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Ambulatory Care, Insurance, and Avoidable Emergency Department Utilization in North Carolina

Carlene A. Mayfield, Ph.D., MPH[1]; Marco Geraci, Ph.D., CStat[2]; Brisa Urquieta de Hernandez, BS[1]; Michael Dulin, PhD, MD[3]; Jan M. Eberth, Ph.D.[4]; Anwar T. Merchant, Sc.D., MPH, DMD[2]

[1]Atrium Health, Department of Community Health, Charlotte NC

[2]University of South Carolina, Department of Epidemiology and Biostatistics, Arnold School of Public Health, Columbia, SC

[3]Academy for Population Health Innovation; University of North Carolina Charlotte and Mecklenburg County Health Department, Charlotte, NC

[4]Rural and Minority Health Research Center; University of South Carolina, Department of Epidemiology and Biostatistics, Arnold School of Public Health, Columbia, SC

Correspondence concerning this article should be addressed to:

Carlene A. Mayfield, Department of Community Health, Atrium Health,

4135 South Stream Boulevard, Charlotte NC, 28217.

Contact: carlene.mayfield@atriumhealth.org

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Key words:

Emergency Service, Medicaid, Primary Health Care, Algorithms, Quantile Regression

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Abstract

Objective: To examine whether and how avoidable emergency department (ED) utilization is associated with ambulatory or primary care (APC) utilization, insurance, and interaction effects. **Design and Sample**: A cross-sectional analysis of electronic health records from 70,870 adults residing in Mecklenburg County, North Carolina, who visited an ED within a large integrated healthcare system in 2017. **Methods**: APC utilization was measured as total visits, categorized as: 0, 1, and >1. Insurance was defined as the method of payment for the ED visit as: Medicaid, Medicare, private, or uninsured. Avoidable ED utilization was quantified as a score (aED), calculated as the sum of New York University Algorithm probabilities multiplied by 100. Quantile regression models were used to predict the 25th, 50th, 75th, 95th, and 99th percentiles of avoidable ED scores 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 aED at the lower percentiles and positively associated at higher percentiles. A higher aED was associated with having Medicaid insurance and a lower aED was associated with having private insurance, compared to being uninsured. In stratified models, having >1 APC visit was negatively associated with aED at the 25th percentile for the uninsured and privately insured, but positively associated with aED at higher percentiles among the uninsured, Medicaid-insured, and privately insured. **Conclusions**: The association between APC utilization and avoidable ED utilization varied based on segments of the distribution of ED score and differed significantly by insurance type.

Keywords: Emergency Service, Medicaid, Primary Health Care, Algorithms Quantile Regression

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1 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 other healthcare settings, an ED visit is a waste of resources that lowers health system efficiency and raises healthcare costs [1]. Approximately 13 to 27% of all ED visits in the U.S. are avoidable, with an estimated annual cost of $4.4 billion [2]. Charges for nonurgent care in the ED are 320 to 728% higher than in primary care clinics, resulting in a 69 to 86% potential savings had the patient been treated in a primary care setting [3]. In addition to resource waste, 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 [4,5]. Avoidable ED utilization has increased over time among specific insurance reimbursement groups. Between 1997 and 2009, the 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 in privately insured or uninsured visits [6].

Vulnerable populations across race/ethnicity, insurance, and socioeconomic subgroups are disproportionately impacted by avoidable ED utilization [7]. Using the ED for non-urgent or primary care could be an indicator of inadequate access to healthcare [8]. Poor availability and quality of healthcare, including preventive healthcare, is also associated with increased disease severity [9,10] and mortality [11] in disadvantaged groups. Preventive healthcare is delivered in ambulatory healthcare settings [12], and includes primary care services such as cancer screenings, annual wellness exams, and vaccinations that can prevent or reduce the severity of many chronic diseases and health conditions [13]. However, individuals experiencing social, economic, and environmental health risk factors are less likely to use preventive healthcare [14] and are more likely to experience severe chronic disease that compounds with other health risk factors [15].

A variety of evidence has highlighted complexity in the relationship between healthcare utilization, insurance coverage, and avoidable ED utilization. A longitudinal study of the 2007-2009 National Hospital Ambulatory Medical Care survey found that avoidable ED utilization varied based on race/ethnicity, insurance status, age group, and socioeconomic status [7]. Among a retrospective cohort of patients from state-based hospital discharge data, individuals without insurance were more likely to use the ED for nonurgent or primary care treatable conditions compared to those with private insurance, yet were less likely compared to those with public insurance (i.e., Medicaid or other forms of state-subsidized insurance coverage) [16]. Avoidable ED utilization rates were higher in minority and Medicaid-insured patients and lower in Medicare-insured patients among a county-based population of healthcare system ED users [3]. A recent assessment of Massachusetts All-Payer claims data from 2011-2012 found that primary care treatable ED utilization was positively associated with 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) [17]. Given the widespread investment in hospital-based programs and interventions to improve appropriate healthcare utilization [1,18,19,20] a nuanced evaluation of the relationships between non-emergency healthcare utilization, insurance status, and avoidable ED utilization would benefit the health services research and practitioner communities.

