

The effect of geographic access on severe health outcomes for pediatric asthma

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Background: Access to medical care and severe pediatric asthma outcomes vary with geography, but the relationship between them has not been studied.

Objective: We sought to evaluate the relationship between geographic access and health outcomes for pediatric asthma.

Methods: The severe outcome measures include emergency department (ED) visits and hospitalizations for children with an asthma diagnosis in Georgia and North Carolina. We quantify asthma prevalence, outcome measures, and factors included in the statistical model using multiple data sources. We calculate geographic access to primary and asthma specialist care using optimization models. We estimate the association between outcomes and geographic access in the presence of other factors using logistic regression. The model is used to project the reduction in severe outcomes with improvement in access.

Results: The association between access and outcomes for pediatric asthma depends on the type of outcome measure, type of care, and variations in other factors. The expression of this association is also different for the 2 states. Access to primary care plays a larger role than access to specialist care in explaining Georgia ED visits, whereas the reverse applies for hospitalizations. In North Carolina access to both primary and specialist care are statistically significant in explaining the variability in ED visits.

Conclusions: The variation in the association between estimated access and outcomes affects the projected reductions of severe outcomes with access improvement. Thus applying one intervention would not have the same level of improvement across geography. Interventions must be tailored to target regions with the potential to deliver the highest effect to gain maximum benefit. (J Allergy Clin Immunol 2015;■■■:■■■-■■■.)

Key words: Geographic access, pediatric asthma, severe health outcomes

Abbreviation used

ED: Emergency department

Asthma is a common chronic childhood condition, with more than 7.1 million American children having a current asthma diagnosis.¹ In addition to impairing quality of life, asthma contributes significant costs to the health care system, particularly for emergency department (ED) visits and hospitalizations, which in many cases could be prevented. The prevalence and cost of pediatric asthma demonstrate great disparities. In general, both minority populations and economically disadvantaged areas have lower access to asthma-related health care.² In 2006, the asthma hospitalization rate for children living in a ZIP code with a median income of less than \$37,000 was 76% higher than for other children.³ African American and Hispanic children are more likely to have asthma and experience a severe asthma outcome than white children.⁴⁻⁸

A key contributor to health and health care disparities for chronic conditions, particularly pediatric asthma, is insufficient access to health care services. Appropriate access is important for managing asthma because regular care visits can reduce severe outcomes, controlling asthma is at least as important as its severity, and severity and control of the disease are not always correlated.⁹⁻¹³ In this study we focus specifically on geographic access. Although financial access is at the forefront of the current health policy agenda, it is only salient if care is made accessible and available. Even though asthma is a common disease among children, geographic access to care for asthma is insufficient and exhibits great disparities.

Although it is well understood that geographic access can affect health care use and health outcomes,¹⁴⁻¹⁶ there is little research that addresses whether this relationship varies across states, whether it behaves uniformly across geography within a state, and how it differs across different forms of health outcomes. This is particularly important for pediatric asthma, which is the cause of approximately 170,000 childhood hospitalizations each year.¹⁷ Understanding the extent of this relationship will suggest interventions targeted to reduce severe outcomes.

Potential access is commonly used in place of realized access.¹⁸⁻²⁸ In this article we study the link between potential geographic access and severe outcomes for pediatric asthma while controlling for other potentially contributing factors in Georgia and North Carolina. Improving asthma outcomes is a priority for the Georgia Department of Public Health, which leads the Georgia Asthma Control Program. Data availability, geographic proximity to Georgia, and a different distribution of

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Supported in part by a grant from the National Science Foundation (CMMI-0954283) and by a seed grant from the Institute of People and Technology (IPaT) and Children's Healthcare of Atlanta awarded in 2013.

Disclosure of potential conflict of interest: E. Garcia, N. Serban, and J. Swann have received research support from the National Science Foundation (CMMI-0954283), the Institute of People and Technology, and Children's Healthcare of Atlanta. A. Fitzpatrick has received research support from the National Science Foundation, the Institute of People and Technology, and the National Institutes of Health (National Heart, Lung, and Blood Institute and National Institute for Health Research) and has received consultancy fees from MedImmune, Merck (Scientific Advisory Board), GlaxoSmithKline (Scientific Advisory Board), Genentech, and Boehringer Ingelheim. Received for publication May 6, 2014; revised January 16, 2015; accepted for publication January 21, 2015.

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0091-6749/\$36.00

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<http://dx.doi.org/10.1016/j.jaci.2015.01.030>

distance to receive asthma specialist care contributed to choosing North Carolina as the second state for analysis. We use mathematic modeling to estimate geographic access and apply logistic regression to quantify the relationship between access and outcomes. We also investigate the potential reduction in severe outcomes with access improvement.

METHODS

Study population

The population under consideration consists of children aged 5 to 17 years who were estimated to have a current diagnosis of asthma in Georgia and North Carolina. The age group of 0 to 4 years is excluded because of the difficulty of diagnosing asthma in this age group. The percentage of children who had a current diagnosis of asthma is reported by age group in Table C3 of the 2010 BRFSS survey for Georgia²⁹ and by the 2011 National Survey of Children's Health for North Carolina.³⁰ The census tract population counts of children for each age group were obtained from the 2010 Census data Table B09001.³¹ It is assumed that prevalence for each age group is uniform across each state. The number of asthmatic children in each census tract is estimated by multiplying the population with the percentage of children in each age group in each state with an asthma diagnosis. Census tract estimates are computed for use in the assignment model, and estimates are aggregated at the county level, as shown in Fig E1 in this article's Online Repository at www.jacionline.org, for the regression analysis.

Overall approach for understanding severe outcomes

To predict severe outcomes, we consider covariates that fall into 3 categories: age indicator; health access, which is of primary interest; and socioeconomic to control for other factors over the network. For consistency, the values for all covariates are collected or aggregated at the county level. Georgia has 159 counties, and North Carolina has 100.

In this study a severe outcome is defined as an ED visit or hospitalization caused by the child's asthma. The response variable is the outcome rate calculated as the ratio of ED visits or hospitalizations to the estimated number of children with asthma at the county level for each age group.

For Georgia, ED visits and hospitalizations in 2010 were obtained from the Online Analytical Statistical Information System database.³² For North Carolina, ED visits and hospitalizations for 2009 were obtained from the Healthcare Cost and Utilization Project state databases, which contain deidentified individual records from community hospitals.^{33,34} Institutional review board approval was obtained for this research. Severe outcomes were extracted by using the International Classification for Diseases, ninth edition, codes for asthma and the criterion that at least one of the first 2 diagnostic codes is for asthma.

Covariates of primary interest: Travel distances to asthma care providers

There are 3 variables for potential access in the model: the county-average distances to primary pediatric care ("PrimaryDistance"), the county-average distances to asthma specialist care ("SpecialistDistance"), and the intracounty variance of distance to specialist care ("VarSpecialistDistance"). We consider this third access measure because there can be a large variation across census tract distances to specialist care. The number of hospitals in each county is included as a potential predictor ("NumberHospitals") to control for mobility of the population across county lines for hospital care.³⁵

We calculate potential geographic access to primary and asthma specialist care by using recent methodology to match supply and demand.²¹ The approach accounts for constraints in the network (eg, mobility) along with potential barriers to care (eg, provider's willingness to accept patients with

Medicaid). The approach uses an optimization model that matches patients to providers, mimicking the process through which patients or their parents choose physicians. Similar to Nobles et al,²¹ we use distance as a primary criterion for choosing one physician over another. Using this patient-provider matching, we estimate the access measure for each census tract, which we aggregate at the county level for the regression.

For primary care, we consider physicians with a National Provider Identifier classification of pediatrics, nurse practitioner pediatrics, family medicine, and internal medicine and obtained travel distances for Georgia and North Carolina from the recent work of Gentilli et al.³⁶

For specialist asthma care, we extracted the locations of asthma specialists from the National Provider Identifier Registry using the National Uniform Claim Committee's taxonomy codes.³⁷ Consistent with the identification of asthma specialists in analyses of the importance of specialist care in the literature, we considered allergists and pulmonologists to be asthma specialists.^{38,39} The maximum caseload of visits for pediatric asthma care was adjusted depending on the specialty and whether the provider had a pediatric designation, and this is shown in Table E1 in this article's Online Repository at www.jacionline.org. We computed the street-network distance between specialist offices and centroids of the census tracts, representing the location for the entire population of the census tract, with ArcGIS software.⁴⁰

In the optimization model for matching patients with providers, the utility function is the total statewide travel distance to access care for asthma subject to the following constraints:

- all patient appointments are fulfilled, if feasible;
- physician capacity cannot be exceeded;
- each specialist accepts a limited percentage of patients with Medicaid; and
- no patient can be assigned to a specialist with a travel distance greater than 50 miles.

