein, Sherf, & Dreiher, 2018; Lahiff et al., 2014; McCabe et al., 2017) outcomes.

In Aim 2, we modeled the relationship between insurance, coverage, APC visits, and avoidable ED score. Model 1 included insurance coverage and APC visits as predictors, and adjusted for gender, age, race, ethnicity, and PHPA status. Model 2 included an additional interaction term between APC visits and insurance coverage. Linear regression models were used for comparison of the estimated means. QR models used a linear programming (Frisch-Newton) estimation method. Confidence intervals and standard errors were computed using bootstrap resampling, with 100 replications.

In Aim 3, we assessed the relationship between all individual-level predictors (APC visits, insurance coverage, PHPA status, gender, Race, Ethnicity, and age) and outcomes: ED visits and ED charges. The outcome ED visits (discrete) was modeled using mid-QR (Geraci & Farcomeni, 2019) fitted via a Nelder-Mead algorithm, while the outcome ED charges (continuous) was modeled using QR (Roger Koenker & Bassett, 1978) fitted via a Barrodale-Roberts algorithm. The analytic population was subset into 8 datasets for all combinations of PHPA and insurance status groupings and mid-quantile values of ED visits and ED charges were plotted in separate figures.

For all QR models, we tested the statistical significance of differences in strength of association (i.e. slopes) by quantile using the Khmaladze Test (KT) (Roger Koenker & Xiao, 2002) of the location-shift hypothesis. The KT assesses the null hypothesis that the slopes of the regression models at each quantile are all the same. Therefore, a rejection of the null hypothesis means that the relationship between the independent and dependent variables in the model varies by quantile. Significance was assessed at the 5% level. Due to computational issues in the application of the KT for Aim 3 models, observations of ED visits were jittered by adding a small amount of random noise to create a pseudo-continuous variable, while observations of ED charges were log-transformed to reduce the disproportion between the scale of the outcome and that of the linear predictor.

All analysis was performed using R Studio version 1.1.456 (R Core team, 2015). Data manipulation was performed using standard R Studio base jitter and log transformation functions. Quantile regression models performed using the quantreg (Roger Koenker, 2019), and Qtools (Marco Geraci, 2019) packages.

3.6 LIMITATIONS AND METHODOLOGICAL CONSIDERATIONS

Health System Leakage

Charlotte, Mecklenburg County NC is serviced by EDs from two distinct healthcare systems, Atrium Health and Novant Health. This dissertation focused on data from the Atrium Health System and therefore did not include a comprehensive dataset for all ED utilization in the county. This limitation could introduce measurement error and misclassification bias due to health system leakage, which occurs when an individual utilizes healthcare services from both systems. Additionally, if an individual utilized primary care from both healthcare systems, measurement error will occur as an underestimation of the total number of visits to ambulatory or primary care. The latter is less likely due to the nature of ambulatory or primary care treatment and the tendency for individuals to have an established relationship with their providers.

According to several literature reviews, non-comprehensive datasets due to health system leakage are a common limitation in many studies utilizing single-system data sources (LaCalle & Rabin, 2010; Krieg, Hudon, Chouinard, & Dufour, 2016). The purpose of this work was to understand the healthcare utilization patterns of the uninsured and Medicaid populations and to have results that inform intervention efforts by single healthcare systems. Atrium Health serves a majority of the uninsured and Medicaid population in the Mecklenburg County, North Carolina and is the largest provider of healthcare in the state (Lubanski et al., 2017). Thus, the use of data from Atrium Health was an acceptable limitation.

ZCTAs as units of measurement

The neighborhood-level unit of measurement applied in this dissertation, ZCTAs, is larger than other options such as census tracts and block groups. In this dissertation, the dissimilarity index was calculated as a single aggregated measure for the county, and as the individual difference of proportions between ZCTAs. This method did not measure heterogeneity within the ZCTA and thus may have reduced the sensitivity of the analysis and/or attenuated the effect of residential segregation on the outcome. The unit of analysis in this dissertation was limited due to the data access issues with Atrium Health where patient identifiers smaller than ZCTA-level would require a full-board review that would cost more than the in-kind support provided by Atrium Health for this work.

NYU Algorithm vs. Ambulatory Care Sensitive Conditions (ACSC)

Ambulatory Care Sensitive Conditions (ACSCs) are an alternate metric for classifying ED utilization. ACSCs are conditions for which hospital admission could be prevented by interventions in primary care. These conditions use a specific set of acute and chronic diseases that do not require hospital admission including: i) acute exacerbations of chronic conditions that could have been avoided by adequate treatment, ii) acute conditions that could have been avoided managed in primary care, and iii) infectious disease that occurs despite immunization. Hospital admissions for ACSCs are used as an indicator of access to and quality of primary care, and as a quality measure for health care systems(Ansari, Laditka, & Laditka, 2006). The Agency for Healthcare Research and Quality defines ACSCs as a set of Prevention Quality Indicators based on 14 conditions for which hospital admission may often be prevented through improved ambulatory care (Agency for Healthcare Research and Quality, 2007; Agency for Healthcare Research and Quality, 2015).

Both methods have limitations that were considered for this dissertation. The NYU Algorithm was developed using the discharge diagnosis codes from a sample of approximately 6000 ED records that were reviewed by an expert panel and classified. The external validity of this method has been criticized as limited due to the single timepoint, geographic location, and healthcare system used in development (Latham & Ackroyd-Stolarz, 2017). Additionally, while the NYU algorithm has been validated using nationally representative data (Gandhi & Sabik, 2014) and Medicare payer data (Ballard et al., 2010) for single time point classifications, it may be less sensitive to detecting changes in ED usage patterns (Jones, Paxton, Hagtvedt, & Etchason, 2013).

The set of conditions that define an ACSC hospitalization are not consistent across studies, which reduces the comparability of research (Purdy, Griffin, Salisbury, & Sharp, 2009). In addition, the ACSC classification is used for inpatient ED visits (i.e. visits that resulted in a hospitalization), and does not classify outpatient care, or ED visits that are discharged without hospitalization. In most cases, individuals presenting to the ED are evaluated and subsequently discharged without hospitalizations (United States, 2013). Thus, the definition and classification of ACSC hospitalizations would only capture the proportion of ED visits that resulted in impatient care and exclude patients utilizing the ED for outpatient care. One study accounted for this by using the NYU Algorithm to classify the urgency of *outpatient* ED visits, and the AHRQ definition of ACSCs to classify the preventability *inpatient* ED visits resulting in hospitalization (Galarraga & Pines, 2016). The use of the NYU algorithm in this dissertation allowed for the classification of all ED discharge diagnosis codes, and for comparability with other key studies examining ED utilization (McWilliams et al., 2011; W. Chen et al., 2015; Lines et al., 2019; Powell M, Yu, Isehunwa, & Chang, 2016; Ruger, Richter, Spitznagel, & Lewis, 2004).

CHAPTER 4

Manuscript 1- Association of Healthcare Utilization and Residential Segregation Among an Underserved Emergency Department Population[1]

[1] Mayfield, CA, Hernandez, B, Geraci, M, Eberth, JM, Dulin, M, Merchant, AT. To be submitted to *Social Science and Medicine*.

ABSTRACT

Objective

To examine healthcare utilization among Emergency Department (ED) patients living in public health priority areas (PHPAs) and associations with residential segregation.

Design and Sample

A cross-sectional analysis of electronic health records, billing records, and estimates from the 2013-2017 American Community Survey. Data were extracted for 101,060 adults residing in Mecklenburg County, North Carolina who visited an ED within a large integrated healthcare system (Atrium Health) in 2017.

Methods

Healthcare utilization was measured as the total number of billed ambulatory or primary care (APC) visits, ED visits, and associated ED charges. Residential segregation was measured using the dissimilarity index. PHPAs were defined by the county Health Department as areas with disproportionately low educational attainment and high poverty. PHPA prevalence was estimated using a modified Poisson regression model and the associations between healthcare utilization and residential segregation were estimated using negative binomial (visits) and linear regression (cost) models with block bootstrap resampling.

Results

ED users were more likely to live in a PHPA if they were uninsured (PR: 1.56; 95% CI: 1.53 to 1.60), or Medicaid insured (PR: 1.55; 95% CI: 1.51 to 1.59) compared to those having private insurance, and be Black (PR: 2.35; 95% CI: 2.28 to 2.42) compared

to White after multivariable adjustment. Mecklenburg county is moderately segregated; with increasing relative proportions of Black residents associated with PHPAs (PR: 1.21; 95% CI: 1.21 to 1.22). Residential segregation was not associated with the average number of ED visits and was associated with the average number of APC visits (PR: 0.99; 95% CI: 0.98 to 0.99) during the study period. The relationships between residential segregation and not having any visits to APC in the past year, and average ED charges varied based on the race of the individual.

Conclusions

ED users who lived in a PHPA had lower rates of insurance coverage, lived in segregated communities, and were predominantly Black. Residential segregation is associated with APC utilization and ED charges, but not with ED visits.

INTRODUCTION

Emergency departments (EDs) serve as the primary safety net of the U.S. healthcare system. However, the EDs' function is to stabilize seriously ill or injured patients and meet the "last resort" routine care demands that are inaccessible from other parts of the healthcare system (Morganti et al., 2013). EDs have experienced an increasing burden of care relative to the larger healthcare ecosystem. Between 1996 and 2010, the number of ED visits in U.S. increased by 44%, resulting in almost half of hospital-associated medical care, defined as ED visits, outpatient visits, and hospital admissions, now occurring in the ED (Marcozzi et al., 2018). The ED safety net has expanded to serve an increasing proportion of medically underserved patients, particularly adults enrolled in Medicaid. ED utilization increased from 1997 to 2007 at a rate that was almost double what was expected from population growth (352.8 to 390.5 per 1000 persons) with the largest increase occurring among adults enrolled in Medicaid (693.9 to 947.2 visits per 1000 enrollees) (Tang et al., 2010). In 2010, the national cost of ED utilization was $328.1 billion, representing 12.5% of National Health Expenditure (Galarraga & Pines, 2016). Between 2010 and 2016, the nationally representative mean charges per ED visit increased by 56%, from $2,061 in 2010 to $3,516 in 2016 (Lane et al., 2019).

The position of the ED as the most accessible entry point into the healthcare system has made it an indicator of social disfunction within a community (E. S. Anderson et al., 2016). This occurs because the structural, economic, and social inequalities of a community manifest as health disparities that are directly observable in the ED. Residential segregation is a fundamental cause of racial disparities in health outcomes

(Williams & Collins, 2001). Residential segregation is associated with lower rates of health insurance coverage Black residents (K. F. Anderson & Fullerton, 2012) and access to a usual source of care (Caldwell et al., 2017). A meta-analysis found that residential segregation was associated with 20% higher odds of pre-term birth among Black residents when comparing the most segregated neighborhoods to least segregated neighborhoods (OR: 1.20; 95% CI: 1.05 to 1.37) (Mehra et al., 2017). Individuals living in neighborhoods with high racial and economic inequality have higher rates of preventable 30-day readmissions (H. F. Chen et al., 2017), preventable hospitalizations (Bocour & Tria, 2016), all-cause mortality (Warren Andersen et al., 2018), cancer-related mortality (Singh & Jemal, 2017), and heart, stroke, and cardiovascular disease-related mortality (Singh et al., 2015).

Only a few studies have examined the relationship between residential segregation and healthcare utilization, with only two using theoretically-driven metrics. The racial composition of a neighborhood (i.e. 50% or more Black residents) is associated with higher rates of ED utilization (Li et al., 2003), and lower odds of an office-based physician visit (OR: 0.44; $p = 0.001$), outpatient department physician visit (OR: 0.57; $p = 0.037$) or a nurse, physician assistant, or midwife visit (OR: 0.45; $p = 0.011$) among Black residents compared to White residents (Gaskin, Dinwiddie, Chan, & McCleary, 2012a). The geographic concentration of poverty theory operationalizes the negative effects of residential segregation as a function of the spatial concentration of poor minority populations (D. S. Massey & Denton, 1988). Massey and Denton derived several theoretically-driven methods to measure the spatial concentration of race groups, that include the dissimilarity index and isolation index (D. Massey et al., 1994; Douglas

S. Massey, 1990). One study found that increasing racial isolation at the county-level is associated with increased odds of asthma-related ED utilization among Medicaid-enrolled children with asthma (OR: 1.04; 95% CI: 1.01 to 1.08) (Baltrus et al., 2017). Another study found a significant interaction effect between race and residential segregation among adults with end stage renal disease. For each one-unit increase in the dissimilarity index score of a county, the odds of ED readmission among the Black population increased by 0.8 units. This relationship was protective among the White population where increasing dissimilarity index scores were associated with lower odds of ED readmission (Thomas-Hawkins, Flynn, Zha, & Savage, 2019).

The purpose of this study was to: (i) identify key demographic differences among ED patients living in public health priority areas (PHPAs), compared to the larger county (non-PHPAs) (ii) explore the distributions of healthcare utilization and examine heterogeneity between PHPA and non-PHPAs; and (iii) assess the extent to which residential segregation was associated with healthcare utilization. Results from this study can be applied to assessing the impact of future community-based initiatives designed to improve appropriate healthcare utilization.

METHODS

Design and Sample

The study design was a cross-sectional analysis during the project period of January 1st, 2017 to December 31st, 2017. Data for this study were obtained from three distinct sources: (i) Atrium Health Electronic Medical Records (EMR); (ii) Atrium Health billing records; and (iii) the US Census Bureau American Community Survey. The research protocol was reviewed and approved by the Institutional Review Board

(IRB) at Atrium Health and was considered exempt from IRB review by The University of South Carolina because of the use of de-identified secondary data.

Individual-Level Sample

The data were obtained from the Electronic Medical Records (EMRs) (Cerner Corporation, Kansas City KS) and billing records (Epic Systems Corporation, Verona WI) of individuals 18 years and older living in Mecklenburg County, North Carolina who visited an Atrium Health County ED between January 1, 2017 and December 31, 2017 (n=101,810). Records were identified for extraction by the ZIP code tabulation area (ZCTA) associated with the home address of the index visit (i.e. the first visit to the ED during the study period). ZCTAs are a generalized representation of the U.S. Postal Service ZIP code service areas, and are calculated as the most frequently occurring ZIP code in an area. A total of 721 patients who died during the project period were removed to reduce measurement error, along with 16 with unknown gender and 13 with extreme and potentially miscoded ages. The final individual-level analytic sample consisted of 101,060 patients (Figure 4.1). The following individual-level measures were created from this sample:

<u>Healthcare Utilization:</u> The total number of ED visits was calculated as the total billed unique ED encounters during the study period by individual. ED encounters were linked to an individual by the unique patient ID number in the Atrium Health system. The total associated charges for ED visits during the study period was calculated by individual. ED visits were identified in the Atrium Health Billing System using the unique encounter ID associated with each visit. Hospital charges represent the amount billed by the hospital and do not reflect the actual cost, out-of-pocket expenses, or

reimbursement for the visit, which varies based on the type of insurance coverage. ED charges were rounded to the nearest dollar for descriptive analysis and not for regression models.

Utilization of ambulatory or primary care (APC) was measured as the total number of unique encounters to Atrium Health care facilities defined in the EMR system under the specialty categories of: Allergy, Cardiovascular, Dermatology, Endocrinology, Family Medicine, Internal Medicine, Primary Care Behavioral Health, Rheumatology, Sleep Medicine, Sports Medicine, Urgent Care; and the following OBGYN specialty categories: Generalist, and OBGYN.

Insurance Coverage: The primary source of payment indicated for the index visit in the study sample was used as a proxy for insurance coverage during the study period using the following categories: Medicaid, Medicare, private, other, or uninsured. Medicare included both Advantage (commercial) and non-Advantage (public) members. Private represented all commercial insurance categories. The other insurance category included governmental insurance benefits (e.g. Veterans Affairs). For the purpose of this study, patients indicating “self-pay” were recoded to represent the uninsured.

PHPA Status: The Mecklenburg County Public Health Department identified the following six ZCTAs, with disproportionately low educational attainment and high proportion of the population living below the poverty threshold, as public health priority areas (PHPAs): 28217, 28208, 28216, 28206, 28205, and 28212. A binary variable (PHPA versus non-PHPA) was coded to indicate the PHPA status of each patient’s home address ZCTA.

Covariates: Covariates adjusted for at the individual-level were: gender, race, ethnicity, and age. Gender was measured as a categorical variable (male or female). Race (White, Black, and other or unknown) and ethnicity (Hispanic or Latino and non-Hispanic or Latino) were measured as separate categorical variables. Age was measured as a continuous variable for descriptive and regression models.

ZIP Code Tabulation Area (ZCTA) Sample

Data for the ZCTA estimates of demographic and population factors were downloaded from the American Community Survey (ACS), a population survey conducted annually by the U.S. Census Bureau. The 5-year (2013-2017) ACS estimates for all 27 Mecklenburg County ZCTAs were downloaded for this study. The 5-year estimates are more reliable, with a larger sample size and greater precision, compared to the 1-year estimates (United States Census Bureau, 2013). The population counts for following measures were extracted from the ACS: (i) total population; (ii) total Black or African American population alone or in combination with one or more other races; (iii) total number of people living below the federal poverty threshold; and (iv) total number of people with highest level of education as high school or GED equivalent, and bachelor's degree. The proportions of ACS estimates by PHPA and non-PHPA status groups were calculated and reported as percentages. The following ZCTA-level measures were calculated from ACS estimates:

Residential segregation: The dissimilarity index (Cutler et al., 1999) was used to measure residential segregation of Black and non-Black residents by ZCTA, relative to the larger county. In this context, dissimilarity represents the evenness of a population as the percentage of a race group that would have to change residence for each ZCTA to have the same proportions as the larger county. The dissimilarity index compares the relative proportion of Black residents in each ZCTA (i.e. number of Black residents in a ZCTA divided by the total number in the county) to the relative proportion of non-Black residents using the formula:

$$Dissimilarity\ Index = \frac{1}{2}\sum_{i=1}^{N} | \frac{B_i}{B_{total}} - \frac{B_i^c}{B_{total}^c} |$$

in which *B* is the number of Black residents in ZCTA *i*, and B_{total} is the number of Black residents in the county as a whole, B_i^c is number of non-Black residents in ZCTA *i*, and $B_{total}^c$is the number of non-Black residents in the county as a whole. The dissimilarity index ranges between 0 and 1 in which a value ≥ 0.6 indicate high, 0.3 to 0.6 indicates moderate, and ≤ 0.3 indicates low dissimilarities.

The dissimilarity index formula was adapted to measure the contribution of each ZCTA to the overall dissimilarity index score. The dissimilarity percentage was calculated as the difference between the relative proportions of Black and non-Black Residents for each ZCTA multiplied by 100 according to the formula:

$$Dissimilarity\ percentage = \left(\frac{B_i}{B_{total}} - \frac{B_i^c}{B_{total}^c}\right) * 100$$

in which *B* is the number of Black residents in ZCTA *i*, and B_{total} is the number of Black residents in the county as a whole, B_i^c is number of non-Black residents in ZCTA *i*, and $B_{total}^c$is the number of non-Black residents in the county as a whole. Patient ZCTAs in the individual-level sample were scored with dissimilarity percentage values calculated from the ZCTA-level sample.