The purpose of this study was to assess i) the relationship between non-emergency healthcare utilization, insurance coverage, and avoidable ED utilization (outcome); and ii) the degree to which the relationship between non-emergency healthcare utilization and avoidable ED utilization (outcome) varied by type of insurance coverage, using advanced statistical methods to explore complexity in these relationships.

2 Methods

2.1 Overview

2.1.1 New York University Algorithm. Avoidable ED utilization was classified in this analysis using the New York University Emergency Department algorithm (NYU Algorithm), a validated classification system that measures the urgency of an ED visit using nine distinct categories [21]. The first four NYU Algorithm categories classify an ED visit as being: 1) non-emergent, 2) emergent, primary care treatable, 3) emergent, preventable or avoidable, and 4) emergent, not preventable or avoidable. The algorithm assigns a probability for each ED visit being in one of those four categories based on the primary diagnosis code for each ED visit. The sum of probabilities in categories 1-4 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 are treated as mutually exclusive events. Therefore, ED visits for which the urgency is calculated (categories 1-4), exclude visits that are injury, mental health, alcohol, drug-related, or unclassified (categories 5-9).

2.1.2 Study Sample. The data for this cross-sectional analysis were obtained from the electronic medical records (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 a Health System ED between January 1, 2017 and December 31, 2017 (n=101,810). In alignment with standard practice for NYU Algorithm use [22] we excluded individuals with ED visits classified by categories 5-9 as ED visits for injuries, mental health issues, alcohol and drug use, or visits 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. Individuals with "other" insurance (n = 693) reflected less than 1% of sample with governmental insurance benefits (e.g., Veterans Affairs) and other program-specific options that did not conceptually align with larger insurance categories. As this sample size was too small to produce reliable regression model estimates, those with "other" insurance were excluded, resulting in a final analytic sample consisting of 70,870 patients (Figure 1). The research protocol was reviewed and approved by the Institutional Review Board (IRB) at the Health System and was exempt from IRB review by the collaborating university because the protocol used de-identified secondary data.

2.2 Measures

2.2.1 Exposure: Ambulatory or Primary Care Visits. Non-emergency healthcare utilization was narrowed to focus on ambulatory or primary care (APC) utilization where an individual could potentially access preventive healthcare. Through key informant interviews with health system providers, the following list of specialty categories in the electronic medical record system was defined for APC: allergy, cardiovascular, dermatology, endocrinology, family medicine, internal medicine, primary care behavioral health, rheumatology, sleep medicine, sports medicine, urgent care, and general obstetrics and gynecology. Utilization of APC was quantified as the total number of unique encounters at Health System facilities during the study period and categorized as: 0 visits, 1 visit, and > 1 visit for analysis.

2.2.2 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 considered uninsured.

2.2.3 Outcome: Avoidable Emergency Department Score. The score of avoidable ED utilization for each individual was calculated using the sum of probabilities for NYU Algorithm categories 1-3 across all visits during the study period. Since individuals may have multiple ED visits over time, we defined the outcome as the total avoidable ED (aED) score. This method was used and described by prior research [22], which provided the following example: suppose an individual had three ED visits during a 12-month study period with two visits for heart palpitations and one 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 aED score for the study period is 1.66. To improve the interpretation of model estimates, the total aED score was multiplied by 100. In this context, an aED score value of 100 is equivalent to one ED visit that was deemed 100% avoidable, or two visits that were 60% avoidable and 40% avoidable.

2.2.4 Other Confounders. The following confounding factors were adjusted for as covariates: gender, race, ethnicity, age, and public health priority area (PHPA) status. Gender was defined 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 included as separate categorical variables. Age (years) was included as a continuous variable in all analyses. The local county public health department identified six PHPA ZCTAs, which were 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) as a proxy for social and environmental factors associated with healthcare access and utilization.

2.3 Analysis

Descriptive statistics were calculated by APC visit categories to characterize the study sample. The distribution of the outcome, aED score, was summarized by using box plots, histograms, and quantile-based location, scale, and shape measures.

In this study, we used quantile regression (QR) to evaluate the relationship between APC visits, insurance coverage, and aED score. QR is a statistical method that assesses the strength and direction of the effect of an exposure on specific quantiles (e.g., the median or the 90th percentile) of the outcome. If these effects are heterogeneous (i.e., non-constant) across the quantiles of the outcome, then there is evidence that there are sub-populations that are differentially affected by the exposure. In contrast, mean regression, as it models only one value of the outcome, cannot provide information on heterogeneous effects of the exposure by definition. 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) [23, 24].