The full optimization model is shown in Fig E2 in this article's Online Repository at www.jacionline.org, with additional details including parameter information.

We examine the distribution of distances to care for each state along with the Pearson correlation of distances. Similar to Nobles et al,²¹ we estimate the spatial correlation on distance to care by using the Moran I measure, which was used to evaluate systematic disparities in geographic access.⁴¹

Other model covariates

All socioeconomic variables extracted from the 2010 Census data are restricted to data on households that have at least 1 child less than 18 years of age.³¹ We include an indicator (0 or 1) variable ("AgeX-Y") for whether the response variable is for children in each of 3 age ranges (X to Y).^{29,30} For income and education, we select among potential variables by investigating the strength of the association of these variables with the response variable, as plotted in Fig E3 in this article's Online Repository at www.jacionline.org. The variables selected are median family income ("MedianIncome") and percentage of adults with less than a high school diploma ("AdultEducation").

The final set of main effect covariates considered in the model is defined in Table I. The model selection procedure is outlined in the Methods section in this article's Online Repository at www.jacionline.org.

Statistical model

We quantify the effect of geographic access on severe outcomes by using logistic regression with replication (equivalent to binomial regression), and we generate separate models for hospitalizations and ED visits in each state. All of the numeric variables were scaled. To reduce the set of explanatory variables from all combinations of the variables shown in Table I, we applied stepwise model selection in which the models were compared based on the Akaike information criterion. The regression analysis was implemented with R statistical software. For model interpretation, we point

TABLE I. The final set of main effect covariates included for consideration in the regression model

Variable name	Description
Age X-Y	Number of children that are X-Y years old For Georgia: 5-8,9-14,15-17 For North Carolina: 5-9,10-14,15-17
Specialist Distance	Within-county average distance to an asthma specialist
Var Specialist Distance	Within-county variance of distance to an asthma specialist
Primary Distance	Within-county average distance to a primary care pediatrician
Median Income	Median family income households with children <18 y old
Adult Education	Percent of the adult population who have less than a high school diploma and live in a household with children <18 y old
Number Hospitals	Number of hospitals

The final model also includes interaction terms between these covariates.

out that understanding the model coefficients is challenging mainly because of the presence of interactions between covariates. Generally, a positive sign for an interaction term indicates that 2 covariates influence the odds ratio jointly, and thus a larger value of one covariate increases the importance of the other. The opposite is true when the sign is negative. In the models any variable that is used in an interaction term is also included alone.

We also use the results of the regression model to predict the reduction in ED visits if reductions in distance to access care are made. Specifically, we allow travel distance to decrease to 15 miles for primary care, to 5 or 15 miles for specialist care, or both. Using the regression results, we multiply the model coefficients and predictors (including new distances where applicable) to obtain a predicted response. Using the predicted response, we take the inverse of the logit function to determine the percentage of asthmatic children with a severe outcome and then multiply by the number of asthmatic children to get the projected number of ED visits per county and age group.

RESULTS

Geographic access to primary and specialist asthma care

Fig 1 shows the number of counties with distances (primary or specialist) within specific ranges. The maps of travel distances to specialist and primary care are provided in Figs 2 and 3, respectively, with summary statistics in Table E2 in this article's Online Repository at www.jacionline.org. Overall, in Georgia there are more counties with longer travel distances to asthma care than in North Carolina. Specifically, in North Carolina the maximum distance to receive asthma specialist care is 30 miles, and only 5 counties have an average distance of greater than 15 miles. In contrast, the specialist distances in Georgia are as high as 50 miles, with counties having a distance greater than 30 miles. For primary care in Georgia, the residents of 56 counties travel farther than 15 miles, whereas in North Carolina the residents of 11 counties travel farther than 15 miles. Fig E4 in this article's Online Repository at www.jacionline.org shows the difference in access to primary and specialist care in both states.

The Pearson correlation between the travel distances to primary and specialist care in Georgia is 0.3898, whereas the

correlation in North Carolina is 0.0904, as shown in Fig E5 in this article's Online Repository at www.jacionline.org. Both Georgia and North Carolina have significant spatial correlation for primary and specialist care, as indicated by significant z values for the local Moran I measure, as shown in Fig E6 in this article's Online Repository at www.jacionline.org.

Regression results

The detailed results of logistic regression for ED visit and hospitalization rates are shown in Tables II (Georgia) and III (North Carolina). In all models geographic access is statistically significant, although through different access variables and in interaction with different factors. Model R^2 values are provided in Table E3 in this article's Online Repository at www.jacionline.org.

ED visit model: General results

For explaining ED visits in Georgia (Table II), access to primary and specialist care are statistically significant in their interactions with the socioeconomic variables, and access to primary care is also significant in relation to the age of the children. The deviance residuals for this model are provided in Fig E7 in this article's Online Repository at www.jacionline.org.

In North Carolina (Table III) all 3 main effects for access are statistically significant by themselves. Each main effect also has significant interactions with other covariates, including median income and age group 5 to 8 years.

Hospitalization model: General results

The final selected model for hospitalizations in Georgia has fewer significant variables than that for ED visits. For the Georgia hospitalization model, distance to primary care is the access variable with the greatest effect because it is significant by itself and in multiple interaction terms, whereas access to specialist care and the variance of this access are only significant in 1 interaction term each. Adult education is the only socioeconomic variable with a significant interaction with access variables.

In North Carolina, however, all 3 access variables are statistically significant. These access variables are also significant in more interaction terms than in the models for Georgia hospitalizations. Thus the North Carolina model is more complex than the Georgia hospitalization model.

Projecting severe outcome reduction with access improvement

We use the fitted regression model to compute the predicted number of severe outcomes when the distance is reduced at the specified levels while keeping fixed all other predictors in the model. A complete example for one county and distance improvement is in Table E4 in this article's Online Repository at www.jacionline.org.

Fig 4 presents the number of county-age pairs in each state with a predicted reduction in the number of ED visits for each of the 4 distance interventions. For only improving specialist care to be no more than 15 miles, in North Carolina

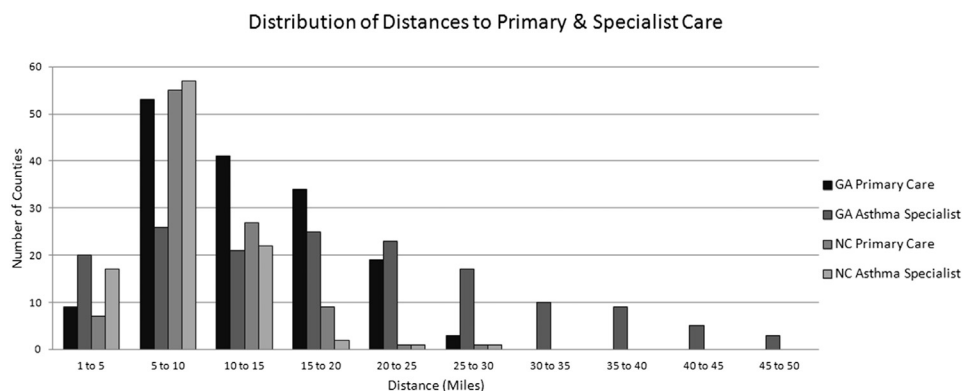


FIG 1. Comparing the distribution of geographic access measures for Georgia (GA) and North Carolina (NC).