Analysis

Individual-Level Models

The individual-level study population was analyzed using descriptive statistics in order to evaluate demographic differences between PHPA and non-PHPA status groups. A modified Poisson regression model with robust variance estimation was used to predict the prevalence ratio of PHPA status among insurance coverage and race groups, adjusting for gender, age, and ethnicity. Living in a PHPA was not a rare occurrence in the study population, therefore the odds ratio would overestimate the prevalence ratio (Barros & Hirakata, 2003). The use of robust standard errors accounted for violation of the Poisson distributional assumptions for a binary outcome (Zou, 2004).

To evaluate heterogeneity of the distribution of healthcare utilization measures, the average values (i.e. mid-percentiles) for the 5th, 25th, 50th, 75th, 95th, and 99th percentiles of each measure were assessed separately by PHPA status populations and for the total population. Percentiles of a distribution depict the value at which a specified percentage of the population is represented. For example, the 75th percentile is the value at which 25% of the population falls above and 75% falls below. The mid-percentile value for the 75th percentile represents the average value for the top 25% of the population. By comparing the mid-percentile values of healthcare utilization among residents living in PHPA and non-PHPAs to those of the total population, we could identify differences between the distributions.

The associations between dissimilarity percentage and APC visit and ED visit outcomes were assessed using negative binomial models to account for overdispersion (Rodriguez, 2013). Zero-truncated negative binomial models were used to model total

ED visits to account for the absence of zero responses. Data were collected from ED EMRs, and therefore all patients in the sample had a minimum of 1 ED visit. A zero-inflated negative binomial model was used to predict APC visits due to excessive zero responses (Zeileis et al., 2008). The association between dissimilarity percentage and ED charges was assessed using a linear regression model. Standard errors were estimated using block bootstrapping by ZCTA with 100 replications to account for correlation between patients. All models were adjusted for insurance type, gender, age, race, and ethnicity. To evaluate the extent to which race impacts the relationship between residential segregation and healthcare utilization metrics, an interaction term between dissimilarity percentage and race was included in the models. Interaction terms that were significant at the 5% level were included in the final models; non-significant interaction terms were excluded.

The residual deviance was used to perform a goodness of fit test on all Poisson regression models. If the residual difference between the current model and the maximum deviance of the ideal model where the predicted values are identical to the observed is small (i.e. the goodness-of-fit chi-squared test is not statistically significant), the model fits reasonably well. For negative binomial models, the significance of the overdispersion parameter was tested using Poisson regression models for comparison. All analysis was performed using R Studio version 1.1.456.

ZCTA-Level Models

The proportion of ACS demographic estimates was calculated for PHPA and non-PHPA ZCTAs to validate the selection criteria designated by the county health department. The relationship between residential segregation and PHPA status was evaluated using a modified univariate Poisson regression model with robust standard errors to predict PHPA status given the dissimilarity percentage of a ZCTA. Residential segregation was visualized as the dissimilarity percentage of each ZCTA using R package mapview (Appelhans et al., 2018).

RESULTS

Individual-Level Population and Characteristics

A total of 101,060 residents of Mecklenburg County ZCTAs visited an Atrium Health ED during 2017. PHPA residents make up approximately 33% (n = 33,709**)** of the ED patient population in this study, compared to 22% of the overall county population. Among the study population, a larger proportion of PHPA residents compared to non-PHPA residents did not have insurance coverage (36.3% versus 25.0%) or were insured through Medicaid (22.8% versus 14.7%). A smaller proportion of PHPA residents were privately insured (26.4% versus 42.0%) compared to non-PHPA residents. Approximately 60% of ED utilizers in both priority area groups were female. The average age of PHPA residents was 2.5 years younger (mean: 40.7; standard deviation [SD]: 16.0) than non-PHPA residents (mean: 43.2, SD: 18.1). A majority of ED utilizers were Black, with a larger proportion living in a PHPA compared to non-PHPA (70.6% versus 47.6%). Approximately 11% of ED utilizers in were Hispanic or Latino, (Table 4.1).

Results from regression analysis showed significant relationships between insurance coverage, race, and PHPA status. ED utilizers were more likely to live in a PHPA if they were uninsured (PR: 1.56; 95% CI: 1.53 to 1.60), or have Medicaid insurance (PR: 1.55; 95% CI: 1.51 to 1.59) compared to those having private insurance, after adjusting for gender, age, ethnicity, and race. ED utilizers were more likely to live in a PHPA if they were Black compared to if they were white (PR: 2.35; 95% CI: 2.28 to 2.42), after adjusting for insurance coverage, gender, age, and ethnicity, (Table 4.2).

Distribution of Healthcare Utilization

The estimated mid-percentile values, and average values of healthcare utilization by PHPA status groups are presented in Table 4.3. Results show heterogeneity between PHPA and non-PHPA groups. On average, PHPA residents have 0.8 fewer visits to APC compared to non-PHPA residents. When examining segments of the distribution of APC visits, the gap between PHPA status groups widens at increasing percentiles. For example, the mid-point value for the top 5% of APC visits, represented by the 95th percentile, is 7.6 among PHPA residents and 10.2 among non-PHPA residents, indicating 2.6 more APC visits in the non-PHPA population. Among the top 1% of APC visits, represented by the 99th percentile, the mid-point value is 4.2 visits higher compared to non-PHPA residents. The opposite trend is observed when examining ED visits and ED charges. PHPA residents on average had 0.3 more ED visits during the study period compared to non-PHPA residents. When comparing the top 5% and 1% of ED users, PHPA residents had 0.9 and 2 more visits than non-PHPA residents. On average, PHPA residents had $180 more in ED charges compared to non-PHPA residents overall. Among the top 1% and 5% of the ED charges distribution, PHPA residents have $1,284 and $3,890 more in ED charges compared to non-PHPA residents. A plot depicting estimated mid-percentile values of ED visits is presented in Figure 4.2.

ZCTA-Level Population Characteristics

According to estimates from the 2013-2017 ACS, PHPAs in Mecklenburg County, North Carolina were disproportionately Black (53.2 % versus 28.2%) and Hispanic or Latino (17.7% versus 11.8%) compared to non-PHPAs. A larger proportion of County residents living in PHPAs are below the Federal Poverty Threshold (15.0%) compared to non-PHPAs (7.7%). The proportion of residents with a high school or GED equivalent as their highest level of educational attainment is larger among PHPAs compared to non-PHPAs (15.9% versus 10.8%).

Residential Segregation and Healthcare Utilization

Mecklenburg County has a dissimilarity index score of 0.38 on a 0 to 1 scale, indicating a moderate level of segregation between Black and non-Black residents by ZCTA. The dissimilarity index compares the relative proportion of Black residents in each ZCTA (i.e. number of Black residents in a ZCTA divided by the total number in the county) to the relative proportion of non-Black residents. The index is calculated as the sum of the absolute value of the difference between the relative proportions of Black and non-Black residents in each ZCTA, divided by 2 to create a 0 to 1 index scale. A dissimilarity index score of 0.38 indicates an overall 38% difference between the relative proportions of Black and non-Black residents in Mecklenburg County ZCTA from the overall proportions in the county.

The dissimilarity percentages represent the contribution of each ZCTA to the overall index score, calculated as the difference between relative proportions in each ZCTA multiplied by 100. The dissimilarity percentages are visualized in Figure 4.2 by ZCTA. A positive value indicates a larger relative proportion of Black residents, and a negative value indicates a larger relative proportion of non-Black residents. The dissimilarity percentages range from approximately –7 to 7, indicating that at most, the relative proportion of Black residents is 7% higher than non-Black residents and at least, the relative proportion of non-Black residents is 7% higher than Black residents. A significant association was observed between the dissimilarity percentage of Mecklenburg's 27 ZCTAs and their PHPA statuses. Every unit increase in the dissimilarity percentage of a ZCTA, equivalent to a percentage point greater relative proportion of Black Residents, was associated with a 21% higher prevalence of PHPA (PR: 1.21; 95% CI: 1.21 to 1.22).

The final models assessing the relationship between residential segregation and healthcare utilization metrics are presented in Table 4.4. In Mecklenburg County, residential segregation was not significantly associated with ED visits on average (PR: 1.02; 95% CI: -1.01 to 1.04). However, among ED users, residential segregation was negatively associated the average number of visits to APC. For every unit increase in the dissimilarity percentage (i.e. percentage point increase in the relative proportion of Black residents) of a patient's ZCTA, the number of visits to APC on average decreased by 1% (PR: 0.99; 95% CI: 0.98 to 0.99). Since dissimilarity percentage is on a -7 to 7 scale from disproportionately non-Black to disproportionately Black, we can interpret the inverse of these relationships. For every 1 unit *decrease* in the dissimilarity percentage (i.e. percentage point increase in the relative proportion of *non-Black* residents), the number of visits to APC on average increased by 1%.

Residential segregation was also associated with ED charges and not having any visits to APC in the past year. These relationships varied based on the race of the individual. Living in a ZCTA with an increasing relative proportion of Black residents was associated with \$21 less in average ED charges among Black individuals (β-interaction = -88.15; p-interaction < 0.05), and with \$67 more in average ED Charges among White individuals ($p < 0.05$). This is equivalent to living in a ZCTA with an increasing relative proportion of non-Black residents being associated with \$21 *more* in average ED charges among Black individuals, and \$67 *less* in average ED Charges among White individuals. The likelihood of not having any visits to APC during the study period was positively associated with increasing Black residential segregation for both Black and White individuals, with a stronger relationship observed among White individuals. For every percentage point increase in the relative proportion of Black residents, the likelihood of not having any APC visits during the study period increased by 1% among Black individuals (PR: 1.01; p-interaction < 0.05), and increased by 6% among White individuals (PR: 1.06). This is equivalent to an association between a percentage point decrease in the relative proportion of *Black residents* and a 1% *decrease* in the likelihood of not having any visits to APC among Black individuals and a 6% *decrease* among White individuals.

DISCUSSION

The overarching purpose of this study was to explore the healthcare utilization of Atrium Health ED patients living in Mecklenburg County, highlight key differences among residents of PHPAs, and to evaluate relationships between residential segregation and healthcare utilization. Our results showed that ED users living in a PHPA had disproportionately worse access to insurance coverage, lower utilization of APC, and higher utilization of the ED compared to those living in a non-PHPA. In our study population, ED users who were Medicaid-insured or uninsured were over 50% more likely to be living in a PHPA when compared to privately-insured ED users, and adjusting for gender, age, race, and ethnicity. When comparing the mid-percentiles of healthcare utilization between PHPA and non-PHPAs, clear disparities were observed that increased in magnitude at higher percentiles. Among the top 5% of the APC visit distribution, PHPA residents had on average 2.6 fewer visits than non-PHPA residents. An opposite trend was observed among the top 5% of ED visit and ED charge distributions where PHPA residents had on average 0.9 more visits and $3,890 more in charges compared to non-PHPA residents.

The PHPAs in our sample were previously selected by the County Health Department as areas with disproportionately lower educational attainment and higher rates of poverty. Our assessment using the 2013-2017 ACS estimates validated this selection criteria. PHPAs had larger proportions of residents below the Federal Poverty Threshold (15.0% vs. 7.7%) and with high school or GED equivalent as their highest level of educational attainment (15.9% versus 10.8%) compared to non-PHPAs. In our individual-level study population, representing ED users, PHPA residents were disproportionally represented (33%) compared to the overall county population (22%). While our study did not examine patient-level income or educational attainment, the representation of our sample is consistent with the other studies showing that living in a census track with higher poverty is associated with increased odds of any ED utilization (Lines et al., 2017) and low educational attainment is associated with increased risk of unplanned healthcare utilization (Jonassaint et al., 2016).

Our results showed that Mecklenburg county ZCTAs are moderately segregated, and that an increasing relative proportion of Black residents was associated with a 21% increase in the likelihood of a ZCTA being a PHPA. Among our sample of ED users, the average number of ED visits was not associated with residential segregation. These finding were in contrast to other studies that found significant positive associations between residential segregation and ED visits. These differences may be explained by important distinctions in the study population and measurement of ED visits. One study found a significant positive association between residential segregation and the odds of any ED visit among children with asthma that were enrolled in Medicaid (Baltrus et al., 2017). This study obtained data from a Medicaid-enrollment database and researchers were able to compare those without ED visits to those with any ED visit during the study period. Another study examining adults from an ED sample found a significant association between residential segregation and readmissions to the ED (Thomas-Hawkins et al., 2019). Our study, by comparison, examined the average number of ED visits among an adult, ED sample. The focus on a Medicaid-enrolled, health risk specific population and/or measuring readmission among our ED sample may have allowed for a more sensitive evaluation.

We found a significant negative association between residential segregation and average APC visits among our sample of ED users, where an increasing relative proportion of Black residents was associated with decreasing APC visits on average. These results controlled for differences in insurance status along with age, gender, and ethnicity. Additionally, we found that the relationship between residential segregation and having any APC visits during the study period was stronger among White residents than Black residents. Prior work exploring the relationship between residential segregation and healthcare utilization supports these results. A study examining data from the 2006 Medical Expenditure Panel Survey and the 2000 Decennial Census found that Black individuals living in predominantly White ZIP codes (> 50% proportion of White residents) or predominantly Black ZIP codes, were less likely to have a physician visit in the past year compared to White individuals living in predominantly White ZIP codes (Gaskin et al., 2012a). Another study examined data from the Exploring Health Disparities in Integrated Community (EHDIC) project in Baltimore, Maryland, an ongoing multisite study with a racially and economically integrated community. Among the EHDIC sample (racially integrated), Black individuals were more likely to have visited a healthcare provider in the past year compared to White individuals, whereas the nationally representative sample (non-racially integrated) showed an opposite relationship. Researchers concluded that residential segregation may be a confounding factor for racial disparities in healthcare utilization (Gaskin et al., 2009). These relationships could be explained through disparities in environmental healthcare access factors such as the spatial concentration of primary care physicians (Gaskin, Dinwiddie, Chan, & McCleary, 2012b), healthcare facilities (Dai, 2010), and physicians accepting Medicaid insurance (Greene, Blustein, & Weitzman, 2006).

Our results also showed that the direction of the relationship between residential segregation and ED charges varied based on the race of the individual. In our study sample, living in a ZCTA with an increasing relative proportion of Black residents was associated with lower average ED charges among Black individuals and higher average ED charges among White individuals. This finding could be explained by differences in the severity of ED visit based on race. Our results showed that Mecklenburg County PHPAs are racially segregated, and results from the 2017-2018 Community Health Assessment show that these areas also have disproportionately higher prevalence of chronic health conditions including: high blood pressure (42.0% vs. 30.1%), high cholesterol (36.3% vs. 30.2%), diabetes (15.8% vs. 9.6%), and cardiovascular disease (11.5% vs. 7.5%) compared to non-PHPAs. Prior research has also indicated that Black individuals overall may be more likely to use the ED as their usual source of care (Gaskin et al., 2007), (Arnett et al., 2016). Therefore, Black individuals in our sample, living in areas that are disproportionately Black may be more likely to use the ED for lower-cost ambulatory or primary care services relative to White individuals living in the same areas that are using the ED for more severe, higher-cost health conditions. Alternatively, racial health disparities could be influenced by the implicit racial bias of physicians (Chapman & Carnes 2013). Studies have demonstrated that Black patients receive less pain medication (Burgess et al., 2008), and differential treatment for myocardial infarction (Green et al., 2007) compared to their white counterparts. Our results could be an indication that Black patients living in Mecklenburg County PHPAs have lower ED charges because they are receiving different, and less expensive healthcare relative to their White counterparts.

These results should be considered with respect to several limitations. Our sample only included data from Atrium Health and therefore does not represent a comprehensive sample of all ED utilization in Mecklenburg county. While Atrium health does serve a majority of Mecklenburg County residents, and the largest proportion of uninsured and underinsured in the area, this limitation could introduce measurement error and misclassification for healthcare utilization. ZCTAs are a large geographic unit of measurement compared to other units, such as census tracts and block groups. Our method of calculating residential segregation does not measure heterogeneity within a ZCTA and thus may reduce sensitivity in the analysis and attenuate the results. Other studies have assessed residential segregation as block groups within counties, which also allows for the measurement of other residential segregation indices such as the isolation index. Lastly, the 1-year, cross-sectional study design did not establish temporal, causal association between variables. A multi-year application of this strategy would allow for a longitudinal assessment of the causal relationship between specific mechanisms intervention mechanisms in healthcare utilization patterns.

CONCLUSIONS

Despite these limitations, our results highlight important insurance access and healthcare utilization disparities in Mecklenburg County, NC that can be used to inform interventions in the local community, and as a model for the evaluation of healthcare utilization patterns in similar communities. A widely-cited study by Chetty and colleagues concerning the economic mobility of low-income families ranked Mecklenburg County, NC at the bottom of intergenerational mobility (50^{th} out of 50 major metropolitan areas). Areas with the highest odds of economic mobility also had the lowest rates of segregation between Black and White residents (Chetty et al., 2014). Healthcare systems participating in community outreach initiatives are uniquely positioned at the intersection of care delivery and prevention. The PHPAs of Mecklenburg County are the focus of an innovative collaborative effort to address community health disparities and economic mobility, in part through improving access to and utilization of preventive healthcare. This partnership, the One Charlotte Health Alliance (OCHA), includes the Atrium Health and the Mecklenburg County Health Department (Cole, 2017). Community-based efforts to improve appropriate ED utilization patterns should include PC and community-level social factors in their evaluation strategies.

Table 4.1. Individual-Level Characteristics by Public Health Priority Area (PHPA) Status (n = 101,060)

Characteristic	PHPA No. (%)	Non-PHPA No. (%)	Total No. (%)
Total Population	33,709 (33.36)	67,351 (66.64)	101,060 (100)
Insurance Type			
Medicaid	7,677 (22.77)	9,880 (14.67)	17,557 (17.37)
Medicare	4,488 (13.31)	11,333 (16.83)	15,821 (15.66)
Private	8,912 (26.44)	28,278 (41.99)	37,190 (36.80)
Other	409 (1.21)	1,014 (1.51)	1,423 (1.41)
Uninsured	12,223 (36.26)	16,846 (25.01)	29,069 (28.76)
Gender			
Female	19,268 (57.16)	39,424 (58.54)	58,692 (58.08)
Male	14,441 (42.84)	27,927 (41.46)	42,368 (41.92)
Age			
Mean (SD)	40.72 (15.96)	43.20 (18.09)	42.38 (17.44)
Race			
White	4,490 (13.32)	22,742 (33.77)	27,232 (26.95)
Black	23,793 (70.58)	32,044 (47.58)	55,837 (55.25)
Other or Unknown	5,426 (16.10)	12,565 (18.66)	17,991 (17.80)
Ethnicity			
Non-Hispanic or Latino	27,18 (80.63)	52,666 (78.20)	79,847(79.01)
Hispanic or Latino	3,865 (11.47)	7,674 (11.39)	11,539(11.42)
Declined or Unknown	2,663 (7.90)	7,011 (10.41)	9,674 (9.57)

Note: PHPA, public health priority areas selected by the county health department as areas with disproportionately low educational attainment and high poverty; SD, Standard Deviation

Table 4.2. Prevalence of Public Health Priority Area (PHPA) Status Among Insurance and Race Groups

Characteristic	PR	95% CI
Insurance Type		
Medicaid	1.55	1.51 to 1.59
Medicare	1.22	1.18 to 1.27
Other	1.15	1.06 to 1.25
Uninsured	1.56	1.53 to 1.60
Private (ref)	--	--
Race		
Black	2.35	2.28 to 2.42
Other or Unknown	1.49	1.42 to 1.56
White (ref)	--	--

Note: PHPA, public health priority areas selected by the county health department as areas with disproportionately low educational attainment and high poverty; PR, Prevalence Ratio; CI, Confidence Interval; Model adjusted for gender, age, and ethnicity; Estimates calculated using Poisson regression with robust standard errors.