In this study, QR models were fitted at the 25th, 50th, 75th, 95th, and 99th percentiles of aED score. Estimation was carried out using linear programming (Frisch-Newton), while confidence intervals and standard errors were computed using bootstrap resampling with 100 replications. The location-shift hypothesis was tested by using a Khmaladze test. The null hypothesis is that the coefficients (slopes) of the regression models are constant (homogeneous) across quantiles. Goodness of fit was evaluated using a cusum test [25]. Model 1 included APC visits and insurance coverage as predictors, and was adjusted for gender, age, race, ethnicity, and PHPA status. Model 2 additionally included an interaction term between APC visits and insurance coverage. Standard mean regression models were used for comparison. All analyses were performed using R 3.6.1 [26], with quantile regression models performed using the quantreg [27], and Qtools [28, 29] packages.

3 Results

3.1 Sample Characteristics

Of the 70,870 individuals in the study sample that attended at least one of six county EDs during 2017, 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%). Participant characteristics by APC visit categories are presented in Table 1. Not having an APC visit in the last year 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%). Individuals with more than one APC visit were approximately eight years older on average (mean: 48.7, SD: 17.8) than those with one visit (mean: 40.8, SD: 15.2) or no visits (mean: 39.6; SD: 16.1).

3.2 Distribution of Avoidable Emergency Department Scores

The aED scores ranged from 0 to 4,551.8 (corresponding to about 45 fully avoidable visits), with a median at approximately 100 (corresponding to one fully avoidable visit). The interquartile range, the range of the middle 50% of the distribution, was 51.3. The histogram of aED scores shows a unimodal distribution, with an extreme right skewness. The skewness index was approximately 0.3, which indicates a moderate right asymmetry (i.e., extreme observations in the right side of the distribution). The shape index was 3.4, indicating that the tails of the distribution were heavier (i.e., extremes more likely) compared to a value of 1.9 of a normal distribution. The conditional box plot of aED scores by APC visit categories is presented in Figure 2 (to remove the distorting effect of extreme values, the y-axis is on the log scale). The distribution of aED score differed by APC visit category, with most extreme outliers observed among those without any APC visits during the study period.

3.3 Percentiles of Avoidable Emergency Department Scores

The 25th, 50th, 75th, 95th, 99th percentiles as well as the mean of aED scores, by APC visit categories and overall, are presented in Table 2. Clear differences were observed between the stratified samples and the total sample for all percentiles except the 95th. For example, at the 25th percentile, the aED score decreased with increased APC visits (67.0 for

>1 APC visits, 72.9 for 1 APC visit, and 84.4 for 0 APC visits). This pattern was consistent across the 50th, 75th, and 99th percentiles. On average, the aED score for those with more than one APC visit was smallest (mean: 120.6), followed by those with one visit (mean: 125.0) and no visits (mean: 126.5).

Results from Model 1 are presented in Table 3. At the 25th percentile, having an APC visit during the study period was negatively associated with the aED score. Individuals with >1 APC visits ($\beta = -2.5$; $p < 0.001$) or with 1 APC visit ($\beta = -1.7$; $p = 0.024$) had a lower aED score compared to those without any APC visits during the study period. At the 75th percentile, the association between APC visits and the aED score was positive for those with >1 APC visits ($\beta = 5.4$; $p < 0.001$) and 1 APC visit ($\beta = 4.5$; $p = 0.002$) compared to those without any APC visits. A similar trend was observed at the 95th percentile. In the top 1% of the distribution (i.e., 99th percentile), having >1 APC visits during the study period was positively associated with the aED score ($\beta = 61.2$; $p < 0.001$) compared to those without any APC visits. At the 99th percentile, no significant differences were observed between those having 1 APC visit and those without any APC visits during the study period. Results from the mean regression model showed a significant positive association between APC visits and aED scores, where the estimated average score was higher among those with >1 ($\beta = 7.8$; $p < 0.001$) or 1 APC visit ($\beta = 4.8$; $p = 0.008$) during the study period compared to those without any APC visits.

Among ED users, having Medicaid insurance was positively associated with aED scores compared to being uninsured. Individuals with Medicaid insurance had a higher aED score at the 25th, 75th, 95th, and 99th percentiles than the uninsured. The coefficients for this relationship were 80-fold larger among those at the 99th percentile ($\beta = 202.2$; $p < 0.001$) compared to the 25th percentile ($\beta = 2.5$; $p < 0.001$). No significant differences were observed between those with Medicare insurance and those who were uninsured at the 25th, 50th, and 75th percentiles. Medicare insurance was positively associated with aED scores at the 95th ($\beta =$

31.4; $p < 0.001$) and 99th percentiles ($\beta = 102.4$; $p = 0.003$) compared to the uninsured. At all percentiles of the distribution, having private insurance was negatively associated with aED scores compared to being uninsured. The magnitude of the estimated coefficient for private insurance at the 25th percentile ($\beta = -7.9$; $p < 0.001$) was about 14-fold the estimate at the 99th percentile ($\beta = -111.2$; $p < 0.001$). The Khmaladze test 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 aED was significantly different across the quantiles of aED score.