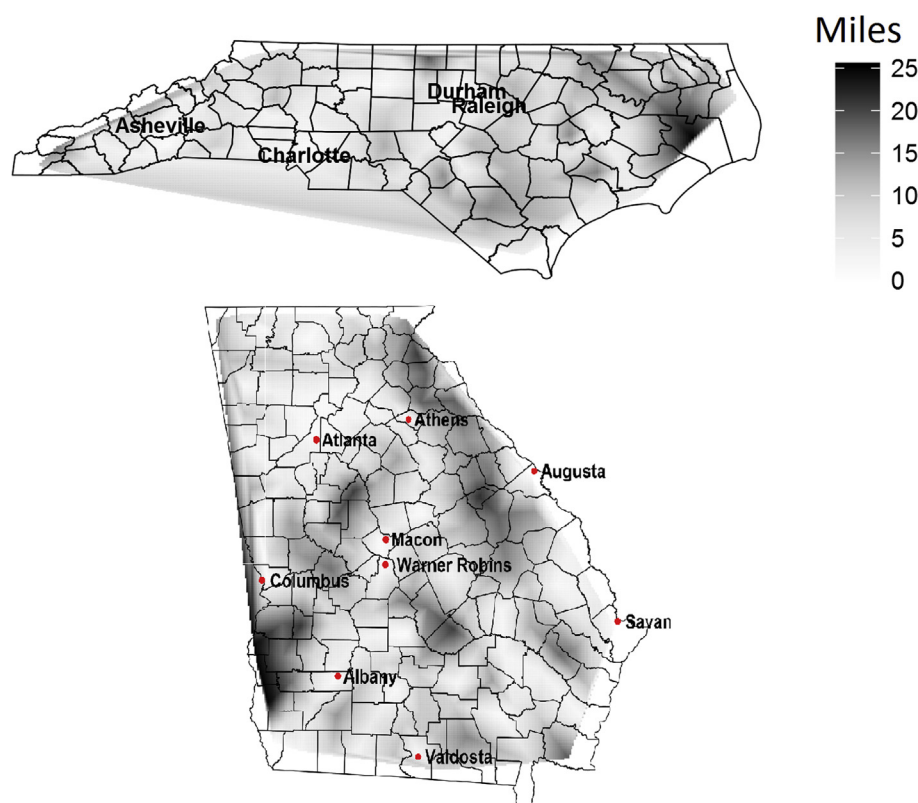


FIG 2. Maps of the census tract-level travel distances to specialist care for Georgia and North Carolina.

131 county-age pairs (of 300) have a reduction in ED visits, and in Georgia 191 county-age pairs (of 477) have a reduction in ED visits. The total reduction in ED visits is higher in North Carolina, but both states have more than 30 county-age pairs in which ED visits are reduced by more than 15.

Fig 5 shows the geographic distribution of locations with a positive improvement in outcome (full data are table available in Tables E5 and E6 in this article's Online Repository at www.jacionline.org). For the intervention of specialist care being no more than 15 miles, adding a reduction of primary care only adds 1 new county in Georgia. In contrast, further reducing specialist

care to no more than 5 miles adds 10 additional counties, although the improvement in ED visits is small for the counties that already had improvements.

DISCUSSION

Our study provides evidence for the association between severe pediatric asthma outcomes and estimated geographic access to health care while underlining that this association is not uniformly effective across geography or types of care. The existing literature has provided evidence for the association between asthma outcomes and a variety of socioeconomic and environmental

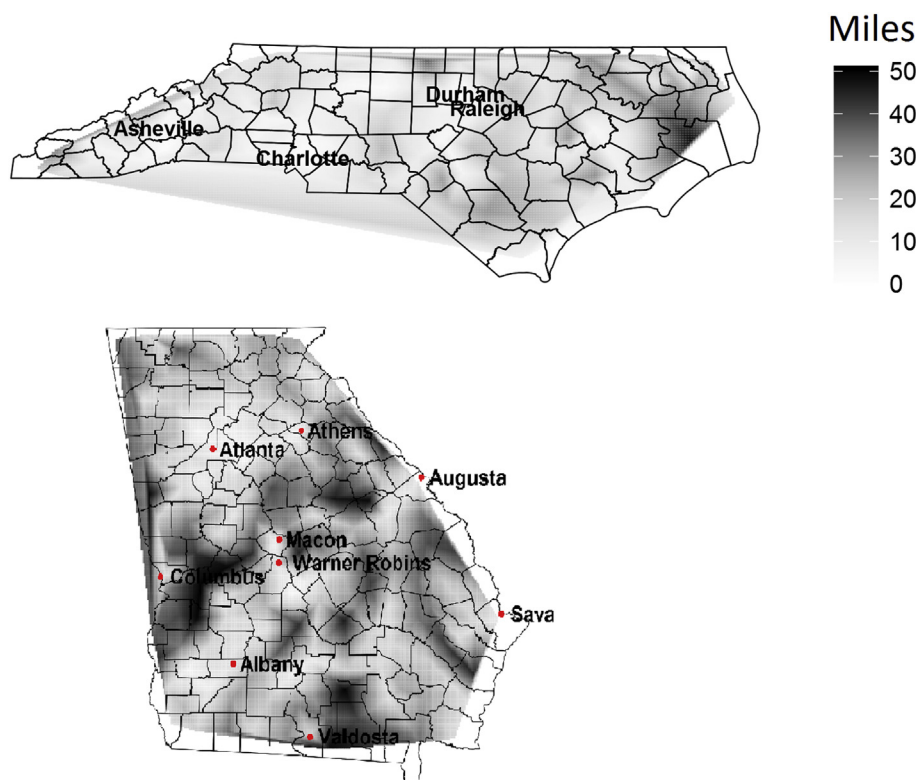


FIG 3. Maps of the census tract-level travel distances to primary care for Georgia and North Carolina.

variables but not geographic access.^{3,6,15,23,42,43} Additionally, there is a relationship between race, lower use of asthma specialists, and the rate of severe asthma outcomes.⁴⁴ Mayer⁴⁵ discussed the geographic proximity of children to a variety of pediatric specialists but without any connection to health outcomes. Other studies analyze the effect of distance on various health outcomes and resource use,^{46,47} but the connection between geographic access to care and severe outcomes for pediatric asthma has not been investigated.

Geographic access can be quantified by using methods such as distance to the nearest service site,²² gravity-based models,²³ or optimization-based models,²¹ which we use in this study. Although this approach requires more computational effort, it provides more accurate estimates than other methods, especially for dense health care networks as demonstrated by Li et al (unpublished data). The results showed that access to asthma care for pediatric patients varied widely between and within states. Interestingly, the correlation in primary and specialty care distances is smaller in North Carolina than in Georgia.

Because asthma is a chronic condition, we expected to find the relationship between geographic access and severe outcomes to be statistically significant. However, we also find that the expression of this relationship depends on the outcome measure of ED visit versus hospitalization. For example, in Georgia none of the access variables are significantly associated with the occurrence of ED visits by themselves, but access to primary care is significantly associated with the occurrence of hospitalization. Therefore we would expect that improving access to primary care would have a greater effect on the hospitalization rate than the ED visit rate.

Moreover, a different set of access variables are associated with severe outcome rates when comparing Georgia and North Carolina. For example, unlike in Georgia, the main effects of all 3 access variables are significant in the corresponding model for North Carolina. Contrasting the models for hospitalizations, there are more significant interaction terms involving the access variables in North Carolina than in Georgia. This is an important finding because it points to a state-by-state analysis. Different states will show significance for different forms of access measures, suggesting different interventions in improving access, and ultimately, outcomes.