Table 4.3. Estimated Mid-Percentiles of Healthcare Utilization by Public Health Priority Area (PHPA) Status

Measure	Population	5th	25th	50th	75th	95th	99th	Mean
APC Visits	PHPA	0	0	0.35	0.98	7.63	15.69	1.30
	Non-PHPA	0	0	0.54	2.54	10.24	19.85	2.05
	All	0	0	0.47	1.96	9.47	18.82	1.80
ED Visits	PHPA	1	1	1.45	2.18	4.90	9.50	1.87
	Non-PHPA	1	1	1.34	1.90	4.03	7.52	1.61
	All	1	1	1.37	1.96	4.38	8.16	1.69
ED Charges	PHPA	1,241	2,203	4,132	8,071	19,171	37,074	6,520
	Non-PHPA	1,238	2,302	4,317	8,142	17,887	33,184	6,340
	All	1,242	2,238	4,272	8,119	18,397	34,631	6,400

Note: PHPA, public health priority areas selected by the county health department as areas with disproportionately low educational attainment and high poverty; ED, Emergency Department; APC, Ambulatory or Primary Care; Data were collected from ED records, and therefore all patients in the sample had a minimum of 1 ED visit and a minimum charge > $0.

Table 4.4. Associations Between Residential Segregation and Healthcare Utilization

Measure	Estimate	SE	PR	95% CI	p value
ED Visits	0.016	0.52	1.02	-1.01 to 1.04	0.98
PC Visits	-0.0108	0.0036	0.99	0.98 to 0.99	0.0031
*Zero PC Visits	0.054	0.015	1.06	1.02 to 1.09	<.001
Dissimilarity: Black	-0.040	0.016	0.96	0.93 to 0.99	.0011
Dissimilarity: White (ref)	--	--	--	--	--
*ED Charges	66.80	22.77	--	22.18 to 111.44	0.0033
Dissimilarity: Black	-88.15	28.69	--	-144.39 to -31.91	0.0021
Dissimilarity: White (ref)	--	--	--	--	--

Note: SE, Standard Error; PR, Prevalence Ratio; CI, Confidence Interval; PC, Primary Care; ED, Emergency Department; Models adjusted for insurance type, gender, age, race, and ethnicity.
ED visits modeled using zero-truncated negative binomial; PC visits modeled using zero-inflated negative binomial: ED Charges modeled using linear regression;
*Final models included an interaction term between dissimilarity percentage and race
Residential Segregation measured as the dissimilarity percentage where *B* is the number of Black residents in ZIP code tabulation area (ZCTA) *i*, and B_{total} is the number of Black residents in the County as a whole, B_i^c is number of non-Black residents in ZCTA *i*, and $B_{total}^c$is the number of non-Black residents in the County as a whole using the following formula:

$$dissimilarity\ percentage = \left(\frac{B_i}{B_{total}} - \frac{B_i^c}{B_{total}^c}\right) * 100$$

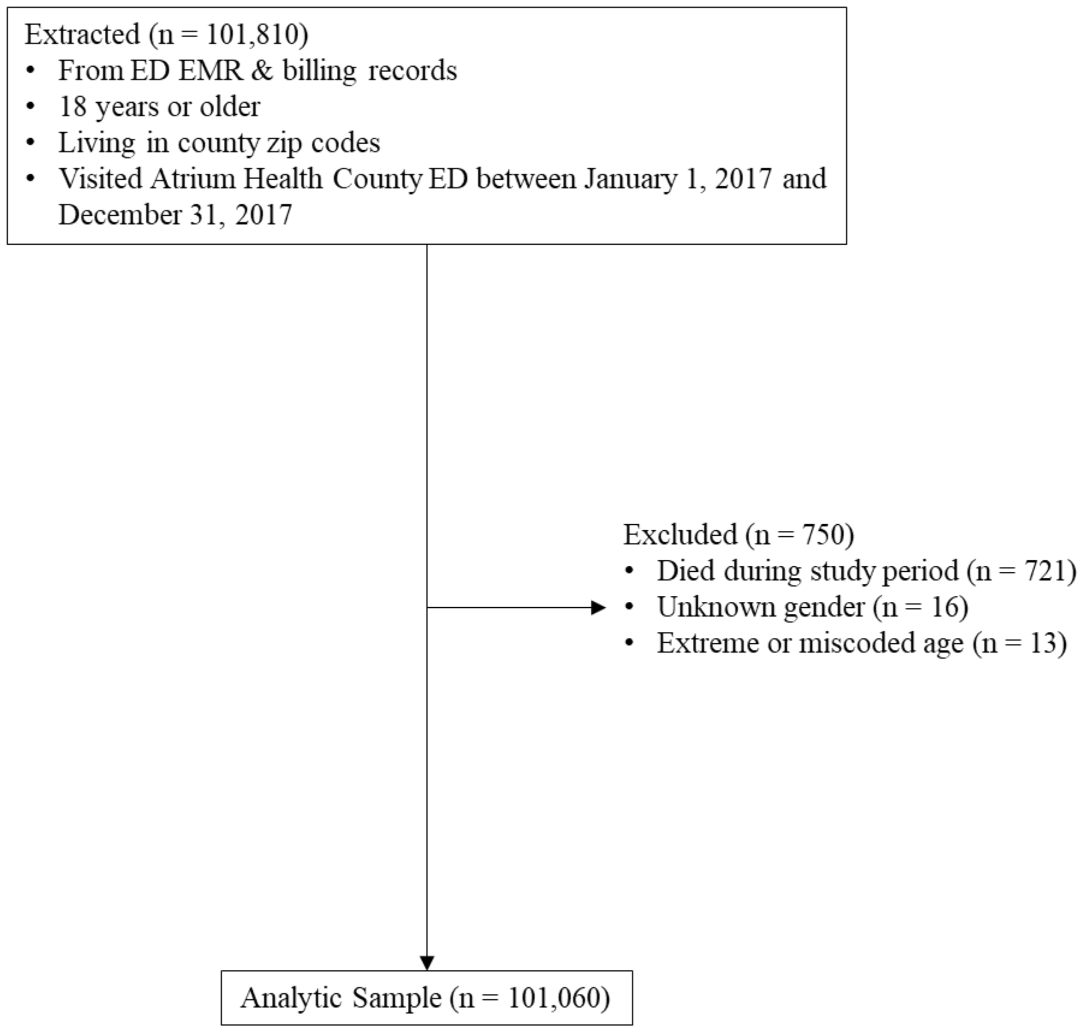

Figure 4.1. Analytic Sample Flow Diagram; ED, Emergency Department; EMR, Electronic Medical Record

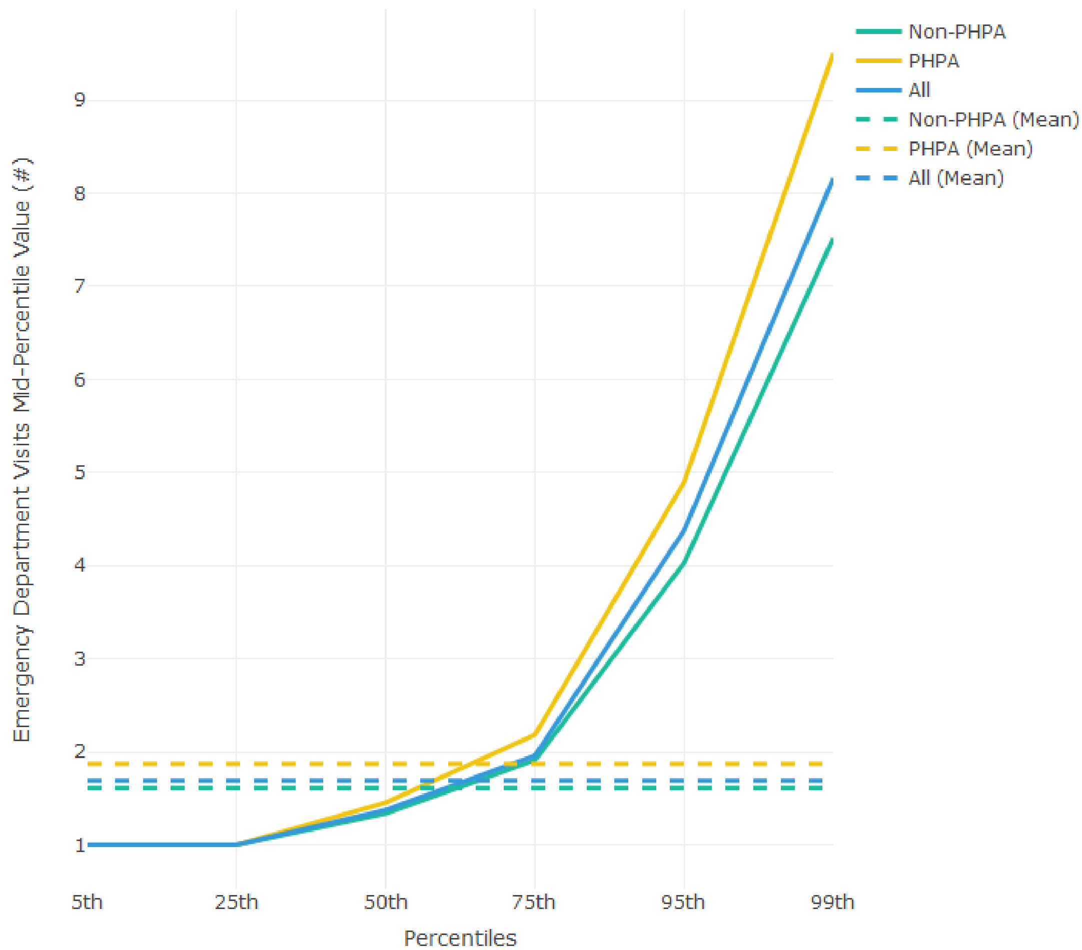

Figure 4.2. Mid-Percentiles of Emergency Department (ED) Visits by Public Health Priory Area (PHPA) Status; Data were collected from ED records, and therefore all patients in the sample had a minimum of 1 ED visit.

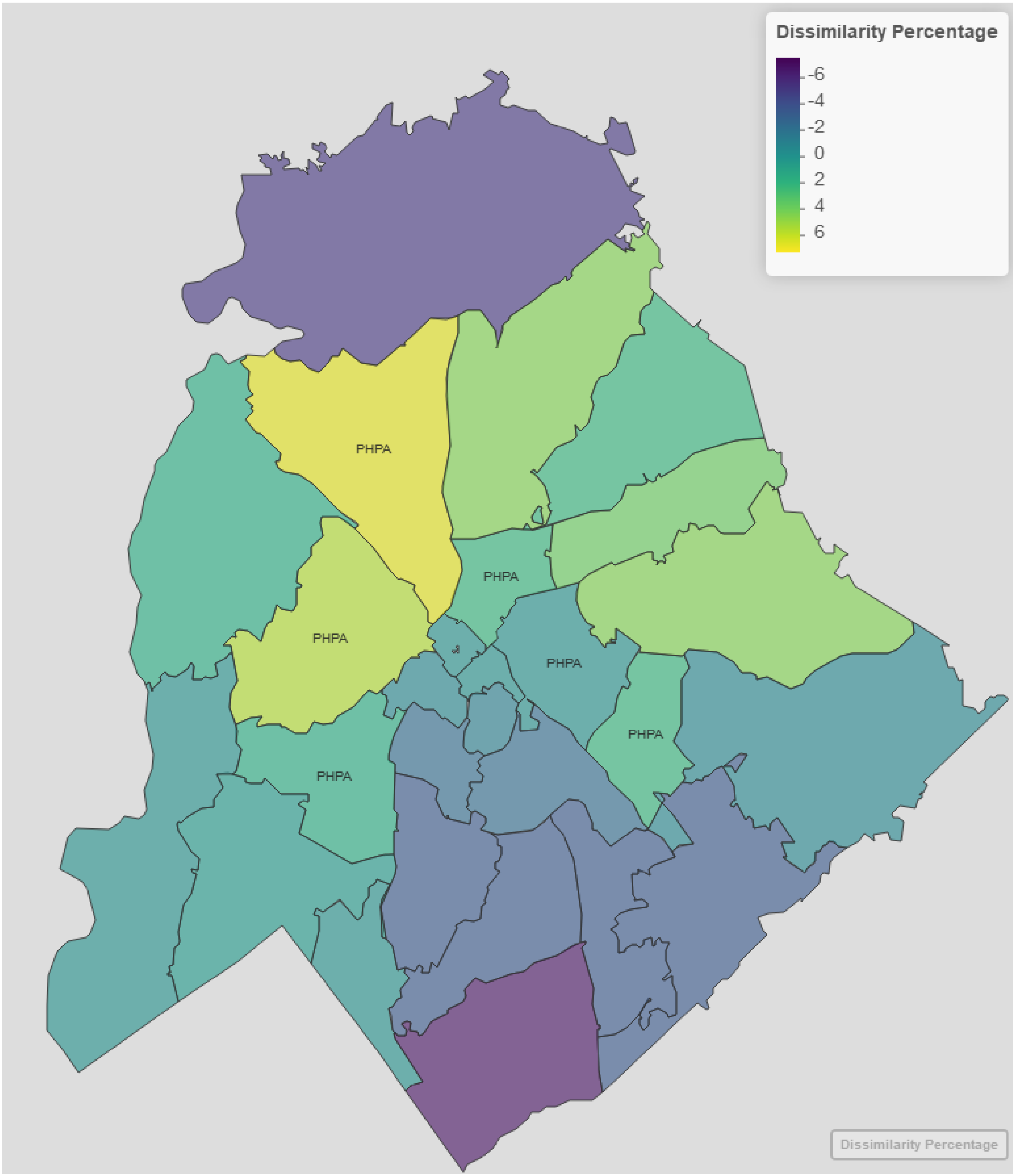

Figure 4.3. Residential Segregation by ZIP Code Tabulation Area (ZCTA) (n = 27); Residential Segregation measured as the dissimilarity percentage where B is the number of Black residents in ZIP code tabulation area (ZCTA) i, and B_{total} is the number of Black residents in the County as a whole, B_i^c is number of non-Black residents in ZCTA i, and B_{total}^c is the number of non-Black residents in the County as a whole using the following formula:

$$dissimilarity\ percentage = \left(\frac{B_i}{B_{total}} - \frac{B_i^c}{B_{total}^c}\right) * 100$$

CHAPTER 5

Manuscript 2- Association of Ambulatory or Primary Care Visits, Insurance, and Avoidable Utilization Among a North Carolina Emergency Department Sample[2]

[2] Mayfield, CA, Geraci, M, Eberth, JM, Hernandez, B, Dulin, M, Merchant, AT. To be submitted to *The Journal of Emergency Medicine*.

ABSTRACT

Objective

To examine associations between ambulatory or primary care (APC) utilization, insurance coverage, and avoidable utilization of the emergency department (ED), and the degree to which the relationship varies by insurance coverage.

Design and Sample

A cross-sectional analysis of electronic health and billing records. Data were extracted for 70,870 adults residing in Mecklenburg County, North Carolina who visited an ED within a large integrated healthcare system (Atrium Health) in 2017, with an ED visit that was classified using the New York University (NYU) Algorithm.

Methods

APC utilization was measured as total number of billed visits, categorized as: 0, 1, and >1. Insurance was measured as the method of payment for the index ED visit as: Medicaid, Medicare, private, or uninsured. Avoidable ED utilization was measured as a score, calculated as the sum of NYU Algorithm probabilities during the study period multiplied by 100. Quantile regression models were used to predict the 25th, 50th, 75th 95th and 99th percentiles of avoidable ED score with APC visits and insurance as predictors (Model 1) and with an interaction term (Model 2).

Results

Having > 1 APC visit was negatively associated with avoidable ED score at the 25th percentile ($\beta = -2.5$; $p \leq .001$) and positively associated at the 75th ($\beta = 5.4$; $p \leq .001$), 95th ($\beta = 32.7$; $p \leq .001$) and 99th ($\beta = 61.2$; $p \leq .001$) percentiles. Higher avoidable ED score was associated with having Medicaid insurance and lower avoidable ED score was

associated with and having private insurance, compared to being uninsured, across quantiles of the distribution. In stratified models, having > 1 APC visit was negatively associated with higher ED scores at the 25^{th} percentile of uninsured and privately insured distributions, and positively associated at the 95^{th} and 99^{th} percentiles among the uninsured, Medicaid-insured, and privately-insured distributions.

Conclusions

The association between APC utilization and avoidable ED utilization varied based on segments of the distribution and was significantly different among insurance stratum.

INTRODUCTION

Avoidable utilization of the Emergency Department (ED) occurs when individuals seek treatment for nonurgent conditions, for which a delay of several hours to several days would not increase the likelihood of an adverse outcome. If a patient could have received treatment in primary care or urgent care settings, an ED visit is a waste of resources that lowers health system efficiency and raises the cost of healthcare (Enard & Ganelin, 2013). Approximately 13 to 27% of all ED visits in the U.S. are avoidable, with an estimated annual cost of $4.4 billion (Weinick et al., 2010). In the Canadian National Healthcare System, 83% of all ED visits are discharged home and not admitted to a hospital bed, and of those approximately 20% were deemed avoidable with an estimated annual cost of over $200 million (Canadian Institute for Health Information, 2014). In the U.S., charges for nonurgent care are 320 to 728% higher in the ED compared to primary care clinics, resulting in a potential savings of 69 to 86% had the patient been treated in primary care (McWilliams et al., 2011). Using the ED for nonurgent treatment can result in poor quality of care as a consequence of overcrowding, increased wait time, and a lack of follow-up and care continuity (Moskop et al., 2009; Khangura et al., 2012).

Avoidable ED utilization is disproportionate among subgroups of race/ethnicity, insurance, and socioeconomic status (Johnson et al., 2012), and could be an indicator of poor quality and inadequate access to healthcare (Dowd et al., 2014). Poor availability and quality of medical care is associated with increased disease severity (Eachus et al., 1999; Weissman et al., 1991) and mortality (Sommers et al., 2012) among disadvantaged groups. Preventive healthcare is delivered in both primary care and ambulatory healthcare settings (Silverstein et al., 2008) and includes services such as cancer screenings, annual wellness exams, and vaccinations that can prevent and reduce the severity of many chronic diseases and health conditions (Shi, 2012). Individuals experiencing social, economic and environmental health risk factors are less likely to use preventive healthcare (Ross et al., 2007) and are more likely to experience severe chronic disease that contributes to clustering of health risk (Cockerham et al., 2017).

Many efforts and policy recommendations are supported by the assumption that improving access to preventive healthcare through insurance coverage will reduce avoidable ED utilization (Enard & Ganelin, 2013; Seaberg et al., 2017; Natale-Pereira et al., 2011; Peart et al., 2018). However, studies show that the relationship between insurance coverage and avoidable ED utilization is complex and varies based on many socio-demographic factors, including the type of insurance coverage (Johnson et al., 2012) and quality of care (Vasilevskis et al., 2017). Individuals without insurance are more likely to use the ED for nonurgent or primary care treatable conditions when compared to those with private insurance, yet are less likely when compared to those with public insurance (i.e. Medicaid or other forms of state-subsidized insurance coverage)(W. Chen, Waters, & Chang, 2015). Avoidable ED utilization occurs at higher rates among minority and Medicaid-insured patients and lower rates among Medicare-insured patients (McWilliams et al., 2011). Avoidable ED utilization has increased over time among some insurance groups. Between 1997 and 2009, the average probability of ED visits for primary-care treatable conditions increased significantly for Medicaid-insured visits (0.25% per year, 95% CI: 0.13% to 0.37%) and Medicare-insured visits (0.52% per year, 95% CI: 0.38% to 0.65%) in a nationally representative sample, with no significant change observed among privately insured or uninsured visits (Pukurdpol, Wiler, Hsia, & Ginde, 2014).