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

The study sample was stratified by insurance type and modeled separately to estimate the association between APC visits and aED scores in each stratum (Table 4). Among the uninsured, APC utilization was negatively and positively associated with aED scores, based on segments of the distribution. At the 25th percentile, uninsured individuals with > 1 APC ($\beta = -0.7$; $p = 0.0177$) had lower aED scores than those without any APC visits. This relationship was opposite at the 75th ($\beta = 26.7$; $p < 0.001$), 95th ($\beta = 82.8$; $p < 0.001$), and 99th ($\beta = 164.1$; $p = 0.001$) percentiles. For those with Medicaid insurance, having >1 APC visit was associated with a higher aED score at the 75th ($\beta = 9.6$; $p < 0.033$), 95th ($\beta = 41.9$; $p = 0.045$) and 99th ($\beta = 187.3$; $p = 0.033$) percentiles compared to having no APC visits, while there was no statistically significant differences in aED scores were found between individuals with one APC visit and those with no APC visits. The largest negative coefficient of magnitude was observed among individuals with private insurance, at the 25th percentile where having >1 APC visit was negatively associated with aED scores (β= -4.2, $p < 0.001$). At higher percentiles a positive association was observed for those in the 95th (β = 18.6; $p < 0.001$) and 99th percentiles (β = 39.7; p = 0.012). Both coefficients were the smallest in magnitude compared to other significant associations at equivalent percentiles.

4 Discussion

The goal of this study was to assess the independent associations of non-emergency healthcare use (i.e., APC utilization) and insurance coverage, with utilization of the ED for avoidable care during a 12-month study period. We also examined the interaction effect between APC utilization and insurance type on these relationships. Using a robust statistical method, QR, we examined associations across percentiles of the distribution of our outcome variable, aED score. Our results showed that the relationships between APC utilization, insurance coverage, and aED score are heterogenous, with the strength and direction of effect inconsistent across percentiles. For those with lower than typical levels of avoidable utilization (i.e., bottom 25% of aED scores), APC utilization was associated with less avoidable ED utilization. In contrast, for those with higher than typical levels of avoidable ED utilization (i.e., top 25% of aED scores), APC utilization was associated with more avoidable ED utilization. Note that these associations controlled for insurance coverage and other covariates. When adjusting for APC utilization, having Medicaid insurance was consistently associated with more avoidable ED utilization (compared to uninsured), while having private insurance was consistently associated with less avoidable ED utilization (compared to uninsured).

In the stratified analysis, heterogeneous relationships between APC utilization and avoidable ED utilization were also observed. In the bottom 25% of the uninsured, Medicare, and privately insured stratum, having > 1 APC visit during the study period was associated with less avoidable ED utilization. This relationship was strongest in the privately insured stratum, and could be an indicator of greater protective benefit for non-emergency or preventive healthcare utilization among those privately insured. The only significant associations between having 1 APC visit during the study period and avoidable ED utilization were observed in the uninsured stratum. Of note, the largest magnitude of effect for all stratified analysis occurred in the top 1% of the uninsured stratum for those with 1 APC visit (compared to no APC visits) at value equivalent to almost 2.5 ED visits that were 100% avoidable. This relationship was not significant in the Medicaid stratum. Additionally, among the top 1% of the Medicaid stratum, having >1 APC visits (compared to no APC visits) was associated with a magnitude of effect approximately equivalent to 2 ED visits that were 100% avoidable. These results highlight the complexity of the relationship between healthcare utilization, insurance coverage, and avoidable ED utilization and could be an indication of systematically unmet care needs among the uninsured population accessing non-emergency, ambulatory or primary healthcare.

The distribution of the outcome variable, aED 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 [30,31]. 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% [32]. This method of dichotomizing the total probability has been criticized as arbitrary [22] and an unnecessary loss of sensitivity [6] 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 having Medicaid insurance, and largest among those with Medicaid compared to other insurance groups [16,3]. A similar study examining Massachusetts All-Payer claims data from 2011-2012 found that primary care treatable ED utilization was positively associated with primary care visits among stratified samples of insurance groupings and for the combined sample [17]. This study also 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 identified that the strength of the association between APC utilization visits and avoidable ED utilization differed significantly across distribution percentiles. Therefore, interpreting the magnitude of the association at the average mischaracterizes the relationship.

Some limitations should be considered when interpreting the results of this work. Our study utilized a sample from a large county Health System, that was not comprehensive for all healthcare in the area. As reported by other studies [33,34], health system leakage (participants using other facilities) is a limitation in single-system data sources that can induce measurement error. The Health System is the largest provider of healthcare for all of Mecklenburg County and for uninsured and Medicaid-insured populations; thus, the impact of system leakage on results of the study is likely limited. The external validity of the NYU Algorithm has been criticized because of the single timepoint, geographic location, and healthcare system used in its development [35]. However, it has been validated using nationally representative data [32] and Medicare payer data [21] for single time point classifications. Additionally, the cross-sectional study design and single year of data does not allow for temporal, causal interpretations of associations between variables. The observational study design also introduces the potential for residual confounding.