There are many factors that could lead to differences in the relationship between geographic access and health outcomes for the 2 states in addition to those included in our model. Generally, North Carolina scores higher in multiple state health rankings, both in general and with respect to the state Medicaid programs,^{48,49} where the analysis also covers differences related to policies. In addition, the overall population density in North Carolina is higher than that in Georgia, and the distribution of the population in the 2 states is different.⁵⁰

Importantly, we find that the effect of geographic access on severe outcomes for pediatric asthma is not uniform across geographic regions because of the statistical significance of its interaction with the other predictors in the model. To get the maximum benefit from any intervention, it should be tailored such that it will target regions that have the potential to show the highest effect. For instance, if the goal were to reduce the number of ED visits in Georgia, we would expect to see the greatest reduction by improving access to primary care in areas where the percentage of adults with less than a high school diploma is

TABLE II. Georgia regression results

	ED visits		Hospitalizations	
	Estimate (SE)	P value	Estimate (SE)	P value
(Intercept)	−3.068 (0.033)	<.001	−6.214 (0.108)	<.001
Age 5-9	0.554 (0.036)	<.001	1.606 (0.106)	<.001
Age 10-14	0.974 (0.039)	<.001	1.633 (0.111)	<.001
Median Income	−0.375 (0.023)	<.001	−0.479 (0.038)	<.001
Adult Education	−0.187 (0.019)	<.001	−0.120 (0.051)	.02
Nonhospital	0.127 (0.005)	<.001	0.087 (0.015)	<.001
Specialist Distance	0.029 (0.017)	.102	−0.057 (0.047)	.226
Primary Distance	0.013 (0.027)	.648	−0.198 (0.047)	<.001
Var Specialist Distance	−0.005 (0.021)	.808	0.050 (0.052)	.337
Primary Distance:	0.061 (0.023)	.009	0.125 (0.041)	.003
Adult Education				
Var Specialist Distance:	−0.165 (0.029)	<.001	−0.200 (0.051)	<.001
Adult Education				
Primary Distance:	−0.157 (0.027)	<.001		
Age 5-9				
Primary Distance:	−0.145 (0.029)	<.001		
Age 10-14				
Specialist Distance:	−0.070 (0.017)	<.001	−0.134 (0.047)	.005
Primary Distance				
Var Specialist Distance:	0.108 (0.032)	.001		
Age 10-14				
Primary Distance:	−0.104 (0.020)	<.001		
Median Income				
Specialist Distance:	0.115 (0.020)	<.001		
Median Income				
Specialist Distance:	0.083 (0.017)	<.001		
Adult Education				
Var Specialist Distance:	−0.119(0.028)	<.001		
Median Income				

For the categorical age variable, age 15 to 17 years is omitted as the reference variable. The reference value for numeric variables is 0. Boldface rows indicate access variables.

higher and by improving access to primary or specialist care in lower-income areas.

We also project the level of ED visit reduction when improving access. We compared 4 interventions for improving access to specialist and primary care in Georgia. We find that there is a significant spatial trend in ED visit reduction with a more significant reduction in urban areas when the distance is reduced to 5 miles. This suggests that if geographic access is improved only at the level of 15 miles, primarily rural areas should be targeted for intervention. Moreover, the decrease in distance from 15 to 5 miles generally improves outcomes only marginally, whereas the joint improvement of access to primary and specialist care does not lead to a noticeably greater effect on the reduction of ED visits than improving specialist distances alone. This suggests that access to specialist care plays an important role in reduction of severe outcomes, although a level of access similar to the comparative state of North Carolina will suffice.

There are several limitations of this study. The first is the unavailability of detailed data on severe outcomes and other explanatory variables, especially at levels lower than the county. Each county in Georgia has between 1 and 204 census tracts, and in larger counties there is high within-county variation in all of the predictors. Thus a county-level analysis loses some of the descriptive and predictive abilities of the

TABLE III. North Carolina regression results

	ED visits		Hospitalizations	
	Estimate (SE)	P value	Estimate (SE)	P value
(Intercept)	−1.727 (0.018)	<.001	−4.726 (0.063)	<.001
Age 5-8	0.584 (0.023)	<.001	1.974 (0.063)	<.001
Age 9-14	0.165 (0.021)	<.001	0.485 (0.065)	<.001
Median Income	−0.088 (0.013)	<.001	−0.278 (0.036)	<.001
Adult Education	0.071 (0.012)	<.001	0.043 (0.033)	.2
Num Hospitals	0.120 (0.007)	<.001	0.053 (0.037)	.1524
Specialist Distance	0.050 (0.016)	.002	0.072 (0.036)	.045
Var Specialist Distance	−0.184 (0.023)	<.001	0.218 (0.046)	<.001
Primary Distance	0.066 (0.018)	<.001	−0.094 (0.042)	.029
Primary Distance:	0.061 (0.021)	.005	0.098 (0.039)	.013
Age 5-8				
Primary Dist: Age 9-14	−0.052 (0.019)	.009		
Primary Dist:	−0.030 (0.014)	.033	−0.089 (0.042)	.035
Adult Education				
Specialist Distance:	−0.061 (0.012)	<.001		
Median Income				
Var Specialist Dist:	−0.120 (0.018)	<.001		
Median Income				
Primary Distance:	0.101 (0.014)	<.001	−0.086 (0.048)	.073
Median Income				
Specialist Distance:	−0.060 (0.025)	.017		
Age 5-8				
Var Specialist Distance:	0.156 (0.037)	<.001		
Age 5-8				
Var Specialist Distance:	−0.156 (0.015)	<.001		
Adult Education				
Primary Dist:			0.299 (0.046)	<.001
Specialist Dist				
Specialist Distance:			−0.154 (0.039)	<.001
Adult Education				
Specialist Distance:			−0.095 (0.031)	.002
Var Specialist Distance				
Primary Distance:			0.064 (0.023)	.0074
Num Hospitals				
Var Specialist Distance:			−0.318 (0.056)	<.001
Primary Distance				
Median Income:			−0.079 (0.029)	.007
Adult Education				
Median Income:			0.241 (0.032)	<.001
Num Hospitals				
Adult Education:			0.302 (0.048)	<.001
Num Hospitals				
Age 9-14: Adult Education			0.075 (0.035)	.034

For the categorical age variable, age 15 to 17 years is omitted as the reference variable. The reference value for numeric variables is 0. Boldface rows indicate access variables.

model. There are many potential covariates that are not included in the model because the data are not completely available across larger geographic areas. Examples of other potentially contributing factors are the percentage of adults who smoke, the percentage of children exposed to secondhand smoke and indoor allergens,^{51,52} air pollution and outdoor allergen measurements,^{43,53-61} obesity,^{59,61} and the percentage of children with insurance.⁶²

A second limitation is the simplicity of the calculation of the number of children with asthma, as described in the Methods section. The age breakdowns used for each state are slightly different based on data availability.

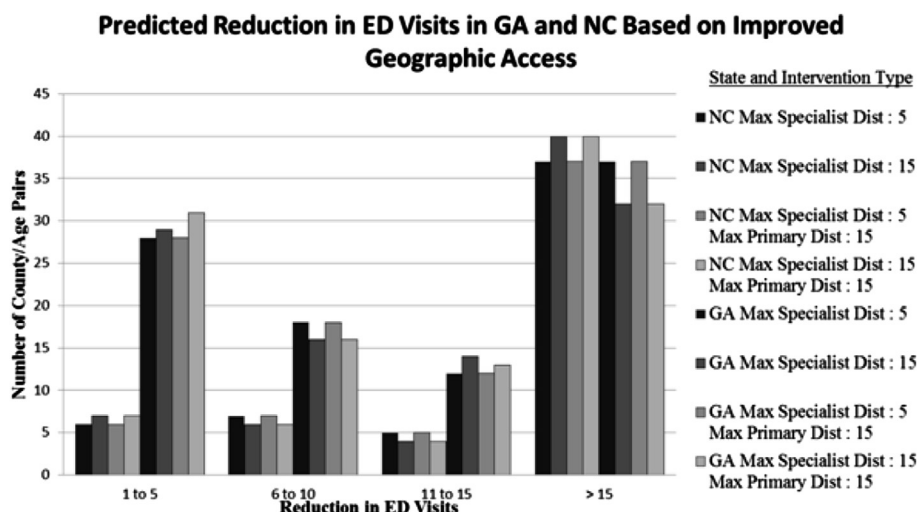


FIG 4. The graph shows the number of county-age pairs with an expected reduction in ED visits under 4 types of interventions on access. The interventions include reducing the distance to specialist care to no more than 5 or 15 miles, possibly in combination with reducing the distance to primary care to no more than 15 miles. GA, Georgia; NC, North Carolina.