The purpose of this study was to assess i) the relationship between visits to ambulatory or primary care (ACP), type of insurance coverage, and avoidable ED utilization; and ii) the degree to which the relationship between ACP visits and avoidable ED utilization varied by type of insurance coverage.

METHODS

Study Population

The data for this cross-sectional analysis were obtained from the Electronic Medical Records (EMRs) (Cerner Corporation, Kansas City KS) and billing records (Epic Systems Corporation, Verona WI) of individuals 18 years and older living in selected county zip code tabulation areas (ZCTAs) in the Charlotte Mecklenburg area who visited an Atrium Health County ED between January 1, 2017 and December 31, 2017 (n=101,810). After excluding individuals visiting the ED for injuries, mental health issues, alcohol and drug use related visits, or those that could not be classified (n = 29,710), those who died during the study period (n = 721), had unknown gender (n = 3) or had extreme and potentially miscoded ages (n = 3) were also excluded. Less than 1% of the study population were covered through insurance classified as “other”, including governmental insurance benefits (e.g. Veterans Affairs) and other program-specific options that did not conceptually align with larger insurance categories. The sample size of individuals with “other” insurance was too small to produce regression model estimates as a stand-alone group, and was subsequently excluded (n = 693), resulting in a final analytic sample consisting of 70,870 patients (Figure 5.1). The research protocol was reviewed and approved by the Institutional Review Board (IRB) at Atrium Health and was exempt from IRB review by The University of South Carolina because of the use of de-identified secondary data.

Measures

Exposure: Ambulatory or Primary Care Visits (APC); Utilization of ambulatory or primary care (APC) was measured as the total number of unique encounters to Atrium Health care facilities defined in the EMR system under the specialty categories of: Allergy, Cardiovascular, Dermatology, Endocrinology, Family Medicine, Internal Medicine, Primary Care Behavioral Health, Rheumatology, Sleep Medicine, Sports Medicine, Urgent Care; and the following OBGYN specialty categories: Generalist, and OBGYN. The total number of APC visits was categorized as: 0 visits, 1 visit, and > 1 visit for analysis.

Exposure: Insurance Coverage; The primary source of payment indicated for the index visit (i.e. the first visit to the ED during the study period) was used as a proxy for insurance coverage during the study period using the following categories: Medicaid, Medicare, private, or uninsured. Medicare included both Advantage (commercial) and non-Advantage (public) members. Private represented all commercial insurance categories. For the purpose of this study, patients indicating "self-pay" were recoded to represent the uninsured.

Outcome: Avoidable ED Score; The score of avoidable ED utilization for each individual was calculated using the sum of probabilities for The New York University Emergency Department algorithm (NYU ED Algorithm) categories 1-3 across all visits during the study period. The NYU Algorithm is a validated classification system used to measure the urgency of an ED visit using 9 distinct categories of probability (Ballard et al., 2010). The first 4 categories of the NYU Algorithm are used to classify the probability of an ED visit being: 1) non-emergent, 2) emergent, primary care treatable, 3) emergent, preventable or avoidable, and 4) emergent, not preventable or avoidable. In categories 1-4, a probability between 0 and 1 is estimated by the algorithm based on the primary diagnosis code for each ED visit. The sum total of all 1-4 categories equals 1. If the primary diagnosis code aligns with an injury, mental health, alcohol, drug-related diagnoses, or is unclassified, the remaining categories 5-9 will be populated as either a 0 or 1, and are treated as mutually exclusive probabilities. Therefore, ED visits for which the urgency is calculated (categories 1-4), exclude visits that are injury, mental health, alcohol, drug-related or are unclassified (categories 5-9).

This method was used and described by prior research and with the following example: suppose an individual has 3 ED visits during a 12-month study period with 2 visits for heart palpitations and 1 visit for chest pain. The probability of avoidable ED utilization for each visit is 0.61, 0.61, and 0.44, respectively. Therefore, the patient's total score of avoidable ED utilization for the study period is 1.49 (Lines et al., 2017). To improve the interpretation of model estimates, the total score of avoidable ED utilization was multiplied by 100. In this context, an avoidable ED score value of 100 is equivalent to 1 ED visit that was deemed 100% avoidable, or 2 visits that were 60% avoidable and 40% avoidable during the study period.

<u>Other Covariates</u>: Other covariates adjusted for were: gender, race, ethnicity, and age. Gender was measured as a categorical variable (Male or Female). Race (White, Black, other or unknown) and Ethnicity (Hispanic or Latino, non-Hispanic or Latino,

other or unknown) were measured as separate categorical variables. Age was measured as a continuous variable for descriptive and regression models. The local county public health department identified six public health priority area (PHPA) ZCTAs selected based upon disproportionately low educational attainment and high percent of the population living below the poverty threshold. The PHPA status of a patient's ZCTA was included as a binary variable (PHPA vs. non-PHPA) to adjust for social and environmental factors associated with healthcare access and utilization.

Analysis

The study population was assessed using descriptive statistics to evaluate the population characteristics by levels of primary care visit categories. The distribution of the outcome metric, avoidable ED score, was evaluated using box plots, histograms, and unconditional quantile-based location, scale, and shape measures. A box plot of avoidable ED score, conditional on levels of PC visit categories was presented on the log scale due to extreme outliers.

Quantile regression (QR) is a statistical method to assess the strength and direction of the effect of an exposure on specific quantiles (e.g., the median) of a dependent variable (i.e. outcome). It is particularly useful when the effects of the exposure (or independent variable) are heterogeneous across the quantiles of the outcome. In contrast, mean regression focuses on only one value of the outcome, the mean, thus providing a partial picture of the effects. QR is nonparametric and does not have distributional assumptions. Other advantages of QR include robustness of the results to outliers in the outcome and robustness to different shapes of the error distribution (e.g., skewed or heavy-tailed) (Yu, Lu, & Stander, 2003). A conditional QR (R Koenker, 2005) estimates the effect of a change in the independent variable in the *conditional* (i.e., for sub-populations) on quantiles of the outcomes. This is most useful to answer the question "what is the difference between the 75^{th} percentile of the outcome in those exposed to the independent variable compared to those not exposed?".

In this study, QR models were used to evaluate the relationship between APC visits, insurance coverage, and avoidable ED score at the 25^{th}, 50^{th}, 75^{th}, 95^{th} and 99^{th} percentiles of the outcome distribution with using a linear programming (Frisch-Newton) method. Confidence intervals and standard errors were computed using bootstrap resampling, with 100 replications. The location-shift hypothesis was evaluated using a Khmaladze Test, which tests the null hypothesis that the slopes of the regression models at each quantile are all the same. The goodness of fit was evaluated using the cusum test based on the gradient vector process (He and Zhu, 2013) which obtains a critical value for significance test using resampling. Model 1 included insurance coverage and APC visits as predictors, and adjusted for gender, age, race, ethnicity, and PHPA status. Model 2 included an additional interaction term between APC visits and insurance coverage. Linear regression models were used for comparison of the estimated means. All analysis was performed using R Studio version 1.1.456 (R Core team, 2015), with quantile regression models performed using the quantreg (Roger Koenker, 2019), and Qtools (Marco Geraci, 2019) packages.

RESULTS

Population Characteristics

Of the 70,870 individuals in the study population approximately 70.8% (n = 50,200) had some form of insurance coverage, while the remaining 29.2% (n = 20,670) were uninsured. A majority were privately insured (36.0%) followed by Medicaid (19.3%), and Medicare (15.5%) insurance types. The characteristics of participants are presented in Table 5.1, separately by APC visit categories. Not visiting having an APC in the last year visit varied by insurance status (36.7% for uninsured versus 28.2% for those with private insurance), gender (55.8% for Females), race (62.9% for Black versus 19.1% for White) ethnicity (79.5% for non-Hispanic or Latino versus 12.2% for Hispanic or Latino) and living in a PHPA (38.2% versus 61.9%). The average age of individuals with more than 1 APC visit was approximately 8 years older (mean: 48.7, SD: 17.8) than for those with 1 visit (mean: 40.8, SD: 15.2) and no visits (mean: 39.6; SD: 16.1).

Distribution of Avoidable ED Score

The values of avoidable ED score range from a minimum of 0 to a maximum of 4,551.8, with a median at approximately 100. The interquartile range (IQR), the range of the middle 50% of the distribution, is 51.3. A histogram of avoidable ED score shows a unimodal distribution, with an extreme right skewness. At the 10th centile, the skewness index is approximately 0.3, which indicates a strong right asymmetry (i.e. extreme observations in the right side of the distribution). The shape index is 3.4 indicating that the tails of the distribution are heavier compared to a normal distribution value of 1.9, meaning that more observations are at the extreme ends of the distribution than compared to that of a normal distribution. The conditional box plot of avoidable ED score is presented in Figure 5.2 by APC visit categories. The distributions of the APC visit categories are heterogeneous, and the most extreme outliers were observed among those without any APC visits during the study period.

Quantiles of Avoidable ED Score

The unconditional quantiles of avoidable ED score are presented in Table 5.2, separately by APC visit categories and for the total population. Clear differences were observed between the stratified populations and the total population for all quantiles except for the 95^{th}. For example, at the 25^{th} quantile, the avoidable ED score reduced with increasing number of APC visits (67.0 for >1 APC visits, 72.9 for 1 APC visit, and 84.4 for 0 APC visits). This trend was consistent across the 50^{th}, 75^{th} and 99^{th} centiles. On average, the avoidable ED score among those with > 1 APC visits is smallest (mean: 120.6), followed by the 1 visit (mean: 125.0) and 0 visit (mean: 126.5) populations.

Results from Model 1 are presented in Table 5.3. At the 25^{th} percentile, having an APC visit during the study period was negatively associated with avoidable ED score. Individuals with more than 1 APC visit ($\beta = -2.5$; $p \leq 0.001$) or 1 APC visit ($\beta = -1.7$; $p < 0.05$) had a lower avoidable ED score compared to those without any APC visits during the study period. Among those in the 75^{th} percentile, the association between APC visits and avoidable ED score was positive for >1 APC visit ($\beta = 5.4$; $p \leq 0.001$) and 1 APC visit ($\beta = 4.5$; $p \leq 0.01$) categories compared to those without any APC visits. A similar trend was observed at the 95^{th} percentile. Among the top 1% of the distribution (99^{th} percentile), having more than 1 APC visit during the study period was positively associated with avoidable ED score ($\beta = 61.2$; $p < 0.001$) compared to those with no APC visits. No significant differences were observed between those having 1 APC visit and no APC visits during the study period among the 99^{th} percentile. Results from the mean regression model showed a significant positive association between APC visits and avoidable ED score where the estimated average score was higher among those with > 1

($\beta = 7.8$; $p \leq 0.001$) or 1 APC visit ($\beta = 4.8$; $p \leq 0.01$) during the study period compared to those without any APC visits. These relationships were adjusted for insurance type, gender, age, race, ethnicity, and living in a PHPA.

Among ED users, having Medicaid insurance was positively associated with avoidable ED score when compared to being uninsured. Individuals with Medicaid insurance had a higher avoidable ED score at the 25^{th}, 75^{th}, 95^{th} and 99^{th} percentiles than the uninsured. The coefficients for this relationship were almost 100% larger among those in the 99^{th} percentile ($\beta = 202.2$; $p \leq 0.001$) compared to the 25^{th} percentile ($\beta = 2.5$; $p \leq 0.001$). No significant differences were observed between those with Medicare insurance and those who were uninsured at the 25, 50^{th} and 75^{th} percentiles. Medicare insurance was positively associated with avoidable ED score at the 95^{th} ($\beta = 31.4$; $p \leq 0.001$) and 99^{th} percentiles ($\beta = 102.4$; $p \leq 0.01$) compared to uninsured. Having private insurance, was negatively associated with avoidable ED score when compared to those who were uninsured at all percentiles of the distribution. The coefficient for this relationship was increased by 90% from the 25^{th} percentile ($\beta = -7.9$; $p \leq 0.001$) to the 99^{th} percentile ($\beta = -111.2$; $p \leq 0.001$). These relationships were adjusted for APC visit categories, gender, age, race, ethnicity, and living in a PHPA. The Khmaladze test (KT) for the location-shift hypothesis test was significant at the 1% level along with the individual slopes of Model 1 quantiles. This supports the hypothesis that the association (i.e. slope) between APC visits, insurance coverage, and avoidable ED is significantly different between quantiles of the distribution.

In Model 2 we tested the interactions between APC visit categories and insurance coverage types at the 25^{th} 50^{th}, 75^{th}, 95^{th} and 99^{th} percentiles. The interaction terms were significant at the 5% level for most coefficients. The KT for the location-shift hypothesis test was significant at the 1% level for the Model 2 individual slopes of the interaction meaning that the association (i.e. slope) between APC visits and avoidable ED score varied by the type of insurance coverage, and was significantly different between quantiles of the distribution.

The study population was stratified by insurance type, and modeled separately to estimate the association between APC visits and avoidable ED score in each stratum (Table 5.4). Among the uninsured, APC utilization was negatively and positively associated with avoidable ED score based on segments of the distribution. At the 25th percentile, uninsured individuals with > 1 APC (β = -0.7; $p < 0.05$) had a lower avoidable ED score compared to those without any APC visits. This relationship was opposite at the 75th (β = 26.7; $p \leq 0.001$), 95th (β = 82.8; $p \leq 0.001$) and 99th (β = 2.44; $p < 0.05$) percentiles. For those with Medicaid insurance, no statistically significant differences in avoidable ED scores were found between individuals with 1 APC visit and those with 0 APC visits. Among those with Medicaid insurance, having > 1 APC visit was associated with a higher avoidable ED score at the 95th (β = 41.9; $p < 0.05$) and 99th (β = 187.3; $p < 0.05$) percentiles compared to having 0 APC visits. Among individuals with private insurance, having > 1 APC visit during the study period was negatively associated with avoidable ED score, with the largest coefficient magnitude (β= -4.2, $p \leq 0.001$), and positively associated at the 95th (β = 18.6; $p \leq 0.001$) and 99th percentiles (β = 39.7; $p < .05$). Both coefficients were the smallest in magnitude compared to other significant associations at equivalent percentiles.

DISCUSSION

The overarching goal of this study was to assess the independent associations of APC visits and insurance coverage with avoidable ED utilization, and their subsequent interaction effect with avoidable ED utilization. Our results showed that the relationship between APC utilization and avoidable ED score varied by segments of the distribution. Among the bottom 25% of ED users, having more than 1 APC visit was negatively associated with avoidable ED score, whereas for those in the top 25% of the distribution, the association was positive, when controlling for insurance coverage type and other covariates. Having Medicaid insurance was consistently associated with higher avoidable ED scores across quantiles of the distribution compared to being uninsured, and having private insurance was consistently associated with lower avoidable ED score. In stratified analyses, having more than 1 APC visit during the study period was associated with lower avoidable ED scores among the uninsured and privately-insured at the 25th percentile, and was associated with higher ED scores at the 95th and 99th percentiles among the uninsured, Medicaid-insured, and privately-insured.

The distribution of the outcome variable, avoidable ED score, was heavily skewed and did not align with normal distribution assumptions. Prior studies have measured avoidable ED utilization using a dichotomized outcome as a solution for having a bounded, continuous outcome variable, and a distribution that violated the standard linear regression assumption of constant variance (Kieschnick & Mccullough, 2003)(Coe et al., 2018). For example in one study, an ED visit was non-emergent (i.e. avoidable) when the sum of NYU Probability categories 1 and 2 was greater than 50% and emergent (i.e. non-avoidable) when the sum of categories 3 and 4 was greater than 50% (Gandhi & Sabik, 2014). This method of dichotomizing the total probability has been criticized as arbitrary (Lines et al., 2017) and an unnecessary loss of sensitivity (W. Chen et al., 2015) when it can be modeled as a continuous variable using appropriate regression methods. Our study applied QR to model avoidable ED utilization as a continuous outcome; a method that is robust to skewness and heavy tailed error distributions.

Consistent with other studies, we found that avoidable ED utilization was positively associated with Medicaid insurance, and highest among those with Medicaid compared to other insurance groups (W. Chen et al., 2015; McWilliams et al., 2011). A recent assessment of Massachusetts All-Payer claims data from 2011-2012 found that primary care treatable ED utilization was positively associated with the number of primary care visits among stratified samples of private insurance (rate ratio [RR] = 1.006; 95% CI: 1.005 to 1.007), any public insurance (RR: 1.003; 95% CI: 1.002 to 1.003), and for the combined sample (RR: 1.01; 95% CI: 1.005 to 1.007) (Lines et al., 2019). This study similarly measured ED utilization as a continuous sum of NYU Algorithm probabilities and used a generalized linear model with a log link and gamma family (i.e. mean regression model) to estimate the associations for the population on average. Using QR, our study was able to identify that the strength of the association between care utilization visits and avoidable ED utilization was significantly different between percentiles of the distribution. Therefore, interpreting the magnitude of the association at the average may mischaracterize the relationship. In our study, specifically, we found associations in opposite directions among the bottom 25% and the top 25% of the distribution of the overall sample and among some insurance stratum.

These findings could be explained by differences in quality of care and the severity of healthcare need in the population. In a survey of 2 large urban hospitals, frequent ED users self-reported having twice as many primary care visits as non-frequent ED users and were significantly less likely to report getting what they need from their primary care provider (76%) compared to non-frequent ED users (93%) (Cunningham et al., 2017). Frequent utilization of the ED was associated with higher non-ED healthcare cost among Medicaid-insured patients in The Boston Health Care for the Homeless program (Mitchell et al., 2017) and having ≥10 outpatient visits in the past 12 months among a nationally representative sample (Vinton et al., 2014). Frequent utilization of the emergency department is associated with having at least 1 chronic mental or physical condition (Peppe et al., 2007) and having multiple chronic conditions is associated with the largest increase in nonurgent ED utilization over time (35%) compared to having 1 chronic condition (23%) and no chronic conditions (8%) (Powell M et al., 2016).

Some limitations should be considered when interpreting the results of this work. Our study utilized a sample from a large county healthcare system, Atrium Healthcare, that was not comprehensive for all healthcare in the area. As is consistent with other studies, (LaCalle & Rabin, 2010; Krieg et al., 2016), health system leakage (participants using other facilities) is a limitation in single-system data sources that can induce measurement error. Atrium Healthcare is the largest provider of healthcare for all of Mecklenburg County and for uninsured and Medicaid insured populations, and thus the impact of system leakage on results of the study is likely limited. The external validity of the NYU Algorithm has been criticized due to the single timepoint, geographic location, and healthcare system used in its development (Latham & Ackroyd-Stolarz, 2017), although it has been validated using nationally representative data (Gandhi & Sabik, 2014) and Medicare payer data (Ballard et al., 2010) for single time point classifications. Other studies have measured avoidable ED utilization using an alternative metric, Ambulatory Care Sensitive Conditions (ACSCs), as conditions for which hospital admission could be prevented by interventions in primary care. The set of conditions that define an ACSC hospitalization are not consistent across studies, and reduces the comparability of research (Purdy et al., 2009). In addition, the ACSC classification is used for inpatient ED visits (i.e. visits that resulted in a hospitalization), and does not classify outpatient care, or ED visits that are discharged without hospitalization. In most cases, individuals presenting to the ED are evaluated and subsequently discharged without hospitalizations (United States, 2013). Thus, the definition and classification of ACSC hospitalizations would only capture the proportion of ED visits that resulted in impatient care and exclude patients utilizing the ED for outpatient care. Additionally, the use of a cross-sectional study design and a single year of data does not allow for temporal, causal interpretation of associations between variables. The possibility of residual confounding is possible because of the observational study design.