5 Conclusions

The relationships between APC utilization, insurance coverage, and avoidable ED utilization are inconsistent across percentiles of the outcome distribution. Studies applying mean regression models to evaluate these relationships may mischaracterize the associations and fail to account for heterogeneity in the population. Using APC is associated with less avoidable ED utilization among those with lower than typical levels, and more avoidable ED utilization among those with higher than typical levels. The protective effect of this relationship is strongest among the private insurance stratum, while the harmful effect is strongest among the uninsured stratum. Future studies evaluating relationships between insurance coverage and healthcare utilization, particularly those exploring solutions for inappropriate healthcare utilization, should consider quantile regression methods as an alternative to traditional mean regression techniques.

References

[1] Enard KR, Ganelin DM. (2013). Reducing preventable emergency department utilization and costs by using community health workers as patient navigators. J Healthc Manag 2013;58(6):412–427; discussion 428.

https://doi.org/10.1016/j.biotechadv.2011.08.021.Secreted

[2] Weinick RM, Burns RM, Mehrotra A. (2010). Many emergency department visits could be managed at urgent care centers and retail clinics. Health Affairs 2010;29(9):1630–1636. https://doi.org/10.1377/hlthaff.2009.0748

[3] McWilliams A, Tapp H, Barker J, Dulin M. Cost analysis of the use of emergency departments for primary care services in Charlotte, North Carolina. N C Med J 2011;72(4):265–271. http://www.ncbi.nlm.nih.gov/pubmed/22128684

[4] Moskop JC, Sklar DP, Geiderman JM, Schears RM, Bookman KJ. Emergency department crowding, Part 1-Concept, causes, and moral consequences. Ann Emerg Med 2009;53(5):605–611. https://doi.org/10.1016/j.annemergmed.2008.09.019

[5] Khangura JK, Flodgren G, Perera R, Rowe BH, Shepperd S. Primary care professionals providing non-urgent care in hospital emergency departments. Cochrane Database Syst Rev 2012;11: CD002097. https://doi.org/10.1002/14651858.CD002097.pub3

[6] Pukurdpol P, Wiler JL, Hsia RY, Ginde AA. Association of medicare and medicaid insurance with increasing primary care-treatable emergency department visits in the U.S. Acad Emerg Med 2014;21(10):1135–1142. https://doi.org/10.1111/acem.12490

[7] Johnson PJ, Ghildayal N, Ward AC, Westgard BC, Boland LL, Hokanson JS. Disparities in potentially avoidable emergency department (ED) care: ED visits for ambulatory care sensitive conditions. Med Care 2012;50(12):1020–1028. https://doi.org/10.1097/MLR.0b013e318270bad4

[8] Dowd B, Karmarker M, Swenson T, Parashuram S, Kane R, Coulam R, Jeffery MM. Emergency department utilization as a measure of physician performance. Am J Med Qual 2014;29(2):135–143. https://doi.org/10.1177/1062860613487196

[9] Eachus J, Chan P, Pearson N, Propper C, Smith GD. An additional dimension to health inequalities: Disease severity and socioeconomic position. J of Epidemiol Community Health 1999;53(10):603–611. https://doi.org/10.1136/jech.53.10.603

[10] Weissman JS, Stern R, Fielding SL, Epstein AM. Delayed access to health care: Risk factors, reasons, and consequences. Ann Intern Med 1991;114(4):325–331. https://doi.org/10.7326/0003-4819-114-4-325

[11] Sommers BD, Baicker K, Epstein AM. Mortality and access to care among adults after state Medicaid expansions. N Engl J Med 2012;367(11):1025–1034. https://doi.org/10.1056/NEJMsa1202099

[12] Silverstein MD, Ogola G, Mercer Q, Fong J, Devol E, Couch CE, Ballard DJ. Impact of clinical preventive services in the ambulatory setting. Proceedings (Baylor University. Medical Center) 2008;21(3):227–235. https://doi.org/10.1080/08998280.2008.11928400

[13] Shi L. The impact of primary care: A focused review. Scientifica, 2012;2012:1–22. https://doi.org/10.6064/2012/432892

[14] Ross JS, Bernheim SM, Bradley EH, Teng HM, Gallo WT. Use of preventive care by the working poor in the United States. Prev Med 2007;44(3):254–259. https://doi.org/10.1016/j.ypmed.2006.11.006

[15] Cockerham WC, Hamby BW, Oates GR. The social determinants of chronic disease. Am J Prev Med 2017;52(1):S5–S12. https://doi.org/10.1016/j.amepre.2016.09.010

[16] Chen W, Waters TM, Chang CF. Insurance impact on nonurgent and primary care-sensitive emergency department use. Am J Manag Care 2015;21(3):210–217. http://www.ncbi.nlm.nih.gov/pubmed/25880625

[17] Lines LM, Li NC, Mick EO, Ash AS. Emergency department and primary care use in

Massachusetts 5 years after health reform. Med Care 2019;57(2):1. https://doi.org/10.1097/MLR.0000000000001025