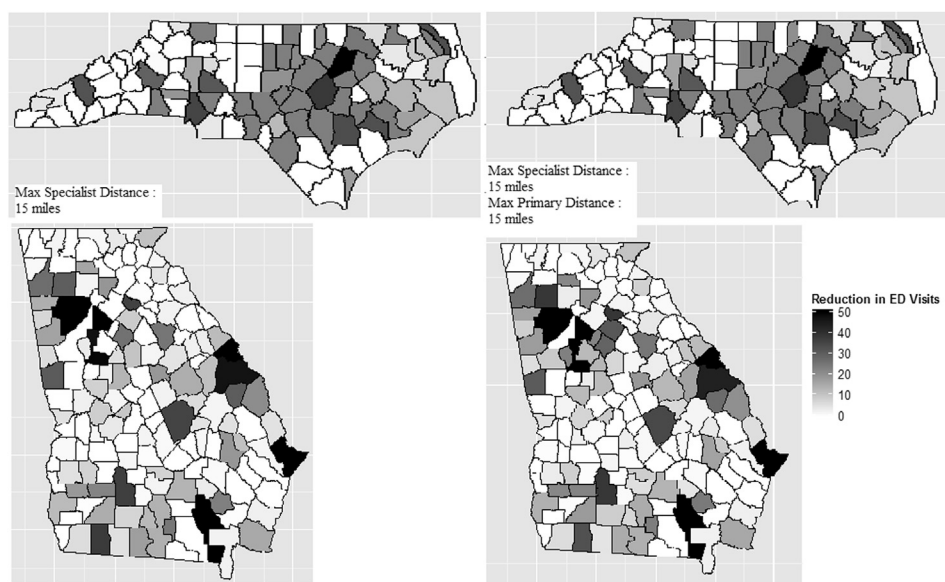


FIG 5. Reduction in ED visits when access to primary and specialist care is improved.

A third limitation is that we allow pediatric patients to be seen by adult specialists; access to specialist care would be even worse under the alternative. Standard limitations about regression apply to this study, where findings point to associations rather than to causality. Finally, we are using models to quantify potential access to care.

Taking these known limitations into consideration, the work in this article demonstrates there is a significant relationship between geographic access to both primary and asthma specialist care and severe pediatric asthma outcomes. The results clearly indicate areas that can be targeted for interventions and an approach that can be applied to other states. Finally, the framework presented can be extended to study the relationship between access and other outcomes, offering great potential for targeting interventions effectively.

Key messages

- Access to care is important for managing pediatric asthma because regular visits can improve disease control and reduce severe outcomes.
- This study estimates geographic access and finds it is statistically significant in explaining severe pediatric asthma outcomes, but the effect varies with other geographic factors.
- Improved geographic access is expected to reduce severe outcomes.
- With limited resources, interventions can be targeted to areas with the greatest potential for improvement and tailored to each community's needs.

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Online Repository

Model Data Collection

The number of children with asthma is computed using the US 2010 Census and BRFSS survey prevalence estimates. Supplemental figure E1 below shows the number of children with a current diagnosis of asthma in each county in GA and NC. Up to 50% of children with asthma may be referred to a specialist, and a new asthma patient should visit the doctor every 2-6 weeks until the asthma is controlled. On average, each child who is referred to a specialist is expected to visit the specialist twice per year. From this information we compute the number of specialist appointments that are needed for each census tract. It is possible that some patients might choose to visit a primary care physician instead of a specialist for some or all of their treatment, or require fewer visits to gain control of their asthma. However, to avoid underestimating demand, we do not reduce the number of appointments from the values calculated.

We assume that each specialist sees patients for 49 weeks each year, has 40 hours per work-week available to see patients, and can see up to two new asthma patients per half day. Each new patient appointment is expected to take 40 minutes, while each returning patient appointment is expected to take only 20 minutes. In order to determine the appointment capacity of the specialist, the specific type, allergist or pulmonologist, and whether or not he is classified as a pediatric specialist, must be known. Supplemental Table E1 below summarizes the annual number of appointments available for each specialist type.

Specialist Category	% appointments for asthma	% appointments for children	available pediatric asthma visits per year
Adult Allergists	75%	50%	1715
Pediatric Allergists	75%	100%	3920
Adult Pulmonologist	25%	50%	490
Pediatric Pulmonologist	25%	100%	1225

Supplemental Table E1: Annual appointments available to pediatric asthma patients for an individual asthma specialist by type.

The number of appointments needed per census tract and the number of available appointments per specialist office location are data inputs for the optimization model, as described in the next section.

The final data input to the model is the distance between each census tract centroid and specialist office. ArcMap10 was used to geocode each specialist office location and calculate the distance between each census tract centroid and specialist location using the US Highway Network.

Centralized Optimization Model to Assign Patients to Specialists

We set up a centralized optimization model that assigns patients in each census tract to specialists so that the distance to receive specialist care is minimized and the system constraints are not violated. The notation and model description are below, and the mathematical model is shown in Supplemental Figure E2.

Decision Variables:

x_{ij} : percent of patients in census tract i that are assigned to specialist office j

Data:

P : the set of all pediatric asthma patients

D : the set of all specialist offices

d_{ij} : distance in miles from the centroid of census tract i to specialist office j

u_j : maximum number of appointments available at specialist office j

m_i : maximum distance a patient in county i can travel to receive specialist care

g : Maximum congestion allowed per county

Model Description:

Objective: Minimize total assigned driving distance

Subject to the following constraints:

- 1) Each patient is assigned to at most 1 doctor
- 2) No more patients are assigned than are in the system
- 3) Each doctor has a maximum number of patients that can be assigned
- 4) Each patient has a maximum allowable drive distance
- 5) At least 90% of patients must be assigned to a doctor
- 6) There is a maximum congestion allowed for doctors in each county

For both Georgia and North Carolina, there is sufficient specialist capacity to meet the full demand for specialist appointments. In addition, patients in every census tract can be assigned to a specialist no more than 50 miles from the tract centroid. Therefore we were able to require that 100% of the patients be assigned to a physician instead of only 90%, and the maximum drive distance did not force any patients to remain unassigned.

The output of the optimization model above is the percent of asthma patients in each county that are assigned to each asthma specialist. From these values, we compute the average distance that patients in each census tract will travel to receive specialist care, and then we further aggregate to obtain the county level distance so that the distance data can be matched with the outcomes data at the county level. This distance is the predictor SpecialistDistance in the regression models. We also use the census tract and county level distances to compute the variance of the distance to specialist care within each county, which is the predictor VarSpecialistDistance in the regression models.

Geographic Access to Primary and Specialist Care

Georgia and North Carolina have different levels of geographic access to both primary and specialist care. Overall, the distance to receive treatment for asthma is shorter for the majority of North Carolina than it is in Georgia, which we can see clearly in the paper in Figure 1 where there is a long tail for distances to specialist care in Georgia, while North Carolina has a smaller maximum distance and the 96% of counties have a distance under 15 miles.

We consider the difference and correlation between access to primary and specialist care in each state. Supplemental Figure E4 shows the difference in the distance to receive each type of medical care for GA and NC (specialist distance minus primary care distance). Supplemental Table E2 provides summary statistics for all three access variables in GA and NC. We can see that overall the differences in access to primary and specialist care are greater in GA than in NC.

	Georgia			North Carolina		
	Primary Distance	Specialist Distance	Variance Specialist Distance	Primary Distance	Specialist Distance	Variance Specialist Distance
Minimum	2.21	2.33	0.10	3.57	1.19	0.85
Median	13.16	17.20	25.50	8.98	7.53	33.87
Mean	13.52	18.47	60.16	9.82	8.33	55.28
Maximum	25.00	50.00	705.33	25.00	28.75	311.50
Variance	60.49	134.18		16.47	17.30	

Supplemental Table E2: Summary statistics for the three access variables at the county level in GA and NC.

From the scatter plots of the county level distance to receive primary and specialist care in GA and NC, shown in Figure E5 below, we can see clearly that the range of specialist distances differs greatly between the two states, and that there is a higher correlation between the distances in GA than NC. The numeric correlation values shown are the Pearson correlation coefficients.

It is also possible that the distances to receive both primary and specialist care have spatial correlation, where the distances for neighboring census tracts are correlated with each other. Moran's I is used to compute the spatial autocorrelation for each of the distance variables, shown in Supplemental Figure E6a, and the weight matrix is determined using the proximity of each census tract's immediate neighbor. From the maps of the z-values of the local Moran's I shown below in Supplemental Figure E6b, we can see that while there are some pockets of high correlation for both provider types between the distances of neighboring census tracts in Georgia, there is lower correlation for the majority of the state. North Carolina has a similar range of correlation values for primary and specialist care, but the correlated areas are fewer in number and smaller in size than the ones in Georgia. Z-values for the local Moran's I measure that are outside of the range (-1.96, 1.96) indicate significant spatial correlation. The z values for GA specialist care range from -3.3 to 11.3, and for GA primary care the z-values have a maximum of 14.4. In NC the z-values for primary care have a smaller range, but still with significant values on both ends (-2.2, 8.5), and specialist care z-values reach even higher, (-5.2, 39.6). When the z-value is negative, this indicates a negative spatial correlation where better access in one census tract indicates worse access in a neighboring census tract, while a positive z-value indicates the opposite, where better access in one census tract indicates that we should expect better access in the neighboring census tracts as well. .