A strength of our study was demonstrating that the relationship between APC visits, insurance, and avoidable ED utilization varied based on segments of the distribution by using quantile regression. The commonly used method of dichotomizing the outcome of avoidable utilization probability and estimating a population average may not adequately characterize this relationship.

CONCLUSIONS

Compared to being uninsured, having Medicaid insurance is associated with more avoidable ED utilization and having Private insurance is associated with less avoidable ED utilization. Among the uninsured and privately insured with lower than typical avoidable ED utilization, using APC during the study period is associated with less avoidable ED utilization. Among those with higher than typical avoidable ED utilization, APC visits are associated with more avoidable ED utilization.

Table 5.1. Participant Characteristics by Ambulatory or Primary Care (APC) Visit Categories (n = 70,870)

Characteristic	0 Visits No. (%)	1 Visit No. (%)	> 1 Visits No. (%)	Total
Total Population	45,784 (64.6)	4,886 (6.9)	20,200 (28.5)	70,870 (100)
Insurance Type				
Uninsured	16,823 (36.7)	1,196 (24.5)	2,651 (13.1)	20,670 (29.2)
Medicaid	10,443 (22.8)	929 (19.0)	2,305 (11.4)	13,677 (19.3)
Medicare	5,622 (12.3)	511 (10.5)	4,848 (24.0)	10,981 (15.5)
Private	12,896 (28.2)	2,250 (46.0)	10,396 (51.5)	25,542 (36.0)
Gender				
Female	25,533 (55.8)	3,336 (68.3)	14,768 (73.1)	43,637 (61.6)
Male	20,251 (44.2)	1,550 (31.7)	5,432 (26.9)	27,233 (38.4)
Age				
Mean (SD)	39.6 (16.1)	40.8 (15.2)	48.7 (17.9)	42.2 (17.1)
Race				
White	8,741 (19.1)	1,269 (26.0)	7,287 (36.1)	17,297 (24.4)
Black	28,809 (62.9)	2,801 (57.3)	9,973 (49.4)	41,583 (58.7)
Other or Unknown	8,234 (18.0)	816 (16.7)	2,940 (14.6)	11,990 (16.9)
Ethnicity				
Non-Hispanic or Latino	36,415 (79.5)	3,940 (80.6)	16,546 (81.9)	56,901 (80.3)
Hispanic or Latino	5,577 (12.2)	511 (10.5)	1,774 (8.8)	7,862 (11.1)
Declined or Unknown	3,792 (8.3)	435 (8.9)	1,880 (9.3)	6,107 (8.6)
PHPA Status				
PHPA	17,465 (38.2)	1,638 (33.5)	5,435 (26.9)	24,538 (34.6)
Non-PHPA	28,319 (61.9)	3,248 (66.5)	14,765 (73.1)	46,332 (65.4)

Note: APC Visits measured as total visits to ambulatory or primary care during the study period January 1-December 31st 2017; PHPA = Public Health Priority Areas are 6 ZIP code tabulation areas selected by the county health department with disproportionate poverty and educational attainment relative to the larger county.

Table 5.2. Quantiles of Avoidable Emergency Department (ED) Score by Ambulatory or Primary Care (APC) Visit Category

APC Visit Category	25th	50th	75th	95th	99th	Mean
>1 Visit	67.0	93.8	121.3	300.0	567.4	120.6
1 Visit	72.9	100.0	133.3	300.0	590.2	125.0
0 Visits	84.4	100.0	133.0	300.0	570.6	126.5
Total Population	81.1	100.0	132.4	300.0	573.4	124.7

Note Avoidable ED Score calculated as the total probability of avoidable ED utilization during the study period, as scored by the New York University Algorithm 0 to 1 scale, multiplied by 100. A value of 100 is equivalent to 1 ED visit that was scored as 1 (i.e. 100% avoidable) or 2 visits that were scored as .60 and .40 (i.e. 60% avoidable and 40% avoidable) during the study period; APC Visits measured as total visits to ambulatory or primary care during the study period January 1- December 31st 2017.

Table 5.3. Regression Quantiles of Avoidable Emergency Department (ED) Score

Factor	Quantile regression estimates (SE) 25th	50th	75th	95th	99th	KT p value	Mean regression estimate (SE)
APC Visit Category							
> 1 Visit	-2.5 (0.5)‡	-0.0 (0.1)	5.4 (0.8)‡	32.7 (4.5)‡	61.2 (14.6)‡	≤ 0.01	7.8 (1.1)‡
1 Visit	-1.7 (0.8)*	0.1 (0.1)	4.5 (1.5)†	17.4 (7.3)*	28.3 (19.4)	≤ 0.01	4.8 (1.8)†
0 Visit (ref)	--	--	--	--	--	--	--
Insurance Type							
Medicaid	2.5 (0.4)‡	0.2 (0.2)	40.0 (2.8)‡	83.0 (7.2)‡	202.2 (29.1)‡	≤ 0.01	25.4 (1.3)‡
Medicare	0.9 (0.6)	0.1 (0.1)	0.6 (2.6)	31.4 (7.0)‡	102.4 (35.2)†	≤ 0.01	9.9 (1.8)‡
Private	-7.9 (0.9)‡	-6.4 (0.5)‡	-17.3 (2.5)‡	-55.0 (4.0)‡	-111.2 (14.9)‡	≤ 0.01	-20.5 (1.2)‡
Uninsured (ref)	--	--	--	--	--	--	--

Note: Avoidable ED Score calculated as the total probability of avoidable ED utilization during the study period, as scored by the New York University Algorithm 0 to 1 scale, multiplied by 100. A value of 100 is equivalent to 1 ED visit that was scored as 1 (i.e. 100% avoidable) or 2 visits that were scored as .60 and .40 (i.e. 60% avoidable and 40% avoidable) during the study period;
Quantile and mean regression estimates obtained from fitting linear models adjusted for Gender, Age, Race, Ethnicity, and Public Health Priority ZIP code tabulation area;
SE, Standard Error; APC Visits = total visits to ambulatory or primary care during the study period January 1- December 31st 2017;
KT = Khmaladze Test for the location-shift hypothesis test for individual slopes.
*Significant at $p < 0.05$
†Significant at $p \leq 0.01$
‡Significant at $p \leq 0.001$

Table 5.4. Regression Quantiles of Avoidable Emergency Department (ED) Score, Stratified by Insurance Type

Insurance Type	APC Visit Category	Quantile regression estimates (SE)					
		25th	50th	75th	95th	99th	KT p value
Uninsured	> 1 Visit	-0.7 (0.3)*	0.0 (0.0)†	26.7 (2.8)‡	82.8 (13.1)‡	164.1 (53.7)†	≤ 0.01
	1 Visit	-0.5 (0.6)	0.0 (0.0)†	25.6 (3.1)‡	61.3 (19.5)†	243.8 (114.8)*	≤ 0.01
	0 Visit (ref)	--	--	--	--	--	--
Medicaid	> 1 Visit	-0.2 (0.6)	0.0 (0.0)*	9.6 (6.2)	41.9 (18.7)*	187.3 (79.7)*	≤ 0.01
	1 Visit	-0.9 (1.3)	0.0 (0.0)	1.0 (3.9)	28.0 (24.5)	43.2 (48.2)	≤ 0.01
	0 Visit (ref)	--	--	--	--	--	--
Medicare	> 1 Visit	-2.3 (1.3)	-1.0 (0.4)*	-1.9 (1.6)	4.0 (8.4)	-29.9 (43.3)	> 0.10
	1 Visit	-2.7 (2.3)	-0.5 (0.8)	-7.1 (4.4)	-23.6 (16.7)	-63.3 (106.6)	≤ 0.01
	0 Visit (ref)	--	--	--	--	--	--
Private	> 1 Visit	-4.2 (0.9)‡	-0.3 (0.4)	0.1 (0.3)	18.6 (4.7)‡	39.7 (18.1)*	≤ 0.01
	1 Visit	-3.1 (1.7)	-0.7 (0.6)	0.0 (0.1)	-6.8 (8.4)	17.1 (23.7)	≤ 0.01
	0 Visit (ref)	--	--	--	--	--	--

Note: The study sample was stratified by insurance coverage type; Avoidable ED Score calculated as the total probability of avoidable ED utilization during the study period, as scored by the New York University Algorithm 0 to 1 scale, multiplied by 100. A value of 100 is equivalent to 1 ED visit that was scored as 1 (i.e. 100% avoidable) or 2 visits that were scored as .60 and .40 (i.e. 60% avoidable and 40% avoidable) during the study period;
Quantile regression estimates obtained from fitting linear models adjusted for Gender, Age, Ethnicity, and Public Health Priority Area ZIP code tabulation area;
APC Visits = Ambulatory or Primary Care Visits during the study period January 1- December 31st 2017.
*Significant at $p < 0.05$; †Significant at $p \leq 0.01$**;** ‡Significant at $p \leq 0.001$

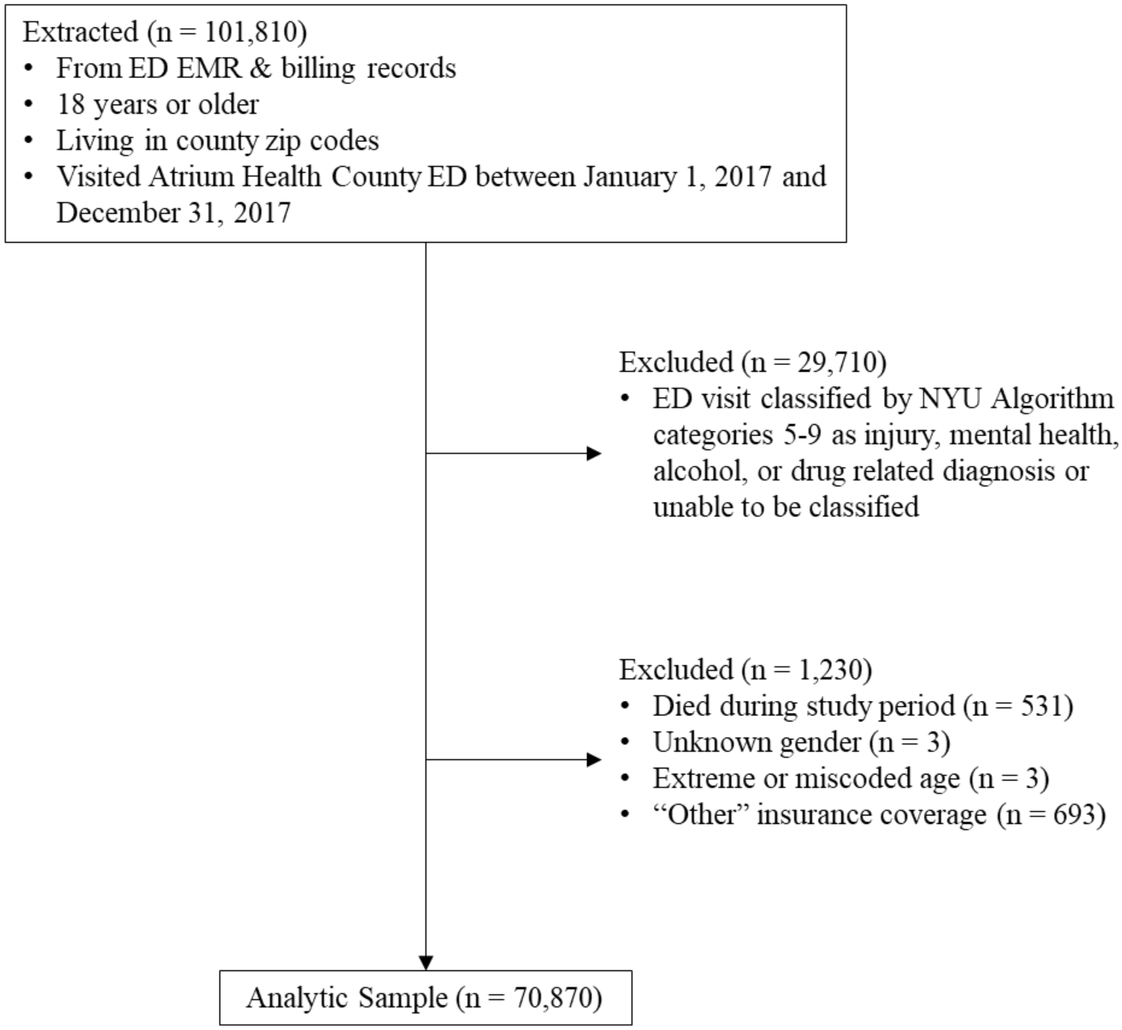

Figure 5.1. Analytic Sample Flow Diagram; ED, Emergency Department; EMR, Electronic Medical Record; NYU Algorithm, New York University Algorithm

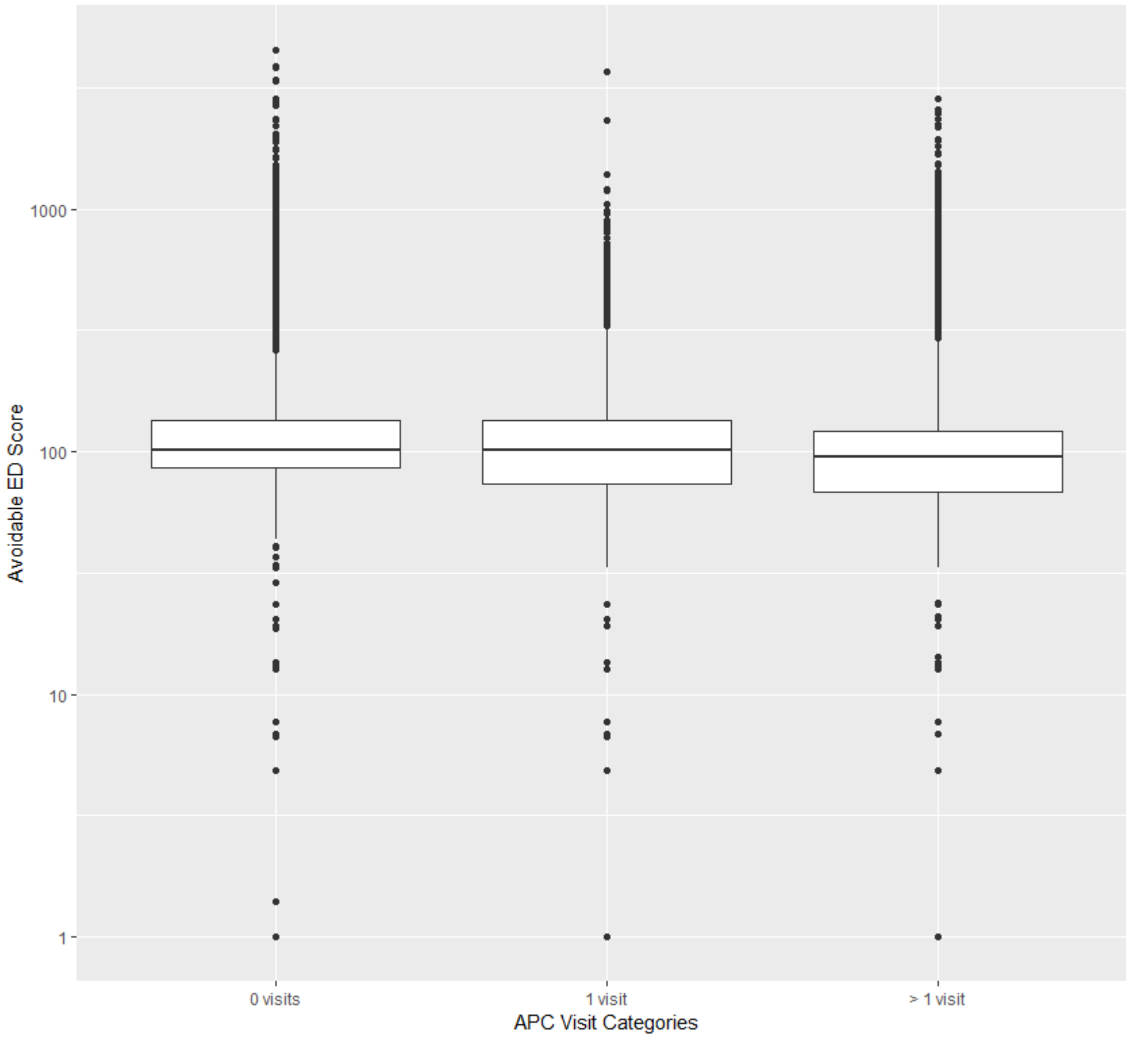

Figure 5.2. Box-Plot of Avoidable Emergency Department (ED) Score by Ambulatory or Primary Care (APC) Visit Categories; Avoidable ED Score calculated as the total probability of avoidable ED utilization during the study period, as scored by the New York University Algorithm 0 to 1 scale, multiplied by 100. A value of 100 is equivalent to 1 ED visit that was scored as 1 (i.e. 100% avoidable) or 2 visits that were scored as .60 and .40 (i.e. 60% avoidable and 40% avoidable) during the study period; APC Visits measured as total visits to ambulatory or primary care during the study period January 1-December 31st 2017.

CHAPTER 6

MANUSCRIPT 3- CHARACTERISTICS OF EMERGENCY DEPARTMENT FREQUENCY AND CHARGES AMONG A NORTH CAROLINA, HEALTH SYSTEM POPULATION[3]

[3] Mayfield, CA, Geraci, M, Eberth, JM, Hernandez, B, Dulin, M, Merchant, AT. To be submitted to *Journal of Epidemiology and Community Health*.

ABSTRACT

Objective

To identify characteristics associated with percentiles of Emergency Department (ED) utilization frequency and charges, and percentiles among select demographic groupings.

Design and Sample

A cross-sectional analysis of electronic health and billing records. Data were extracted for 99,637 adults residing in Mecklenburg County, North Carolina who visited an ED within a large integrated healthcare system (Atrium Health) in 2017.

Methods

Outcomes were measured as the total number of billed ED visits and the total associated charges. Participant characteristic predictors were: insurance coverage (Medicaid, Medicare, private, uninsured), total visits to ambulatory or primary care (APC) (0, 1, >1), and patient demographics: age, gender, race, ethnicity, and living in an underprivileged community called a county public health priority area (PHPA). Quantile regression models were used to measure associations at the 25th, 50th, 75th, 95th and 99th percentiles of outcome distributions. Select demographic groupings were subset and plotted.