[18] Seaberg D, Elseroad S, Dumas M, Mendiratta S, Whittle J, Hyatte C, Keys J. Patient navigation for patients frequently visiting the emergency department: A randomized, controlled trial. Acad Emerg Med 2017;24(11):1327–1333. https://doi.org/10.1111/acem.13280

[19] Natale-Pereira A, Enard KR, Nevarez L, Jones LA. The role of patient navigators in eliminating health disparities. Cancer 2011;117(SUPPL. 15):3543–3552. https://doi.org/10.1002/cncr.26264

[20] Peart A, Lewis V, Brown T, Russell G. Patient navigators facilitating access to primary care: A scoping review. BMJ Open 2018;8(3). https://doi.org/10.1136/bmjopen-2017-019252

[21] Ballard DW, Price M, Fung V, Brand R, Reed ME, Fireman B, et al. Validation of an algorithm for categorizing the severity of hospital emergency department visits. Med Care 2010;48(1):58–63. https://doi.org/10.1097/MLR.0b013e3181bd49ad

[22] Lines LM, Rosen AB, Ash AS. Enhancing administrative data to predict emergency department utilization: The role of neighborhood sociodemographics. J Health Care for the Poor and Underserved 2017;28(4):1487–1508. https://doi.org/10.1353/hpu.2017.0129

[23] Yu K, Lu Z, Stander J. Quantile regression: Applications and current research areas. J R Stat Soc Ser D: The Stat 2003;52(3). https://doi.org/10.1111/1467-9884.00363

[24] Koenker R. Quantile Regression. Cambridge University Press, New York, NY. 2005

[25] He X, Zhu LX. A lack-of-fit test for quantile regression. Journal of the American

Statistical Association 2003;98(464):1013-1022. https://doi.org/10.1198/016214503000000963

[26] R Core team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, http://www.R-project.org/. 2019.

[27] Koenker R. quantreg: Quantile Regression, https://cran.r-project.org/package=quantreg; 2019 [accessed 15 August 2019].

[28] Geraci M. Qtools: A collection of models and tools for quantile inference. The R Journal 2016; 8:117-13. https://journal.r-project.org/archive/2016/RJ-2016-037/index.html

[29] Geraci M. Qtools: Utilities for quantiles. Retrieved from https://cran.r-project.org/package=Qtools; 2019 [accessed 15 August 2019].

[30] Kieschnick R, Mccullough BD. Regression analysis of variates observed on (0, 1): Percentages, proportions and fractions. Stat Model 2003;3(3):193–213. https://doi.org/10.1191/1471082X03st053oa

[31] Coe AB, Ogbonna KC, Moczygemba LR, Mazmanian PE, Slattum PW, Parsons PL. Predictors of emergent emergency department visits and costs in community-dwelling older adults. Health Serv Insights 2018;11:117863291879025. https://doi.org/10.1177/1178632918790256

[32] Gandhi SO, Sabik L. Emergency department visit classification using the NYU algorithm. Am J Manag Care 2014;20(4):315–320. http://www.ncbi.nlm.nih.gov/pubmed/24884862

[33] LaCalle E, Rabin E. Frequent users of emergency departments: The myths, the data, and the policy implications. Ann Emerg Med, 2010;56(1):42–48. https://doi.org/10.1016/j.annemergmed.2010.01.032

[34] Krieg C, Hudon C, Chouinard MC, Dufour I. Individual predictors of frequent emergency department use: A scoping review. BMC Health Serv Res, 2016;16(1):594. https://doi.org/10.1186/s12913-016-1852-1

[35] Latham LP, Ackroyd-Stolarz S. Defining potentially preventable emergency department visits for older adults. Intern J Healthc, 2017;3(2). https://doi.org/10.5430/ijh.v3n2p1

Figure 1. Analytic Sample Flow Diagram

Abbreviations: ED, Emergency Department; EMR, Electronic Medical Record; NYU Algorithm, New York University Algorithm

Figure 2. Box Plot of Avoidable Emergency Department (ED) Score by Ambulatory or Primary Care (APC) Visit Category

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 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 Sample	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 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
Overall	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 3. Regression Quantiles of Avoidable Emergency Department (ED) Score

Quantile regression estimates (SE)

Factor	Quantile regression estimates (SE) 25th	50th	75th	95th	99th	KT p value	Mean regression estimate (SE)
APC Visits							
> 1 Visit	-2.5 (0.5)‡	-0.0 (0.1)	5.4 (0.8)‡	32.7 (4.5)‡	61.2 (14.7)‡	< 0.01	7.8 (1.1)‡
1 Visit	-1.7 (0.7)*	0.1 (0.1)	4.5 (1.5)†	17.4 (7.3)*	28.3 (19.3)	< 0.01	4.8 (1.8)†
0 Visit (ref)	--	--	--	--	--	--	--
Insurance Type							
Medicaid	2.5 (0.4)‡	0.2 (0.2)	40.0 (2.9)‡	83.0 (7.2)‡	202.2 (29.0)‡	< 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 (33.9)†	< 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 31, 2017; KT = Khmaladze test for the location-shift hypothesis test for individual slopes.