Exploratory Data Analysis

In this supplemental material we present details on the model fitting and model evaluation for the application of logistic regression with replications to explain the variability in the ED visit and hospitalization rates.

In fitting the models for the ED visit and hospitalization rates, we transformed the access specific predictors using the logarithmic transformation. The reason for using this transformation is that the models with the log-transformed access predictors provide a better fit for both severe outcome rates.

In Supplemental Figure E7, we show a display of the correlation between the predictors included in the model and the correlation with the logit-transformed ED visit rate (TrEDRate). Panel A shows the Person correlation, a measure of linear relationship between two variables, and panel B shows the Kendall tau correlation, a measure of the nonlinear relationship between two variables. From these two plots, we find that the correlation between transformed ED visit rate and the predictors included in the model is weak, with the strongest correlation for the county-average distances to specialist and primary care. The correlation between predictors is not strong enough to suggest removing predictors from this initial set.

122 Regression Models

123 Because we included five predictors and many of the relevant interactions between these
124 predictors, we performed model selection using forward, backward and forward-backward
125 stepwise regression. Of the three resulting models for each state and outcome pair (GA ED
126 Visits, GA Hospitalizations, NC ED Visits, NC Hospitalizations), the one with the smallest AIC
127 value was selected.

128 This process can be explained with the following algorithm.

129 Let S be the set of states, Georgia and North Carolina

130 $S = \{GA, NC\}$

131 Let Y be the set of severe outcomes, ED Visits (ED) and Hospitalizations (H)

132 $Y = \{ED, H\}$

133 Let R be the set of selection methods, Forward (F), Backward (B), and Forward-Backward (FB)

134 $R = \{F, B, FB\}$

135 Let $M_{S,Y,R}$ be the set of regression models for each state, severe outcome, and selection method
136 with associated AIC values $AIC_{S,Y,R}$ and 10-fold cross validation (CV) score $CV_{S,Y,R}$

137 ex: $M_{GA,ED,F}$ has value $AIC_{GA,ED,F}$, and $M_{NC,H,B}$ has value $AIC_{NC,H,B}$

138 For each state s in S :

139 For each outcome y in Y :

140 For each selection method r in R :

141 Perform model selection using method r and obtain final model $M_{s,y,r}$ and
142 corresponding AIC value, $AIC_{s,y,r}$

143 Select model $M_{s,y,r}$ corresponding to $\min\{AIC_{s,y,F}, AIC_{s,y,B}, \text{and } AIC_{s,y,FB}\}$

144 end

145 The selected models with the estimated coefficients and their corresponding significance p-
146 values are provided in the paper in Table 2 for Georgia and Table 3 for North Carolina.

147 For model evaluation, we performed extensive diagnostics of the deviance residuals of all four
148 fitted models. To illustrate this analysis, we only include the residual plots for the ED visits
149 model for Georgia. Supplemental Figure E8 includes the plots for the deviance residuals against
150 the estimated counts (row 1 left), the histogram (row 1 right), and the deviance residuals against
151 the three access measures and the median income variable (rows 2 and 3). The blue lines provide
152 nonparametric estimated trends of the residuals. A flat blue line around the zero line shown in

red corresponds to no trend or no pattern in the residuals. According to these plots, there is no pattern left to be explained by the predictors although the blue line shows a slight decrease in the plot of the residuals against the estimated counts. This suggests that other predictors would be needed to provide a further reduction in the absolute value of the log-likelihood measure. This is confirmed by the low pseudo R-square for this model, which is equal to 64.2%. (See Supplemental Table E5.) Similar conclusions can be drawn for the other three models.

	ED Visits	Hospitalizations
Georgia	64.2%	42.7%
North Carolina	41.8%	68.3%

Supplemental Table E3: *Pseudo-R square for logistic regression with replications as provided by the selected fitted models for all four cases.*

Supplemental Table E6 presents the odds ratio calculation from the ED visits model for McDuffie County in Georgia under the status quo and a change in distance to set the maximum distance primary and specialist care to 15 miles. This calculation shows that the direct interpretation of the individual coefficients is challenging primarily because of the presence of the interaction terms.

Regression Model		Original Distance To Primary & Specialist Care : 23.4 & 36.5 miles		Decreased Distance To Primary & Specialist Care : 15 miles	
Coefficients	Estimate	X Values	$\beta * X$	X Values	$\beta * X$
(Intercept)	-3.068	1	-3.068	1	-3.068
Age 5-9	0.554	0	0	0	0
Age 10-14	0.974	1	0.974	1	0.974
MedianIncome	-0.375	0.0299	-0.01121	0.0299	-0.01121
AdultEducation	-0.187	1.5727	-0.29409	1.5727	-0.29409
NumHospitals	0.127	0.1307	0.016599	0.1307	0.016599
SpecialistDistance	0.029	1.3155	0.03815	0.1182	0.003428
PrimaryDistance	0.013	1.0745	0.013969	0.4546	0.00591
VarSpecialistDistance	-0.005	-0.2749	0.001375	-0.2749	0.001375
SpecialistDistance: AdultEducation	0.083	2.068887	0.171718	0.185893	0.015429
SpecialistDistance: MedianIncome	0.115	0.039333	0.004523	0.003534	0.000406
SpecialistDistance: PrimaryDistance	-0.07	1.4135	-0.09895	0.0537	-0.00376
PrimaryDistance: AdultEducation	0.061	1.6898	0.103078	0.715	0.043615
PrimaryDistance: Age 5-9	-0.157	0	0	0	0
PrimaryDistance: Age 10-14	-0.145	1.0745	-0.1558	0.4546	-0.06592
PrimaryDistance: MedianIncome	-0.104	0.0321	-0.00334	0.0136	-0.00141
VarSpecialistDistance: Age 10-14	0.108	-0.2749	-0.02969	-0.2749	-0.02969
VarSpecialistDistance: MedianIncome	-0.119	-0.00822	0.000978	-0.00822	0.000978
VarSpecialistDistance: AdultEducation	0.083	-0.43234	-0.03588	-0.43234	-0.03588
Odds Ratio			-2.372		-2.448
Severe Outcome Rate - From Odds Ratio			0.0853		0.0796

171

172 **Supplemental Table E4: Odds Ratio and Severe Outcomes Rate Computations for McDuffie**
173 **County, GA.**

174 For each intervention, the predicted number of ED visits was computed for each county and age
175 group in GA and NC. We then aggregate at the county level to see an overview of the impact of
176 each intervention. Supplemental tables E7 and E8 show the predicted county level reduction in
177 ED visits when each of the four intervention of improving the distance to asthma specialist care
178 to no more than 15 miles for GA and NC respectively. In both tables, a positive value indicates
179 that the predicted number of ED visits is less than the total number of actual visits for that
180 county, and a negative number indicates that the predicted number of ED visits is higher than the
181 actual number.