Results

Having Medicaid or Medicare insurance was positively associated with ED visits compared to those that were uninsured, at the 50th and 75th percentiles of the distribution. Medicaid and Medicare were positively associated with ED charges and having Private insurance was positively associated with ED charges across all percentiles of the

distribution. Having > 1 APC visit was positively associated with ED visits at the 75th percentile ($\beta = 0.12$; $p \leq 0.001$) and having 1 APC visit was negatively associated with ED visits at the 95th percentile ($\beta = 0.35$; $p \leq 0.001$). Living in a PHPA community was negatively associated with ED charges at the 25th ($\beta = -76.4$; $p \leq 0.001$) and 50th ($\beta = -80.5$; $p \leq 0.01$) percentiles and positively associated with ED charges at the 95th ($\beta = 700.9$; $p \leq 0.01$) and 99th ($\beta = 2{,}351.7$; ≤ 0.001) percentiles.

Conclusions

The relationship between ED visits or associated charges and type of insurance and primary care visits varied by percentile of ED visits or associated charges, and included relationships that were in qualitatively opposite directions. Modeling ED utilization frequency and charge outcomes using internal, distribution-based cut points describes their relationships with independent variables more accurately than conventional methods that evaluate the average of the entire distribution.

INTRODUCTION

The U.S. healthcare system experiences a disproportionate burden of Emergency Department (ED) utilization among a high-need, high-cost group of patients that reflects a small overall percentage of the population (LaCalle & Rabin, 2010; Martin et al., 2013). Up to 30% of all ED visits are directed towards 1-8% of the patient population identified as frequent ED utilizers (Jiang, Weiss, & Barrett, 2017; Hunt, Weber, Showstack, Colby, & Callaham, 2006; Fuda & Immekus, 2006; Mandelberg, Kuhn, & Kohn, 2000). There is no standard definition for "frequent use" of the ED, making it difficult to compare results between studies (Pines et al., 2011). Frequent utilization is typically measured as dichotomous (i.e. yes/no) outcome based on some predetermined threshold for the total number of visits in a calendar year. The most common threshold for frequent utilization is greater than 3 or more visits in a year (Hunt et al., 2006), but can range from 4 to 20 visits in a year (Fuda & Immekus, 2006; Blank et al., 2005; Mandelberg et al., 2000; Peppe, Mays, & Chang, 2007). The use of common cut-off points for frequent ED utilization has been criticized as an oversimplification based on previous research showing that risk factors associated with frequent ED use exist along a continuum without clear-cut breakpoints (Weber, 2012).

Frequent utilization increases the overall financial burden of healthcare. According to the Agency for Healthcare Research and Quality, the top 1% of patients ranked by healthcare expenditure account for ~20% of the total healthcare spending, with an average annual cost of $90,000 per person (Cohen et al., 2013). In 2010, a total of $328.1 billion was spent on ED care, representing 12.5% of the National Health Expenditure (Galarraga & Pines, 2016). The individual cost burden of ED care is high, with an average price of $1,917 for an outpatient emergency room visit that has increased over 30% between 2012 and 2016 (Health Care Cost Institute, 2016). Similar healthcare services are more expensive in the ED compared to other areas of the healthcare system, with variable charges based on an individual's insurance status. A 2017 study examining Medicaid billing records from over 2,700 US hospitals found that ED physicians had a higher overall markup ratio (4.4; 340% excess charges), defined as the charges submitted by the hospital divided by the Medicare allowable amount, when compared to internal medicine physicians (2.1; 110% excess charges). Results also showed that higher ED markup ratios were associated with hospitals serving a greater percentage of uninsured patients (median, 5.0; Inter Quartile Range = , 3.5-6.7 for hospitals with $\geq$ 20% uninsured)(Xu et al., 2017).

Utilization of the ED is associated with patient characteristics, and prior ED charges. Studies examining predictors of frequent utilization found that minority patients (Mandelberg et al., 2000; Saef et al., 2016;Agarwal et al., 2016), and individuals with social and economic risk factors such as poverty (Hunt et al., 2006) and homelessness (Mandelberg et al., 2000) are at increased risk for frequent ED use. Frequent ED use is associated with having Medicaid insurance (Hunt et al., 2006), and the risk of frequent ED utilization and is higher among those with Medicaid insurance compared to those who are uninsured, or privately insured (Zuckerman & Shen, 2004). These associations were measured using a dichotomously defined cut point for frequent utilization that was inconsistent across studies. Among a cohort of uninsured patients in Mecklenburg County, NC, the strongest predictors of future healthcare cost were baseline healthcare costs and ED utilization rates (Lubanski et al., 2017).

The purpose of this study was to examine frequent utilization and ED charges using internal-cut points based on percentiles of the distributions to i) identify characteristics of the study population associated with the percentiles of ED visit frequency and ED charges and ii) plot percentiles of utilization among select demographic groupings.

METHODS

Design and Sample

The study was a cross-sectional analysis of data from January 1st, 2017 to December 31st, 2017. Data were extracted from Cerner Millennium (Cerner Corporation, Kansas City KS) Electronic Medical Records (EMRs) and billing records (Epic Systems Corporation, Verona WI) from all five Atrium Health EDs in Mecklenburg County (Main, Pineville, University, Mercy, and South Park). Records were identified for extraction by the zip code tabulation area (ZCTA) associated with the home address of the index visit (i.e. the first visit to the ED during the study period). ZCTAs are a generalized representation of the U.S. Postal Service zip code service areas, and are calculated as the most frequently occurring zip code in an area. The extracted dataset included a total of 101,810 patients, 18 years or older, with a home address in one Mecklenburg county's 27 ZCTAs and visited one of 5 Mecklenburg County Atrium Health EDs during the project period. ED encounters were linked to an individual by the unique patient ID number in the Atrium Health system. ED visits were identified in the Atrium Health Billing System using the unique encounter ID associated with each visit. The research protocol was reviewed and approved by the Institutional Review Board

(IRB) at Atrium Health and was exempt from IRB review by The University of South Carolina because of the use of de-identified secondary data.

A flow chart depicting the selection of the analytic sample is presented in Figure 6.1. A total of 721 patients who died during the project period were removed to reduce measurement error, along with 16 with unknown gender and 13 with extreme and potentially miscoded ages. Approximately 1% of the study population was covered through insurance that was classified as “other” by Atrium Health billing. The “other” insurance category included governmental insurance benefits (e.g. Veterans Affairs) in addition to other program-specific options that did not conceptually align with larger insurance categories and was too small to produce model estimates as a stand-alone group. Thus, a total of 1,423 individuals with “other” insurance were removed from the study population, resulting in a final analytic sample of 99,637 patients.

Measures

Outcomes: The total number of ED visits was calculated as the total billed unique ED encounters during the study period by individual. ED encounters were linked to an individual by the unique patient ID number in the Atrium Health system.

The total associated charges for ED visits during the study period was calculated by individual. Hospital charges represent the amount billed by the hospital and do not reflect the actual cost, out-of-pocket expenses, or reimbursement for the visit, which varies based on the type of insurance coverage. ED charges were rounded to the nearest dollar for descriptive analysis and not for regression models.

Insurance Coverage: The primary source of payment indicated for the index visit in the study sample was used as a proxy for insurance coverage during the study period using the following categories: Medicaid, Medicare, private, or uninsured. Medicare included both Advantage (commercial) and non-Advantage (public) members. Private represented all commercial insurance categories. For the purpose of this study, patients indicating "self-pay" were recoded to represent the uninsured.

Ambulatory or Primary Care Visits (APC); Utilization of ambulatory or primary care was measured as the total number of visits to Atrium Health care facilities defined in the EMR system under the specialty categories of: Allergy, Cardiovascular, Dermatology, Endocrinology, Family Medicine, Internal Medicine, Primary Care Behavioral Health, Rheumatology, Sleep Medicine, Sports Medicine, Urgent Care; and the following OBGYN specialty categories: Generalist, and OBGYN. The total number of APC visits was categorized as: 0 visits, 1 visit, and > 1 visit for analysis.

PHPA Status: The county health department has identified six public health priority area (PHPA) ZCTAs selected based upon disproportionately low educational attainment and high percent of the population living below the poverty threshold. The ZCTAs of patients in the analytic sample were scored using a binary variable (PHPA versus. Non-PHPA) to indicate the PHPA status of their home environment.

Patient Characteristics: Patient demographic characteristics included in models were: gender, race, ethnicity, and age. Gender was measured as a categorical variable (male or female). Race (White, Black, and other or unknown), and ethnicity (Hispanic or Latino and non-Hispanic or Latino) were measured as separate categorical variables. Age was measured as a continuous variable for descriptive and regression models.

Analysis

The population characteristics for the study sample were assessed using descriptive statistics. The distribution of outcome metrics, ED visits and ED charges, were evaluated using box plots, histograms, and unconditional quantile-based location, scale, and shape measures. The distribution of the outcome metrics, conditional on levels of insurance coverage, was assessed using a box plot, and presented on the log scale due to extreme outliers.

Quantile regression (QR) models were used to estimate the percentiles for both the discrete (total number of ED visits), and continuous (total cost of ED utilization) outcomes at the 25^{th}, 50^{th}, 75^{th}, 95^{th}, and 99^{th} percentiles. Quantile regression (QR) is a statistical method to assess the strength and direction of the relationship between a predictor and specific quantiles (e.g. the median) of the outcome distribution. QR is a non-parametric linear model that does not have distributional assumptions and therefore is robust to outliers in the outcome and different shapes of the error distribution (e.g., skewness or heavy-tails) (Yu et al., 2003). QR can be applied to both discrete, hospital admission counts (Congdon, 2017; Winkelmann, 2006) and continuous, healthcare cost (Fliss et al., 2018; Lahiff et al., 2014; McCabe et al., 2017) outcomes.

The outcome ED visits (discrete) was modeled using mid-QR (Geraci & Farcomeni, 2019) fitted via a Nelder-Mead algorithm, while the outcome ED charges (continuous) was modeled using QR (Roger Koenker & Bassett, 1978) fitted via a Barrodale-Roberts algorithm. Predictors for both models were: insurance coverage, APC visits, gender, age, race, ethnicity, and PHPA status. The location-shift hypothesis was evaluated for both models using a Khmaladze Test (KT)(Roger Koenker & Xiao, 2002), which tests the null hypothesis that the slopes of the regression models at each quantile are all the same. Due to computational issues in the application of the KT for either model, observations of ED visits were jittered by adding a small amount of random noise to create a pseudo-continuous variable, while observations of ED charges were log-transformed to reduce the disproportion between the scale of the outcome and that of the linear predictor. The analytic population was subset into 8 datasets for all combinations of PHPA and insurance status groupings and mid-quantile values of ED visits and ED charges were plotted in separate figures. All analysis was performed using R Studio version 1.1.456 (R Core team, 2015). Data manipulation was performed using standard R Studio base jitter and log transformation functions. Quantile regression models performed using the quantreg (Roger Koenker, 2019), and Qtools (Marco Geraci, 2019) packages.

RESULTS

Population and Characteristics

A total of 99,637 residents of county ZCTAs had at least 1 visit to an Atrium Health ED in 2017. A majority of the sample had private insurance coverage (37.3%) followed by Medicaid (17.6%) and Medicare (15.9 %) insurance coverage types. Approximately 30% of the sample was uninsured. On average, individuals had 1.8 (standard deviation [SD] = 4.0) visits to primary care during the study period. The sample was comprised of primarily Female (58.4%), Black (55.3%), and non-Hispanic or Latino (79.1%) individuals. The average age of the sample was 42.4 years old (SD = 17.5). Approximately 33% of the sample was living in a one of 6 county PHPAs during their index visit to the ED. The characteristics of the sample are presented in Table 6.1.

Distribution of Outcome Measures

Data were collected from ED EMRs and billing records and therefore the study sample had a minimum of 1 ED visit and a minimum charge greater than \$0. The total number of ED visits ranged from 1 to 86, and the total charges ranged from \$102 to \$419,692. The interquartile range (IQR), the range of the middle 50% of the distribution, for ED visits was 1, and for ED charges was \$ 5,890. At the 10^{th} centile, the skewness index was approximately 1 for ED visits and 0.5 for ED charges, which indicated a strong right asymmetry (i.e. extreme observations in the right side of the distribution) for both outcome variables. The shape index was 2 for ED visits and ED charges, indicating that the tails of the distribution are heavier compared to a normal distribution value of 1.9, meaning that more observations are at the extreme ends of the distribution than compared to that of a normal distribution. The conditional box plots of ED visits (Figure 6.2) and ED charges (Figure 6.3) showed that the distributions vary by insurance coverage categories. The mid-quantile values of ED visits and ED charges are presented in Table 6.2. On average individuals in the bottom 25% (i.e. 25^{th} quantile) of the distributions had 1 ED visit and \$2,251 of charges. When examining the top 5% of the distributions (i.e. 95^{th} quantile), these values increased to 4.4 visits and \$18,433. The mean values for the total sample were 1.7 visits and \$6,416.

Predictors of ED Visits Regression Quantiles

Having Medicaid insurance was positively associated with the mid-quantiles of ED visits at the 50^{th} ($\beta = 0.40$; $p \leq 0.001$) and 75^{th} ($\beta = 0.51$; $p \leq 0.001$) percentiles compared to being uninsured. Results were similar for those with Medicaid at the 50^{th} ($\beta = 0.31$; $p \leq 0.001$) and 75^{th} percentiles ($\beta = 0.16$; $p \leq 0.001$). No significant differences were observed between the uninsured and privately insured groups. At the 75th percentile, having > 1 APC visit was positively associated with mid-quantiles of ED visits ($\beta = 0.12$; $p \leq 0.001$) while at the 95th percentile having 1 APC visit was negatively associated with ED visits ($\beta = 0.35$; $p \leq 0.001$). Among other patient demographics, increasing age, Black race, and Female gender, and living in a PHPA were positively associated with mid-quantiles of ED visits. At the 50th percentile, Hispanic or Latino ethnicity was positively associated with mid-quantiles of ED visits ($\beta = 0.09$; $p \leq 0.001$) compared to non-Hispanic or Latino, and negatively associated at the 75th percentile ($\beta = -0.02$; ≤ 0.001). The KT test for the location-shift hypothesis was significant for the individual slopes at the 1% or 5% level for all predictors in the model, meaning that the associations (i.e. slopes) between predictors and mid-quantiles of ED visits were significantly different between quantiles of the distribution.

Predictors of ED Charges Regression Quantiles

ED charges for those with Medicaid and Medicare insurance were significantly higher than for the uninsured at all quantiles of the distribution. The strength of association increased in magnitude at higher percentiles. For example, Medicaid insurance was associated with $356 more in ED charges at the 25th percentile ($p \leq 0.001$) and with $13,008 more in ED charges at the 99th percentile ($p \leq 0.001$) compared to uninsured. Private insurance was associated with lower ED charges, compared to uninsured, at all percentiles from the 25th ($\beta = -50.8$; $p <.05$) to the 99th ($\beta = -4{,}020$; $p \leq 0.001$) percentiles. Having 1 or >1 APC visits during the study period was associated with higher ED charges compared to having 0 APC visits across all percentiles. Demographic characteristics of increasing age and female gender were associated with higher ED charges. At the lower percentiles (25^{th}, 50^{th} and 75^{th}) Black race was associated with lower ED charges compared to White race. Living in a PHPA was associated with lower ED charges at the 25^{th} ($\beta = -76.4$; $p \leq 0.001$) and 50^{th} ($\beta = -80.5$; $p \leq 0.01$) percentiles and higher ED charges at the 95^{th} ($\beta = 700.9$; $p \leq 0.01$) and 99^{th} ($\beta = 2{,}351.7$; ≤ 0.001) percentiles. The KT test for the location-shift hypothesis was significant for the individual slopes at the 1% level for all predictors in the model, meaning that the associations (i.e. slopes) between predictors and quantiles of ED charges were significantly different between quantiles of the distribution.

Descriptive Plots

The mid-quantile values for all combinations of insurance type and PHPA status groups were plotted separately by outcome. For the distributions of ED visits, those with private insurance living in a non-PHPA had the lowest values, and those with Medicaid insurance living in a PHPA had the highest values across all percentiles (Figure 6.3). The distributions of ED charges showed clustering among the uninsured and privately-insured groups, and among the Medicaid and Medicare-insured groups. At lower percentiles (i.e. bottom 50%) of ED charges, the mid-quantile value was highest among non-PHPA residents with Medicaid insurance, and at higher percentiles (i.e. top 25%), PHPA residents with Medicaid insurance had the highest mid-quantile values (Figure 6.4).

DISCUSSION

The overarching goal of our study was to expand the knowledge base regarding characteristics of the ED user population by measuring associations using for internal-cut points based on percentiles of the outcome distributions. Our results showed that patient characteristics associated with the 25^{th}, 50^{th}, 75^{th}, 95^{th} and 99^{th} percentiles of ED visit frequency and ED charges varied in magnitude and direction. Having Medicaid and Medicare insurance was positively associated with ED visits at the 50^{th} and 75^{th} percentiles and ED charges across all percentiles, compared to being uninsured. Having private insurance was significantly associated with higher ED charges across all percentiles, and not with ED visits. Visiting APC during the study period was positively associated with ED visits among the bottom 75% of the population and negatively associated among the top 5% of the population. Female gender and increasing age were both positively associated with ED visits and ED charges. Black race was positively associated with ED visits at the 50^{th} and 75^{th} percentiles and negatively associated with ED charges at the 25^{th}, 50^{th}, and 75^{th}, compared to White race. Living in a PHPA was positively associated with ED visits among the bottom 75% population, and both negatively and positively associated with ED charges at lower (bottom 50%) and higher (top 5%) percentiles respectively. Thus, evaluating the associations between patient characterizes and ED frequency and charges at quantiles of the distribution describes their relationship more accurately than conventional methods that evaluate the average of the entire distribution.

Our results were consistent with other studies showing that frequent utilization is associated with having Medicaid insurance (Hunt et al., 2006), and those with Medicaid insurance are at increased risk for frequent utilization over time (Zuckerman & Shen, 2004). We also found that ED utilization at the 50^{th} and 75^{th} percentiles was positively associated with having more than 1 APC visit during the study period, and that ED charges were positively associated with APC utilization across all percentiles of the distribution. Other studies have demonstrated that higher utilization of the overall healthcare system (i.e. primary care or ambulatory care visits) is also associated with frequent utilization (Cunningham et al., 2017)(Ko, Lee, Chen, Chou, & Chu, 2015), as is ED utilization in prior years (Brennan et al., 2014). However, our results showed a significant negative association between having an APC visit and the 95th percentile of ED visits. Thus, APC care utilization may be beneficial for those in top 5% of the distribution of ED visits. This could be explained by the higher burden of chronic disease among the frequent ED utilizer population (Miller et al., 2013).

In our study, living in a PHPA was positively associated with ED visits at the 50th and 75th percentiles of the distribution, and negatively associated with ED charges at the 25th and 50th percentiles. Thus, among the bottom 50 to 75% of ED users, living in a priority health area is associated with more ED visits and lower charges compared to those living in a non-priority health area. Among the top 5% of the distribution, living in a PHPA is associated with higher charges. Our results may highlight that PHPA residents are using the ED for lower cost care that was unable to be accessed from other parts of the healthcare system. PHPAs were selected by the county health department as areas with disproportionately low educational attainment and high poverty, and are subsequently racially segregated. Prior studies have demonstrated that areas with disproportionate income, race, and educational attainment are associated with disparities in other environmental healthcare access factors such as the spatial concentration of PC physicians (Gaskin et al., 2012b), healthcare facilities (Dai, 2010), and physicians accepting Medicaid insurance (Greene et al., 2006). Additionally, living in residentially segregated areas is associated with lower rates of health insurance coverage among Black residents (K. F. Anderson & Fullerton, 2012) and worse access to a usual source of care

(Caldwell et al., 2017). Thus, our results may indicate that PHPA residents are not able to access ambulatory or primary care due to the low physical proximity of physicians and/or insurance coverage barriers, resulting in higher numbers of ED visits for lower cost healthcare.