*Significant at $p < 0.05$

†Significant at $p < 0.01$

‡Significant at $p < 0.001$

		25th	50th	75th	95th	99th	KT p value
Uninsured	> 1 Visit	-0.7 (0.3)*	0.0 (0.0)†	26.7 (3.2)‡	82.8 (12.2)‡	164.1 (49.3)†	< 0.01
	1 Visit	-0.5 (0.5)	0.0 (0.0)†	25.6 (3.2)‡	61.3 (16.2)‡	243.8 (118.7)*	< 0.01
	0 Visit (ref)	--	--	--	--	--	--
Medicaid	> 1 Visit	-0.2 (0.6)	0.0 (0.0)*	9.6 (4.5)*	41.9 (20.9)*	187.3 (88.1)*	< 0.01
	1 Visit	-0.9 (1.1)	0.0 (0.0)	1.0 (4.3)	28.0 (27.5)	43.2 (42.3)	< 0.01
	0 Visit (ref)	--	--	--	--	--	--
Medicare	> 1 Visit	-2.3 (1.1)*	-1.0 (0.4)*	-1.9 (1.8)	4.0 (9.0)	-29.9 (42.4)	> 0.10
	1 Visit	-2.7 (2.4)	-0.5 (0.7)	-7.1 (4.2)	-23.6 (17.2)	-63.3 (104.5)	< 0.01
	0 Visit (ref)	--	--	--	--	--	--
Private	> 1 Visit	-4.2 (0.9)‡	-0.3 (0.4)	0.1 (0.3)	18.6 (5.1)‡	39.7 (15.7)*	< 0.01
	1 Visit	-3.1 (1.7)	-0.7 (0.7)	0.0 (0.1)	-6.8 (7.9)	17.1 (22.7)	< 0.01
	0 Visit (ref)	--	--	--	--	--	--

Table 4. Regression Quantiles of Avoidable Emergency Department (ED) Score, Stratified by Insurance Type

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 31, 2017.
*Significant at $p < 0.05$
†Significant at $p < 0.01$
‡Significant at $p < 0.001$

Credit Author Statement

Carlene A. Mayfield: Investigation, Formal analysis, Writing - Original Draft; **Marco Geraci:** Writing – Software, Review & Editing, Formal analysis; **Brisa Urquieta de Hernandez:** Resources, Data Curation, Project administration; **Michael Dulin:** Conceptualization, Validation, Writing - Review & Editing; **Jan M. Eberth:** Conceptualization, Supervision; **Anwar T. Merchant:** Methodology, Supervision, Writing - Review & Editing

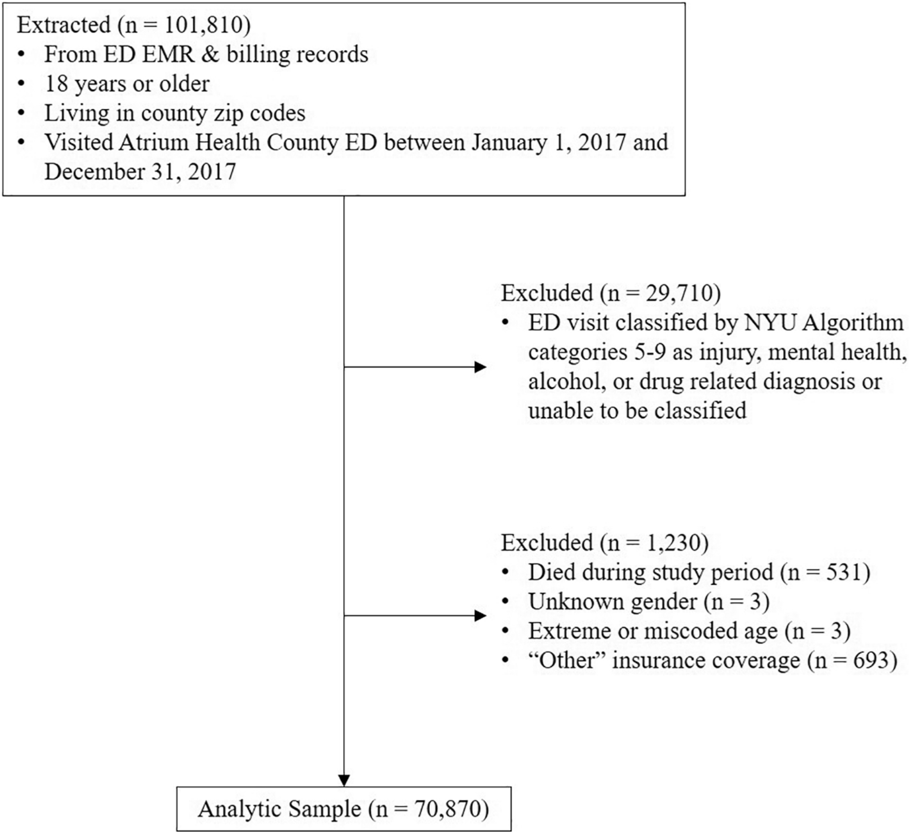
Extracted (n = 101,810)
• From ED EMR & billing records
• 18 years or older
• Living in county zip codes
• Visited Atrium Health County ED between January 1, 2017 and December 31, 2017
Excluded (n = 29,710)
• ED visit classified by NYU Algorithm categories 5-9 as injury, mental health, alcohol, or drug related diagnosis or unable to be classified
Excluded (n = 1,230)
• Died during study period (n = 531)
• Unknown gender (n = 3)
• Extreme or miscoded age (n = 3)
• "Other" insurance coverage (n = 693)
Analytic Sample (n = 70,870)