County	Specialist 15	Specialist 15, Primary 15	Specialist 5	Specialist 5, Primary 15	County	Specialist 15	Specialist 15, Primary 15	Specialist 5	Specialist 5, Primary 15
Appling	-11.9	-11.9	-11.6	-11.6	Jefferson	11.1	9.6	16.6	16.6
Atkinson	-13.1	-13.1	-17.0	-17.0	Jenkins	30.2	30.2	26.8	26.8
Bacon	-0.7	-1.0	3.1	3.1	Johnson	3.1	3.1	3.8	3.8
Baker	-2.1	-2.1	-1.6	-1.6	Jones	-4.7	-4.7	-4.6	-4.6
Baldwin	18.4	18.4	18.4	18.4	Lamar	-2.6	-3.5	0.5	0.5
Banks	-7.9	-8.0	-4.5	-4.5	Lanier	22.5	22.5	21.0	21.0
Barrow	36.0	36.0	38.5	38.5	Laurens	35.4	35.4	34.4	34.4
Bartow	29.9	29.9	38.3	38.3	Lee	-5.9	-5.9	-0.8	-0.8
Ben Hill	-0.2	-0.2	2.0	2.0	Liberty	-22.2	-21.0	-31.8	-31.8
Berrien	11.3	11.3	13.8	13.8	Lincoln	-5.3	-5.3	-12.5	-12.5
Bibb	-92.6	-92.6	-92.6	-92.6	Long	-13.8	-12.9	-18.7	-18.7
Bleckley	-12.8	-12.9	-7.6	-7.6	Lowndes	6.5	6.5	6.5	6.5
Brantley	-6.4	-6.4	-7.4	-7.4	Lumpkin	-14.1	-14.1	-10.2	-10.2
Brooks	17.2	17.2	14.5	14.5	Macon	-13.7	-12.0	-23.9	-23.9
Bryan	-9.8	-9.8	-3.2	-3.2	Madison	-12.6	-12.6	-10.8	-10.8
Bulloch	-14.7	-14.7	-15.3	-15.3	Marion	-9.2	-9.2	-8.0	-8.0
Burke	46.9	47.2	43.6	43.6	McDuffie	2.6	0.6	9.9	9.9
Butts	5.6	2.9	12.7	12.7	McIntosh	-7.5	-7.5	-8.6	-8.6
Calhoun	18.2	17.2	21.5	21.5	Meriwether	-12.6	-12.6	-12.7	-12.7
Camden	9.8	9.8	10.1	10.1	Miller	-8.0	-8.0	-11.1	-11.1
Candler	4.9	4.9	0.9	0.9	Mitchell	14.6	14.2	17.9	17.9
Carroll	14.9	14.9	16.7	16.7	Monroe	13.0	13.0	12.0	12.0
Catoosa	-73.6	-73.6	-64.0	-64.0	Montgomery	0.4	0.4	0.0	0.0
Charlton	-1.3	-1.3	-1.2	-1.2	Morgan	-8.3	-8.4	-7.4	-7.4
Chatham	58.2	58.2	58.2	58.2	Murray	-21.9	-21.9	-18.9	-18.9
Chattahoochee	-16.1	-16.1	-20.6	-20.6	Muscogee	-103.7	-103.7	-103.7	-103.7
Chattooga	-8.9	-8.9	-8.1	-8.1	Newton	16.2	16.2	21.9	21.9
Cherokee	-39.3	-39.3	-27.4	-27.4	Oconee	-23.8	-23.8	-10.7	-10.7
Clarke	-34.8	-34.8	-34.8	-34.8	Oglethorpe	2.2	2.2	4.1	4.1
Clay	-2.4	-1.8	-5.1	-5.1	Paulding	110.8	110.8	128.4	128.4
Clayton	47.1	47.1	53.1	53.1	Peach	2.6	2.6	-1.6	-1.6
Clinch	-4.3	-4.3	-4.8	-4.8	Pickens	14.4	14.4	20.9	20.9
Cobb	21.8	21.8	47.7	47.7	Pierce	23.2	23.2	24.2	24.2
Coffee	9.6	9.6	9.6	9.6	Pike	-17.1	-17.1	-17.0	-17.0
Colquitt	-0.6	-0.6	1.4	1.4	Polk	14.1	14.1	16.7	16.7
Columbia	0.0	0.0	0.0	0.0	Pulaski	-8.9	-10.0	-2.9	-2.9
Cook	12.1	12.1	6.6	6.6	Putnam	-7.3	-7.3	-8.8	-8.8
Coweta	-20.5	-20.5	1.1	1.1	Quitman	-4.1	-3.7	-5.1	-5.1
Crawford	-8.9	-8.9	-14.8	-14.8	Rabun	7.1	7.2	6.1	6.1
Crisp	-4.4	-4.4	-4.3	-4.3	Randolph	4.5	5.4	-0.7	-0.7

Dade	-14.7	-14.7	-15.2	-15.2	Richmond	79.6	79.6	79.6	79.6
Dawson	-6.3	-6.3	-3.8	-3.8	Rockdale	-29.3	-29.3	22.2	22.2
Decatur	5.4	5.4	5.5	5.5	Schley	-0.3	-0.3	2.1	2.1
DeKalb	563.2	563.2	609.0	609.0	Screven	20.5	20.5	20.0	20.0
Dodge	-6.9	-7.2	-5.4	-5.4	Seminole	-13.4	-13.4	-13.4	-13.4
Dooly	-16.6	-16.6	-19.7	-19.7	Spalding	47.8	47.8	60.3	60.3
Dougherty	17.0	17.0	17.0	17.0	Stephens	-10.8	-11.9	-7.4	-7.4
Douglas	68.0	68.0	79.0	79.0	Stewart	-1.5	-1.0	-4.1	-4.1
Early	11.3	10.2	13.6	13.6	Sumter	-30.9	-30.9	-31.1	-31.1
Echols	-5.8	-5.8	-5.9	-5.9	Talbot	-0.4	-0.2	-2.2	-2.2
Effingham	-10.8	-10.8	-6.4	-6.4	Taliaferro	-2.7	-2.7	-3.6	-3.6
Elbert	-11.1	-9.4	-18.8	-18.8	Tattnall	18.6	18.7	16.2	16.2
Emanuel	-5.2	-5.2	-5.0	-5.0	Taylor	6.0	6.3	4.6	4.6
Evans	10.2	10.2	8.0	8.0	Telfair	-10.1	-9.5	-12.2	-12.2
Fannin	-16.7	-16.7	-16.0	-16.0	Terrell	5.3	5.3	6.7	6.7
Fayette	-35.2	-35.2	6.9	6.9	Thomas	4.2	4.2	3.3	3.3
Floyd	14.3	14.3	14.3	14.3	Tift	-8.3	-8.3	-8.3	-8.3
Forsyth	12.0	12.0	12.0	12.0	Toombs	-21.1	-21.1	-21.4	-21.4
Franklin	-2.5	-4.5	4.7	4.7	Towns	-2.2	-2.2	-2.2	-2.2
Fulton	-255.8	-255.8	-255.8	-255.8	Treutlen	4.8	4.8	1.8	1.8
Gilmer	-9.1	-9.1	-9.1	-9.1	Troup	30.6	30.6	30.6	30.6
Glascok	-1.0	-0.7	-1.7	-1.7	Turner	-5.4	-5.4	-4.2	-4.2
Glynn	-3.1	-3.1	-3.1	-3.1	Twiggs	-9.8	-9.8	-11.0	-11.0
Gordon	-26.5	-26.5	-16.1	-16.1	Union	3.6	3.6	4.7	4.7
Grady	37.5	37.5	32.7	32.7	Upson	0.0	0.0	6.7	6.7
Greene	24.9	24.9	24.6	24.6	Walker	-52.0	-52.0	-52.8	-52.8
Gwinnett	-107.0	-107.0	-22.6	-22.6	Walton	0.8	0.8	31.2	31.2
Habersham	-24.6	-24.9	-16.3	-16.3	Ware	85.2	85.2	85.2	85.2
Hall	-77.8	-77.8	-64.6	-64.6	Warren	-0.8	-0.8	-0.7	-0.7
Hancock	0.4	0.4	-3.3	-3.3	Washington	11.1	11.2	7.3	7.3
Haralson	7.0	7.0	8.4	8.4	Wayne	-47.0	-47.0	-47.9	-47.9
Harris	-5.3	-5.3	-4.6	-4.6	Webster	-4.5	-3.4	-8.9	-8.9
Hart	-20.7	-20.7	-22.4	-22.4	Wheeler	-1.4	-1.4	-0.9	-0.9
Heard	1.7	1.8	0.1	0.1	White	-14.7	-14.7	-15.5	-15.5
Henry	-58.6	-58.6	4.7	4.7	Whitfield	-16.5	-16.5	-16.5	-16.5
Houston	-81.5	-81.5	-81.1	-81.1	Wilcox	0.1	0.1	0.1	0.1
Irwin	0.5	0.5	5.4	5.4	Wilkes	-4.8	-4.8	-4.8	-4.8
Jackson	-17.6	-17.6	-7.0	-7.0	Wilkinson	1.2	1.2	-2.5	-2.5
Jasper	9.1	9.1	5.2	5.2	Worth	36.6	36.6	38.3	38.3
Jeff Davis	-8.1	-8.1	-4.0	-4.0					