The distributions of the outcome variables in our sample were heavily skewed, as is consistent with the general understanding that ED utilization measures are typically not normally distributed and have long heavy right tails (Diehr, Yanez, Ash, Hornbrook, & Lin, 2002). In an attempt to account for skewness in continuous and discrete measures, prior studies have applied normal linear regression to log-transformed ED utilization rates (Li et al., 2003). However, log-transforming the outcome has many limitations, including the change in the interpretation of model estimates (Wang et al., 2014). Many studies measure ED visit frequency (i.e. frequent utilization) as a dichotomized outcome based on an threshold that varies by individual study from 3 or more visits in a year to 20 or more visits in a year (Hunt et al., 2006; Fuda & Immekus, 2006; Blank et al., 2005; Mandelberg et al., 2000; Peppe, Mays, & Chang, 2007; Billings & Raven, 2013). The use of common cut-off points for frequent ED utilization has been criticized as an oversimplification based on previous research showing that risk factors associated with frequent ED use exist along a continuum without clear-cut breakpoints (Weber, 2012), and the use of arbitrary cut-points that may or may not align with meaningful groupings of population risk factors.

We used QR models for both discrete and continuous outcomes that are non-parametric linear models without distributional assumptions and therefore robust to outliers in the outcome and different shapes of the error distribution (e.g., skewness or heavy-tails). While QR is commonly applied to measure continuous data, it can also be applied to discrete data (i.e. counts) by using a jitter function to add random noise to each count to create a pseudo-continuous variable without substantially changing the value or direction of the coefficient estimates (Winkelmann, 2006). Traditional methods of jittering can induce instability in estimates when responses have extreme skewness and sparsity in the observations (i.e. large gaps between observations) (Geraci & Farcomeni, 2019). We therefore applied a mid-quantile regression (Geraci & Farcomeni, 2019) using an algorithm to estimate the average mid-point value of each quantile, conditional on other covariates in the model.

Some limitations should be considered when interpreting the results of this work. Our study utilized a sample from a large county healthcare system, Atrium Healthcare, that was not comprehensive for all healthcare in the area. As is consistent with other studies, (LaCalle & Rabin, 2010; Krieg et al., 2016), health system leakage (participants using other facilities) is a limitation in single-system data sources that can induce measurement error. Atrium Healthcare is the largest provider of healthcare for all of Mecklenburg County and for uninsured and Medicaid insured populations, and thus the impact of system leakage on results of the study is likely limited. Additionally, the use of a cross-sectional study design and a single year of data does not allow for temporal, causal interpretation of associations between variables. The possibility of residual confounding is possible because of the observational study design. Due to sparsity in our sample, the standard errors of some quantiles were not able to be estimated for the ED visit outcome, and thus the significance of some associations is not known.

Our study had many strengths including the application of QR to continuous and discrete measured of ED utilization that allowed for the evaluation of associations with internal-cut points based on percentiles of the distributions. This method allowed for a more sensitive and interpretable understanding of ED user population compared to traditional methods of dichomizing or transforming variables. The use of mid-quantile regression for discrete counts, is a more accurate and stable model, compared to traditional methods of jittering, for our data set that had extreme skewness and sparsity at the tails of the distribution.

CONCLUSIONS

The relationships between ED patient characteristics such as race, age, gender, and insurance status and ED utilization outcomes are different based on segments of the distribution (i.e. for those that are lower than typical users compared to higher than typical users). Some relationships are heterogeneous, meaning the direction of the relationship is both positive and negative depending on the point of the distribution. Visiting APC during the study period was associated with a higher number of ED visits among the bottom 75% of users, and a lower number of ED visits among the top 5% of ED users. Living in a PHPA was associated with lower ED charges among the bottom 50% of users, and with higher charges among the top 5% of users. Overall, defining and modeling ED utilization frequency using internal, distribution-based cut points provides a more complete and detailed understanding of characteristics of the population.

Table 6.1. Participant Characteristics (n = 99,637)

Characteristic		No. (%)
Total Population		99,637 (100)
Insurance Type		
	Uninsured	29,069 (29.2)
	Medicaid	17,557 (17.6)
	Medicare	15,821 (15.9)
	Private	37,190 (37.3)
APC Visits		
	Mean (SD)	1.8 (4.0)
Gender		
	Female	58,208 (58.4)
	Male	41,429 (41.6)
Age		
	Mean (SD)	42.4 (17.5)
Race		
	White	26,795 (26.9)
	Black	55,093 (55.3)
	Other or Unknown	17,749 (17.8)
Ethnicity		
	Non-Hispanic or Latino	78,766 (79.1)
	Hispanic or Latino	11,384 (11.4)
	Declined or Unknown	9,487 (9.5)
PHPA Status		
	PHPA	33,300 (33.4)
	Non-PHPA	66,337 (66.6)

Note: SD, Standard Deviation; PC Visits = Total number of primary care visits during the study period January 1- December 31st 2017; PHPA = Public Health Priority Areas are 6 zip code tabulation areas selected by the county health department with disproportionate poverty and educational attainment relative to the larger county.

Table 6.2. Mid-Quantiles of Total Emergency Department (ED) Visits and Charges

Metric	25th	50th	75th	95th	99th	Mean
ED Visits (#)	1	1.4	2.0	4.4	8.2	1.7
ED Charges ($)	2,251	4,279	8,141	18,433	34,759	6,416

Note: Data were collected from ED records, and therefore all patients in the sample had a minimum of 1 ED visit and a minimum charge greater than $0.

Table 6.3. Regression Mid-Quantiles of Emergency Department (ED) Visits

	Quantile regression estimates (SE)					
Characteristic	25th	50th	75th	95th	99th	KT p value
Insurance Type						
Medicaid	0.33 (NA)	0.40 (0.02)[‡]	0.51 (0.04)[‡]	0.78 (NA)	1.07 (2.04)	<.01
Medicare	0.44 (.63)	0.31 (0.02)[‡]	0.16 (0.04)[‡]	-0.43 (0.19)	-1.95 (0.50)	<.01
Private	-0.28 (NA)	-0.01 (0.01)	-0.12 (0.02)	-1.09 (NA)	-0.90 (1.04)	<.01
Uninsured (ref)	--	--	--	--	--	--
APC Visits						
> 1 Visit	0.21 (NA)	0.08 (0.01)[‡]	0.12 (0.02)[‡]	-0.41 (NA)	1.47 (2.16)	<.01
1 Visit	0.14 (0.11)	0.02 (0.02)	0.15 (0.03)	-0.35 (0.18)[‡]	0.90 (2.67)	<.05
0 Visit (ref)	--	--	--	--	--	--
Gender						
Female	0.03 (0.01)[†]	0.04 (0.01)[‡]	0.05 (0.01)[†]	0.88 (NA)	0.36 (1.13)	<.01
Male (ref)	--	--	--	--	--	--
Age						
Mean (SD)	-0.06 (NA)	-0.01 (NA)	NA (NA)	0.04 (0.01)[‡]	0.11 (0.02)[‡]	<.01
Race						
Black	0.22 (NA)	0.17 (0.01)[‡]	0.21 (0.02)[‡]	0.49 (NA)	1.65 (1.71)	<.01

Other or Unknown	-0.10 (0.90)	-0.03 (0.02)	-0.08 (0.02)	-0.12 (0.19)	-0.40 (NA)	<.01
White (ref)	--	--	--	--	--	--
Ethnicity						
Hispanic or Latino	-0.11 (1.54)	0.09 (0.02) ‡	-0.02 (0.03) ‡	-0.33 (0.14)	-1.17 (1.21)	<.01
Declined or Unknown	-0.24 (0.25)	-0.12 (0.02)	-0.23 (0.02)	0.05 (0.37)	-2.24 (0.51)	<.01
Non-Hispanic or Latino (ref)	--	--	--	--	--	--
PHPA Status						
PHPA	0.09 (0.07)	0.07 (0.01) ‡	0.15 (0.02) ‡	-0.01 (0.06)	1.63 (2.02)	<.01
Non-PHPA (ref)	--	--	--	--	--	--

Note: Mid-Quantile regression estimates obtained from fitting linear models; SE, Standard Error;
NA represents estimate and standard error calculations resulting in values that were essentially zero;
PHPA = Public Health Priority Areas are 6 zip code tabulation areas selected by the county health department with disproportionate poverty and educational attainment relative to the larger county;
APC Visits = total visits to ambulatory or primary care during the study period January 1- December 31st 2017;
KT = Khmaladze Test for the location-shift hypothesis test for individual slopes;
[*]Significant at $p < 0.05$
[†]Significant at $p \leq 0.01$
[‡]Significant at $p \leq 0.001$

Table 6.4. Regression Quantiles of Emergency Department (ED) Charges

Characteristic	Quantile regression estimates (SE)					KT
	25^{th}	50th	75^{th}	95^{th}	99^{th}	p value
Insurance Type						
Medicaid	355.6 (31.8) ‡	814.1 (48.0) ‡	2050.9 (106.2) ‡	5,563.5 (396.2) ‡	13,007.7 (1098.6) ‡	<.01
Medicare	301.7 (45.2) ‡	597.8 (64.5) ‡	966.1 (118.5) ‡	3,670.3 (461.3) ‡	10,345.8 (1591.7) ‡	<.01
Private	-50.8 (22.6) *	-121.2 (32.3) ‡	-337.3 (75.1) ‡	-2,150.7 (247.1) ‡	- 4,019.5 (688.0) ‡	<.01
Uninsured (ref)	--	--	--	--	--	--
APC Visits						
> 1 Visit	533.2 (26.8) ‡	655.5 (34.6) ‡	1,328.5 (70.4) ‡	3,204.2 (263.8) ‡	5,899.7 (795.5) ‡	<.01
1 Visit	189.1 (39.7) ‡	309.2 (54.7) ‡	804.6 (128.4) ‡	771.2 (435.2)	2,233.4 (905.5) *	<.01
0 Visit (ref)	--	--	--	--	--	--
Gender						
Female	310.3 (19.8) ‡	432.9 (28.1) ‡	667.9 (60.2) ‡	645.4 (211.4) †	-389.5 (613.6)	<.01
Male (ref)	--	--	--	--	--	--
Age	13.2	23.1	32.7	25.4	10.3	<.01

	(0.8) ‡	(1.1) ‡	(2.2) ‡	(7.8) †	(22.3)	
Race						
Black	-191.9 (25.0) ‡	-334.5 (34.7) ‡	-376.8 (71.6) ‡	-63.3 (251.1)	390.8 (766.2)	<.01
Other or Unknown	-203.0 (37.7) ‡	-341.2 (50.1) ‡	-752.3 (111.2) ‡	-1,904.2 (346.8) ‡	-3,625.8 (1008.4) ‡	<.01
White (ref)	--	--	--	--	--	--
Ethnicity						
Hispanic or Latino	94.7 (40.0) *	125.8 (56.3) *	414.8 (130.7) †	76.5 (407.4)	433.8 (1076.1)	<.01
Declined or Unknown	- 388.9 (28.9) ‡	- 591.1 (39.3) ‡	-1,321.0 (85.6) ‡	- 3,734.9 (251.03) ‡	-8,854.3 (795.0) ‡	<.01
Non-Hispanic or Latino (ref)	--	--	--	--	--	--
PHPA Status						
PHPA	- 76.4 (20.8) ‡	- 80.5 (29.7) †	52.2 (66.1)	700.9 (242.8) †	2,351.7 (663.9) ‡	<.01
Non-PHPA (ref)	--	--	--	--	--	--

Note: Quantile regression estimates obtained from fitting linear models; SE, Standard Error;
PHPA = Public Health Priority Areas are 6 zip code tabulation areas selected by the county health department with disproportionate poverty and educational attainment relative to the larger county;
APC Visits = total visits to ambulatory or primary care during the study period January 1- December 31st 2017;
KT = Khmaladze Test for the location-shift hypothesis test for individual slopes;
*Significant at $p < 0.05$
†Significant at $p \leq 0.01$
‡Significant at $p \leq 0.001$

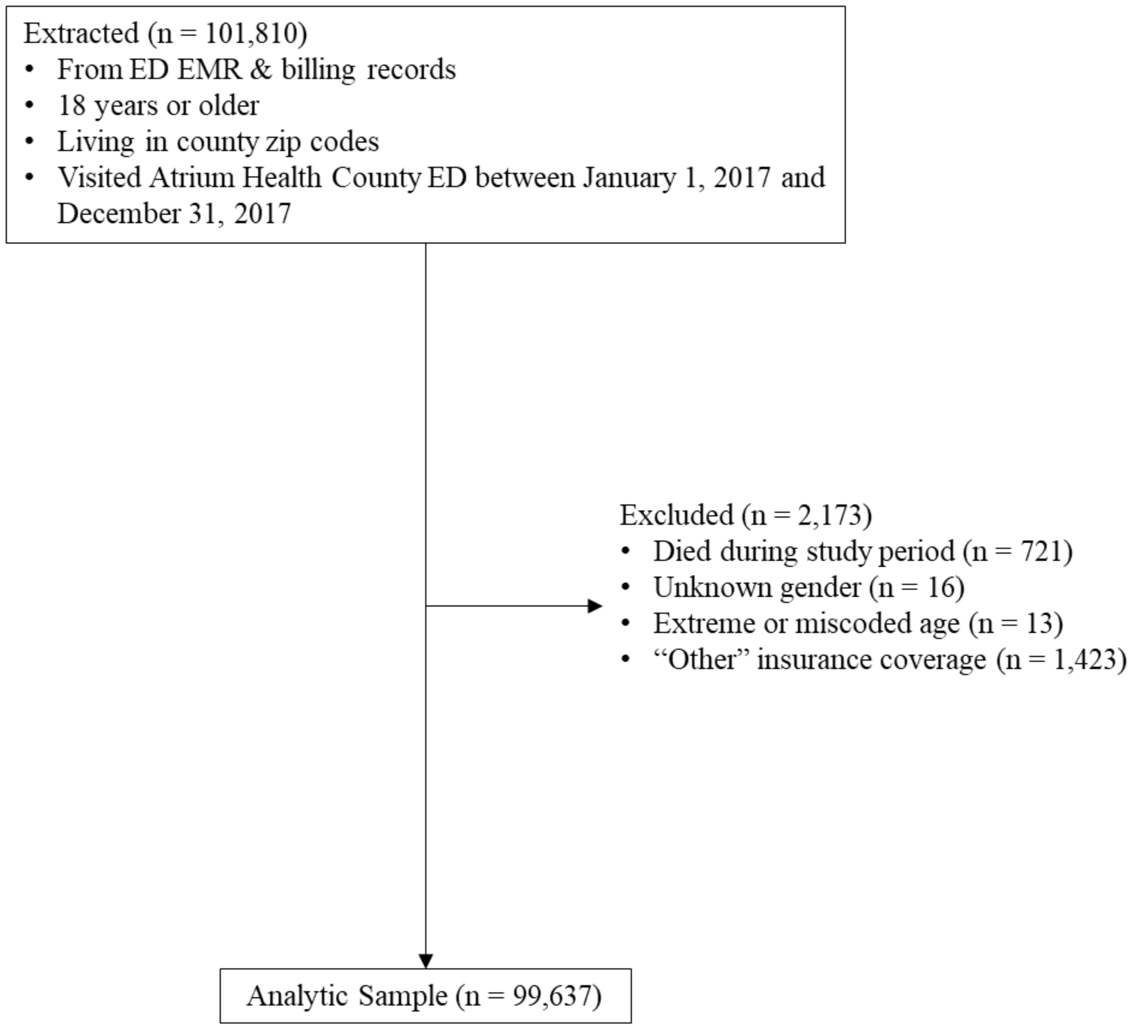

Figure 6.1. Analytic Sample Flow Diagram; ED, Emergency Department; EMR, Electronic Medical Record

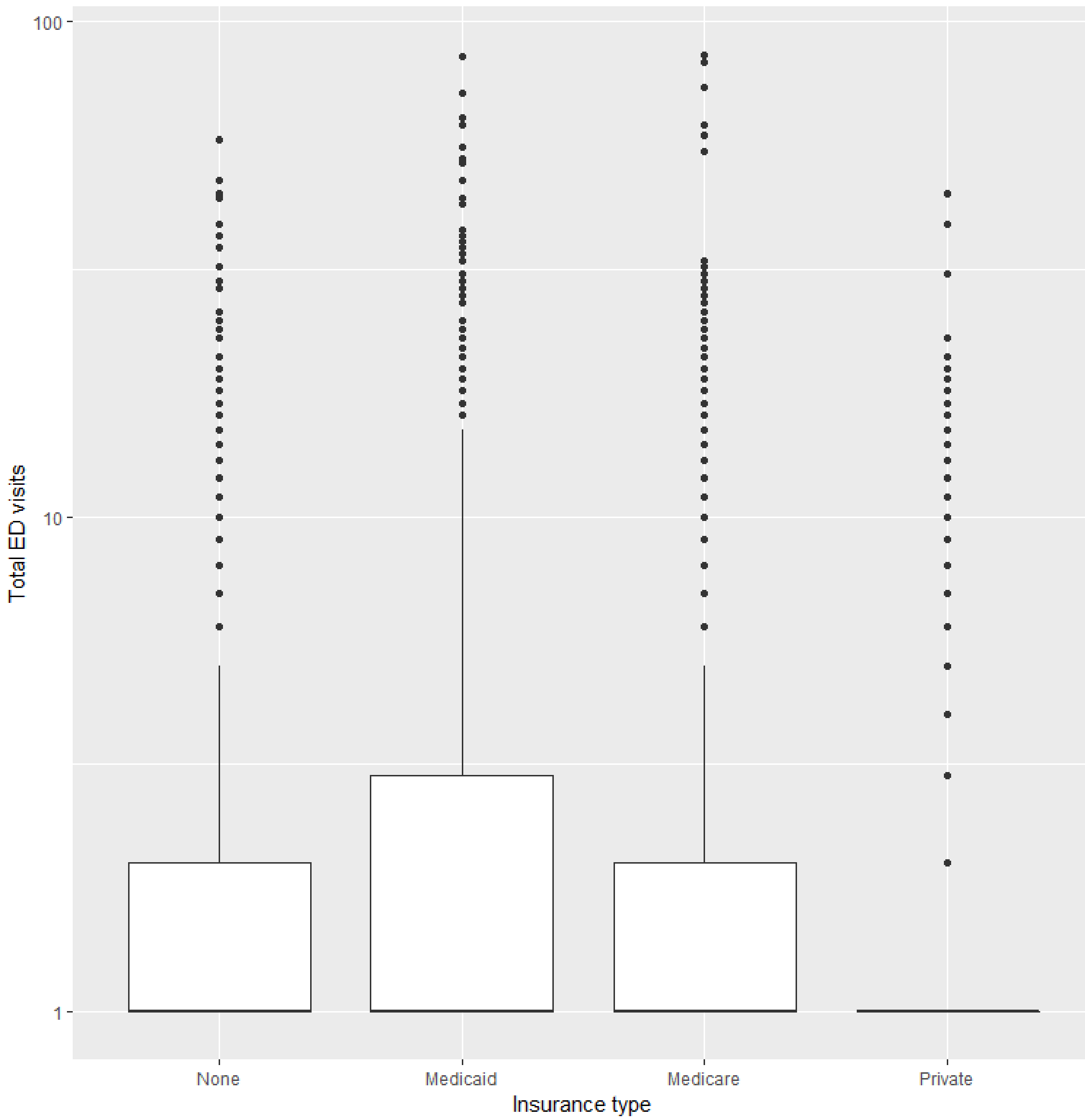

Figure 6.2. Box-Plot of Emergency Department (ED) Visits by Insurance Type; Data were collected from ED records, and therefore all patients in the sample had a minimum of 1 ED visit.