Figure 1

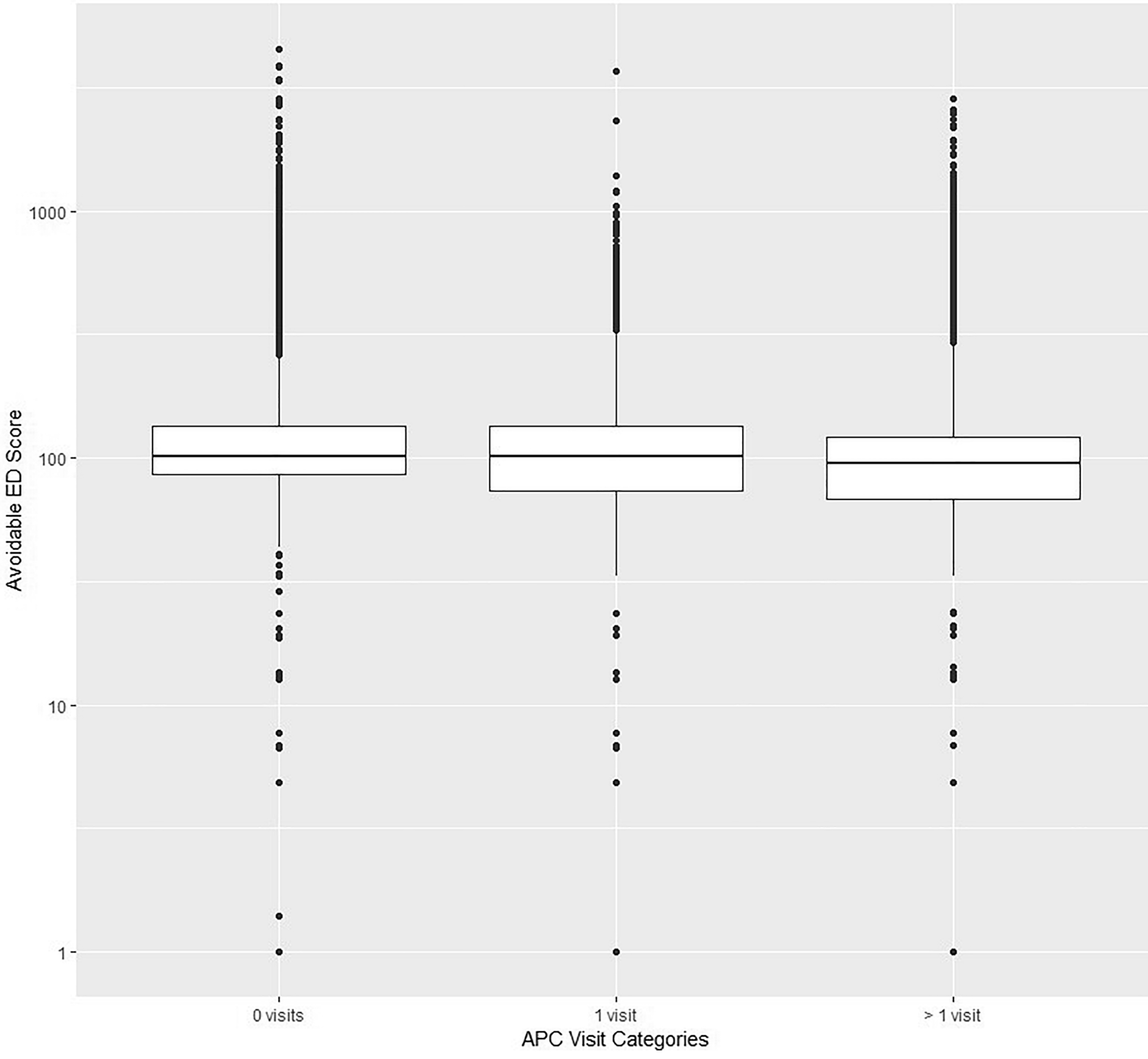
1000
100
10
1
Avoidable ED Score
0 visits
1 visit
> 1 visit
APC Visit Categories

Figure 2