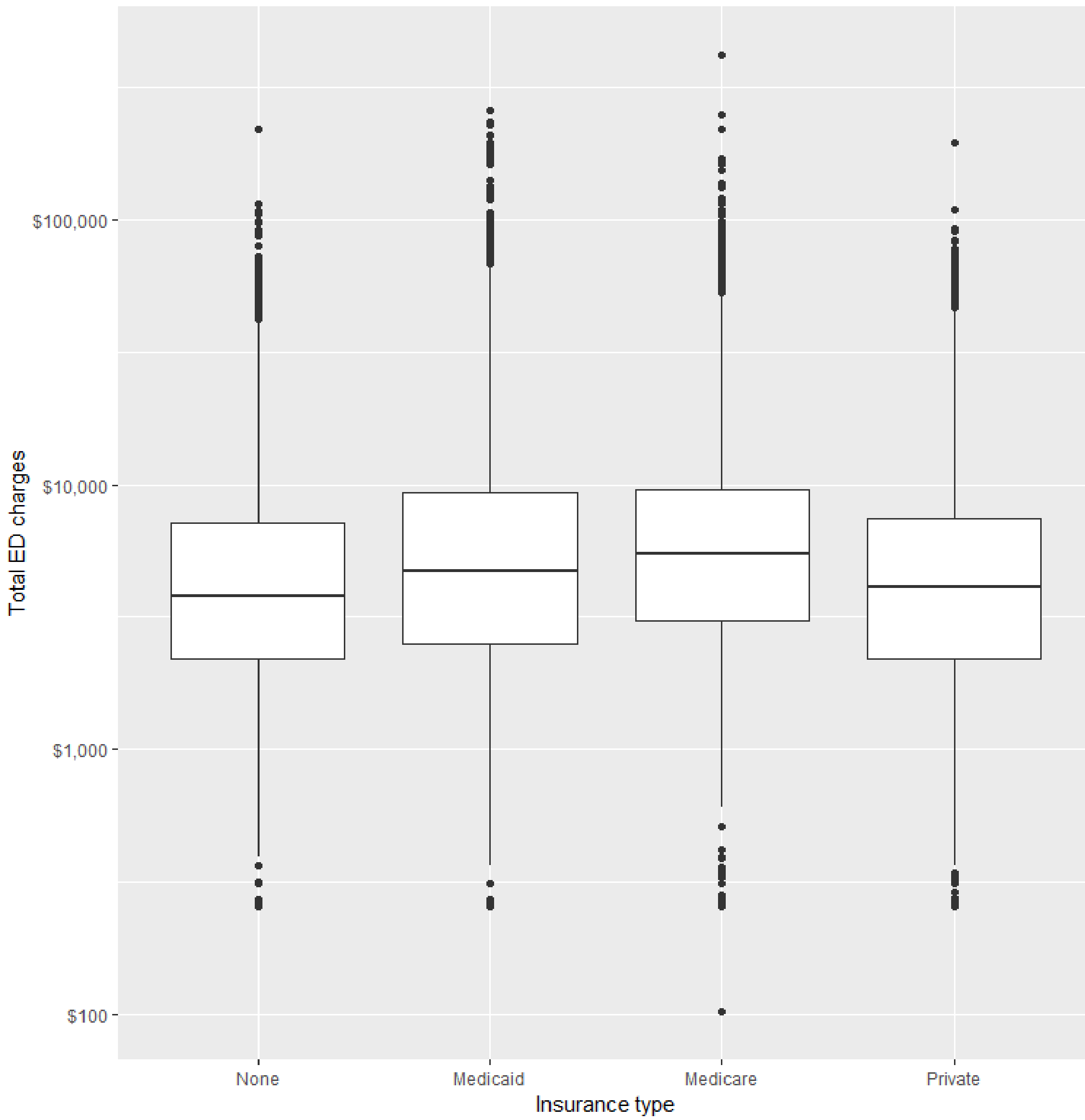

Figure 6.3. Box-Plot of Emergency Department (ED) Charges by Insurance Type; Data were collected from ED records, and therefore all patients in the sample had a minimum charge greater than $0.

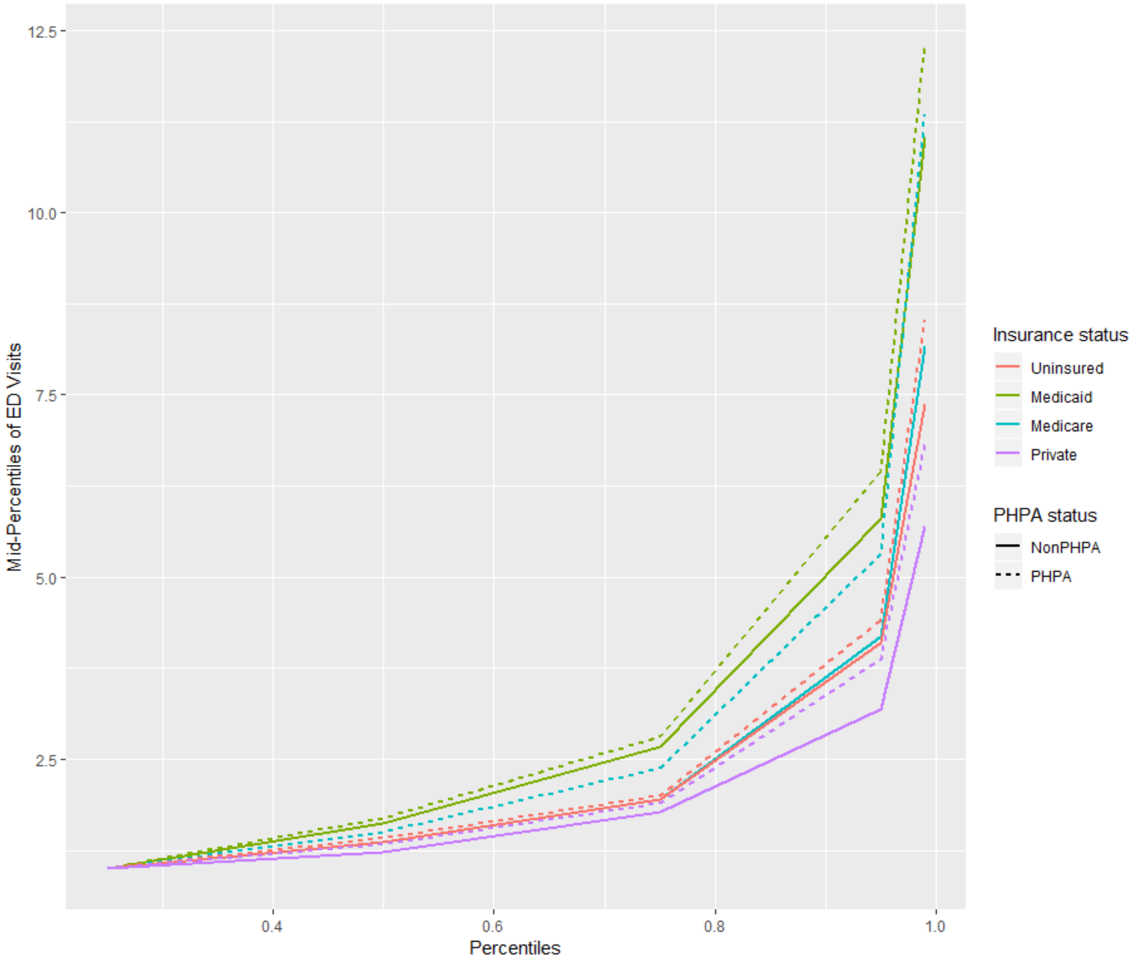

Figure 6.4. Mid-Quantiles of ED Visit by Insurance and PHPA Groups; PHPA, public health priority area measured as ZIP code tabulation areas with disproportionately low educational attainment and high poverty where

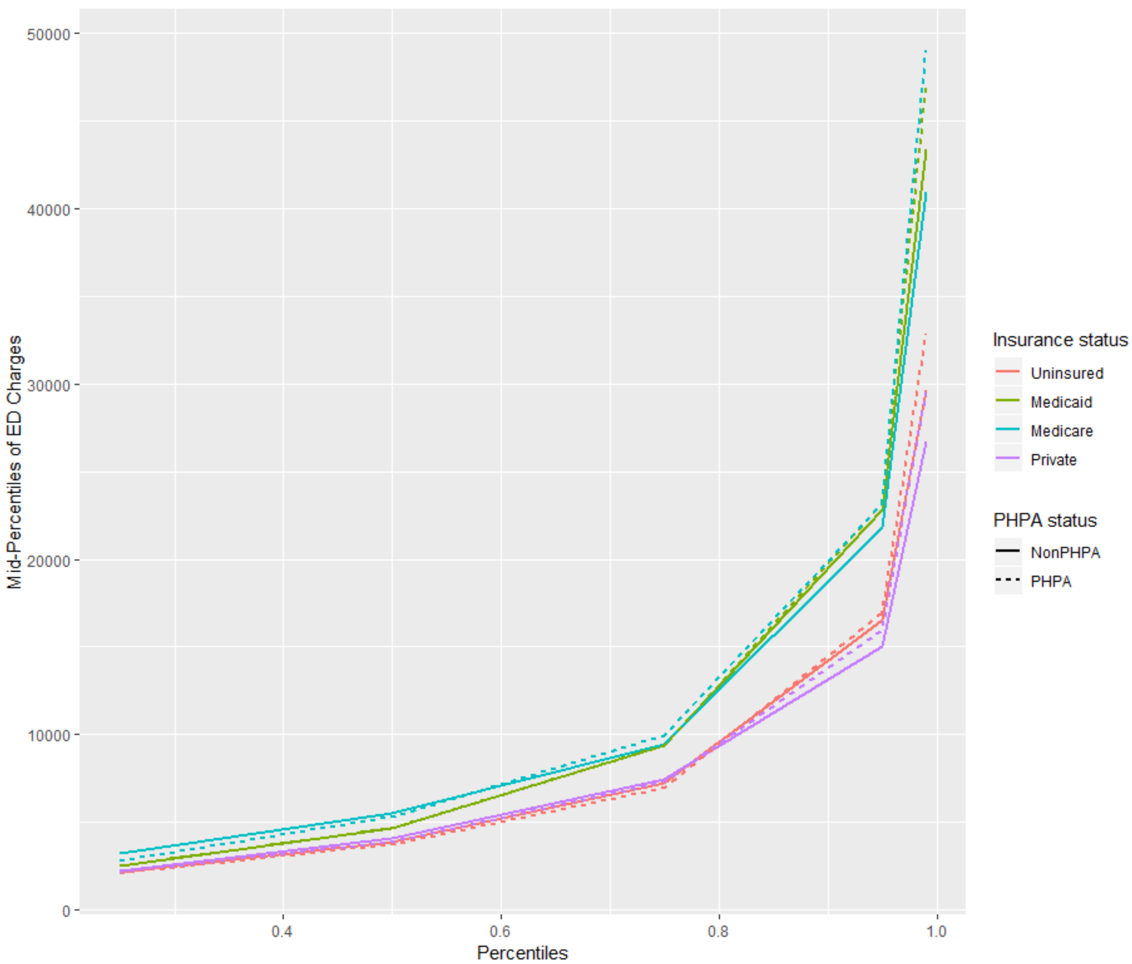

Figure 6.5. Mid-Quantiles of ED Charges by Insurance and PHPA Groups; PHPA, public health priority area measured as ZIP code tabulation areas with disproportionately low educational attainment and high poverty where

CHAPTER 7

DISCUSSION

The primary goal of this study was to examine individual-level and neighborhood-level characteristics associated with ambulatory or primary care utilization, Emergency Department (ED) utilization, and ED charges among a sample of ED patients. In the following sections important themes from the results are discussed:

Underlying Disparities in Public Health Priority Areas (PHPAs)

Public Health Priority Areas (PHPAs) were selected by the county Health Department as 6 ZCTAs with disproportionately lower educational attainment and higher poverty, relative to the larger county. Among our sample of ED patients, living in a PHPAs was also associated with disproportionate healthcare utilization. Residential segregation was associated with PHPA status and may be compounded with other underlying social and economic disparities in Mecklenburg County. In Aim 1, we found that those living in PHPAs had disproportionately worse access to insurance coverage, fewer ambulatory or primary care (APC) visits, and more ED visits during the study period, compared to those living in the larger county. Overall, Mecklenburg County ZCTAs were moderately segregated and PHPAs had significantly higher proportions of Black residents, relative to the proportions in the larger county. Living in an area with increasing proportion of Black residents was not significantly associated with ED visits on average, however it was associated with a fewer APC visits on average (Aim 1).

Our results also indicated that PHPA residents who were Black were affected differently than those who were White. For example, Black individuals, were less likely to use ambulatory or primary care, and were more likely to use the ED at a higher frequency for lower cost care. Results from Aim 1 showed that living in an area with increasing proportion of Black residents was associated with increased likelihood of not having any APC visits during the study period, a relationship that was stronger among White individuals compared to Black individuals. The scale of the outcome measure for this analysis ranged from higher proportion of Black to higher proportion of White. Therefore, the inverse of this relationship can be interpreted as living in areas with increasing proportions of White residents being associated with lower likelihood of not having any APC visits during the study period. Similar trends were observed for the total ED charges. For instance, in areas with higher proportions of Black residents lower ED charges were incurred by Black compared to White residents. These results could be an indication that Black individuals in our sample, living in areas that were disproportionately Black may have been more likely to use the ED for lower-cost APC services relative to White individuals living in the same areas that were using the ED for more severe, higher-cost health conditions (Aim 1).

The Aim 3 results were consistent with these conclusions. When examining patient characteristics associated with percentiles of ED visits, we found that Black race was associated with higher numbers of ED visits at the 50^{th} and 75^{th} percentiles and lower ED charges at the 25^{th}, 50^{th}, and 75^{th}, compared to White race. When controlling for race, we found that living in a PHPA was associated with greater ED visits among the bottom 75% of the population. The relationship between PHPA status and ED charges was in alignment with our results from Aim 1. Among those in the bottom 50% of the distribution (i.e. lower than typical charges likely indicating lower severity of ED utilization) living in a PHPA was associated with lower ED charges compared to those living in the larger county. Among the top 5% of the distribution, (i.e. higher than typical charges indicating higher severity of ED utilization), living in a PHPA was associated with higher ED charges compared to those living in the larger county.

These findings could be explained by underlying disparities in PHPAs that contribute to a cluster of social and economic disadvantage, resulting in health and healthcare utilization disparities. Results from the county health assessment show that these areas also have disproportionately higher prevalence of chronic health conditions including: high blood pressure (42.0% vs. 30.1%), high cholesterol (36.3% vs. 30.2%), diabetes (15.8% vs. 9.6%), and cardiovascular disease (11.5% vs. 7.5%) compared to the larger county. These conclusions are consistent with other studies showing that areas with disproportionate income, race, and educational attainment are associated with disparities in other environmental healthcare access factors such as the spatial concentration of PC physicians (Gaskin et al., 2012b), healthcare facilities (Dai, 2010), and physicians accepting Medicaid insurance (Greene et al., 2006).

Medicaid Insurance, Quality of Care and Access to Care

Our results showed consistently worse outcomes among those with Medicaid insurance, compared to other insurance coverage types as well as those who were uninsured. These results could be an indication of poor quality of care and limited access to preventive healthcare associated with Medicaid and align with studies indicating that Medicaid insurance expansion is not a one-dimensional solution to the burden of inappropriate and frequent ED utilization. Individuals covered by Medicaid may be less healthy and possibly younger than those without any insurance. In Aim 2, our results showed that having Medicaid insurance was associated with higher avoidable ED scores at all percentiles of the distribution compared to being uninsured. Having private insurance, was associated with lower avoidable ED score at all percentiles compared to being uninsured. These results were adjusted for other covariates including APC visits and living in a PHPA. In Aim 3, we found that having Medicaid insurance was associated with more ED visits at the 50th and 75th percentiles of the distribution, with the largest coefficient at comparable percentiles. Having Medicaid insurance was also associated with higher ED charges, compared to the uninsured, at all percentiles of the distribution and with the largest coefficient at all comparable percentiles (Aim 3).

These results are consistent with natural experiment studies examining the effect of Medicaid insurance on ED utilization. In the Oregon Health experiment, previously uninsured or underinsured individuals were randomly assigned over time to receive Medicaid insurance to test the effect of ACA Expansion. Results showed an approximately 40% increase in ED use (Taubman et al., 2014) that remained consistent over the 2 year study period (2008-2010)(Finkelstein et al., 2016) and that newly insured participants were more likely visit the ED for nonurgent conditions compared to participants who were previously insured (Taubman et al., 2014). Discussions of the Oregon Health Experiment results have highlighted that access to primary care and quality of care in preventive healthcare settings are key factors influencing the effect of Medicaid insurance on ED utilization (Heintzman et al., 2014).

Measurement and Definition of ED Utilization Outcomes

Our results showed that the strength of associations between patient characteristics and ED utilization outcomes varied by percentile, and that some relationships were heterogeneous. In the total Aim 2 sample, having more than 1 APC visit was associated with a lower avoidable ED score among those in the bottom 25% of the distribution, and a higher avoidable ED score among those in the top 25% of the distribution, when controlling for insurance coverage type and other covariates. These relationships were consistent for those in the uninsured and privately insured populations when we stratified the Aim 2 population by insurance type. In Aim 3 we found that visiting APC during the study period was associated with more ED visits among the bottom 75% of the population and fewer ED visits among the top 5% of the population. Additionally, living in a PHPA was associated with lower ED charges among the bottom 50% and higher ED charges among the top 5% of the distribution.

These results have important implications for the evaluation and measurement of ED utilization constructs. Consistent with other studies, the distributions of our outcome variables (avoidable ED score, ED visits, and ED charges) were skewed with long heavy right tails and did not align with normal distribution assumptions. Prior studies have used methods such as log transformations or mean regression models that are robust to non-normal error distributions (i.e. generalized linear models) to assess relationships between predictors and ED utilization on average. Experts have argued that mean regression models are inappropriate for evaluating many social science conditions, including those related to inequality and disparity. By focusing on the center of a population distribution, one is unable to understand the margins or evaluate factors associated with the "gap" between margins (Hao & Naiman, 2007). Other studies have used dichotomized outcome variables (yes/no) to define frequent utilization or avoidable utilization based on arbitrary cut-points that reduces the scope and sensitively of the measurement.

In Aim 2, we measured avoidable ED utilization as a continuous score, and in In Aim 3 we assessed the total number of ED visits (discrete) and total ED charges (continuous) during the study period. Quantile Regression (QR) and Mid-QR models were used to estimate associations across percentiles of the outcome distributions. These methods were robust to skewness and heavy tailed error distributions, and provides a more complete understanding of the relationships between predictors and internal, distribution-based cut points of the outcome. These results can be used to inform future interventions efforts to improve appropriate utilization, in Mecklenburg County, NC and as an evaluation model for other similar communities.

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