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183 **Supplemental Table E5: Predicted reduction in ED visits for all counties in GA**

County	Specialist : 15	Specialist : 15, Primary : 15	Specialist : 5	Specialist : 5, Primary : 15	County	Specialist : 15	Specialist : 15, Primary : 15	Specialist : 5	Specialist : 5, Primary : 15
Alamance	101.4	101.4	36.0	36.0	Johnston	37.4	37.4	17.2	17.2
Alexander	-29.3	-29.3	-27.6	-27.6	Jones	32.9	32.9	38.0	38.0
Alleghany	0.2	0.2	7.6	7.6	Lee	59.7	59.7	60.7	60.7
Anson	-15.9	-15.9	-2.6	-2.6	Lenoir	115.1	115.1	134.6	134.6
Ashe	-58.4	-58.4	-43.4	-43.4	Lincoln	19.1	19.1	-13.7	-13.7
Avery	-21.1	-21.1	-12.4	-12.4	Macon	-57.5	-57.5	-55.5	-55.5
Beaufort	0.5	0.5	-1.4	-1.4	Madison	-23.6	-23.6	-24.3	-24.3
Bertie	-2.5	-2.5	-2.5	-2.5	Martin	-16.2	-16.2	-1.2	-1.2
Bladen	-42.6	-42.6	-31.5	-31.5	McDowell	-52.1	-52.1	-38.7	-38.7
Brunswick	-67.4	-67.4	-68.2	-68.2	Mecklenburg	35.3	35.3	-1573.1	-1573.1
Buncombe	-193.2	-193.2	-281.6	-281.6	Mitchell	-9.4	-9.4	-7.4	-7.4
Burke	6.7	6.7	7.5	7.5	Montgomery	52.1	52.1	52.1	52.1
Cabarrus	153.7	153.7	126.8	126.8	Moore	98.1	98.1	86.7	86.7
Caldwell	-42.7	-42.7	-42.7	-42.7	Nash	37.4	37.4	26.8	26.8
Camden	33.0	33.0	33.0	33.0	New Hanover	-1.4	-1.4	-42.7	-42.7
Carteret	9.8	9.8	-9.2	-9.2	Northampton	-6.8	-6.8	7.1	7.1
Caswell	-29.3	-29.3	-22.1	-22.1	Onslow	-283.9	-283.9	-238.9	-238.9
Catawba	-117.5	-117.5	-127.2	-127.2	Orange	97.5	97.5	58.7	58.7
Chatham	19.7	19.7	-47.7	-47.7	Pamlico	16.7	16.7	19.6	19.6
Cherokee	-10.9	-10.9	-20.1	-20.1	Pasquotank	153.0	153.0	153.0	153.0
Chowan	4.2	4.2	26.5	26.5	Pender	-24.3	-24.3	-30.1	-30.1
Clay	-11.4	-11.4	-6.1	-6.1	Perquimans	9.8	9.8	20.8	20.8
Cleveland	128.1	128.1	132.3	132.3	Person	97.6	97.6	103.3	103.3
Columbus	-18.6	-18.6	9.7	9.7	Pitt	-18.2	-18.2	2.6	2.6
Craven	151.2	151.2	151.5	151.5	Polk	-26.4	-26.4	-25.3	-25.3
Cumberland	337.7	337.7	500.0	500.0	Randolph	-298.1	-298.1	-258.1	-258.1
Currituck	-35.9	-35.9	-39.9	-39.9	Richmond	81.9	81.9	118.5	118.5
Dare	-30.6	-30.6	-35.9	-35.9	Robeson	77.9	77.9	77.9	77.9
Davidson	-86.2	-86.2	-90.0	-90.0	Rockingham	-33.1	-33.1	14.1	14.1
Davie	2.2	2.2	-32.6	-32.6	Rowan	-1.1	-1.1	-1.1	-1.1
Duplin	22.1	22.1	22.1	22.1	Rutherford	-39.0	-39.0	-39.0	-39.0
Durham	4.2	4.2	-34.6	-34.6	Sampson	59.1	59.1	70.0	70.0
Edgecombe	142.4	142.4	165.2	165.2	Scotland	-63.8	-63.8	-59.9	-59.9
Forsyth	-63.8	-63.8	-259.2	-259.2	Stanly	-38.5	-38.5	-62.1	-62.1
Franklin	74.9	74.9	74.8	74.8	Stokes	-45.9	-45.9	-45.3	-45.3

Gaston	-63.2	-63.2	-70.4	-70.4	Surry	62.4	62.4	77.0	77.0
Gates	-16.9	-16.9	-17.1	-17.1	Swain	-0.4	-0.4	-0.4	-0.4
Graham	3.7	3.7	3.7	3.7	Transylvania	-46.8	-46.8	-46.8	-46.8
Granville	-60.3	-60.3	-74.0	-74.0	Tyrrell	10.0	10.0	10.0	10.0
Greene	-13.3	-13.3	-7.6	-7.6	Union	-104.1	-104.1	-220.3	-220.3
Guilford	-315.0	-315.0	-393.0	-393.0	Vance	18.6	18.6	31.4	31.4
Halifax	16.2	16.2	40.0	40.0	Wake	226.6	226.6	-595.5	-595.5
Harnett	56.4	56.4	109.8	109.8	Warren	-8.8	-8.8	-5.6	-5.6
Haywood	17.6	17.6	17.6	17.6	Washington	-9.9	-9.9	4.4	4.4
Henderson	-56.0	-56.0	-81.1	-81.1	Watauga	-77.9	-77.9	-78.0	-78.0
Hertford	69.7	69.7	81.0	81.0	Wayne	151.4	151.4	206.5	206.5
Hoke	-10.1	-10.1	-10.1	-10.1	Wilkes	-133.9	-133.9	-130.3	-130.3
Hyde	10.0	10.0	10.0	10.0	Wilson	109.5	109.5	153.5	153.5
Iredell	-14.0	-14.0	-76.2	-76.2	Yadkin	-69.4	-69.4	-69.4	-69.4
Jackson	-41.0	-41.0	-39.0	-39.0	Yancey	-18.3	-18.3	-18.3	-18.3

Supplemental Table E6: Predicted reduction in ED visits for all counties in NC.

Poisson regression is frequently used to fit models for count data and rare events, both of which are appropriate descriptors of the pediatric asthma severe outcomes data. The input data and setup for poisson regression and logistic regression with replications, which is the method used to generate the models that are presented, are very similar, and are based on the number of events (severe asthma outcomes) and the size of the population (the number of asthmatic children). We fit and performed model selection using the poisson family parameter, which uses the appropriate log link function for Poisson regression, and compared the resulting models to the selected logistic regression models. The models for both types of regression contain identical sets of significant predictors and the coefficients have the same signs and similar magnitudes. The singular exception is the difference of only one significant predictor for North Carolina ED Visits, where the logistic regression model contains the interaction term between Age Group 9-14 and the variance of distance to specialist care while the poisson model had the interaction between this same age group and the level parental education instead. The consistency of the significant predictors and the similarities between the coefficient values confirms that the selected models are appropriate and provide a good fit for the data.

203 **Figure Legends:**

204 **Figure E1:** *Number of children with a current diagnosis in each county in GA and NC.*

205 **Figure E2:** *Centralized optimization model to assign patients to specialists*

206 **Figure E3:** *The correlation displays for Person correlation (left plot) and Kendall tau*
207 *correlation (right plot) for GA (top) and NC (bottom). The size and the color are indications of*
208 *how strong or weak the correlation is between any two variables.*

209 **Figure E4:** *The difference in the county level distance to receive specialist and primary care in*
210 *GA and NC.*

211 **Figure E5:** *The scatter plots of primary vs specialist distance for GA and NC with linear trend*
212 *lines and the Pearson correlation coefficient.*

213 **Figure E6:** *The values and z-values for the local Moran's I for spatial auto-correlation of*
214 *distances to receive primary and asthma specialist care in Georgia and North Carolina.*

215 **Figure E7:** *Deviance residual analysis for the ED visits model for Georgia.*

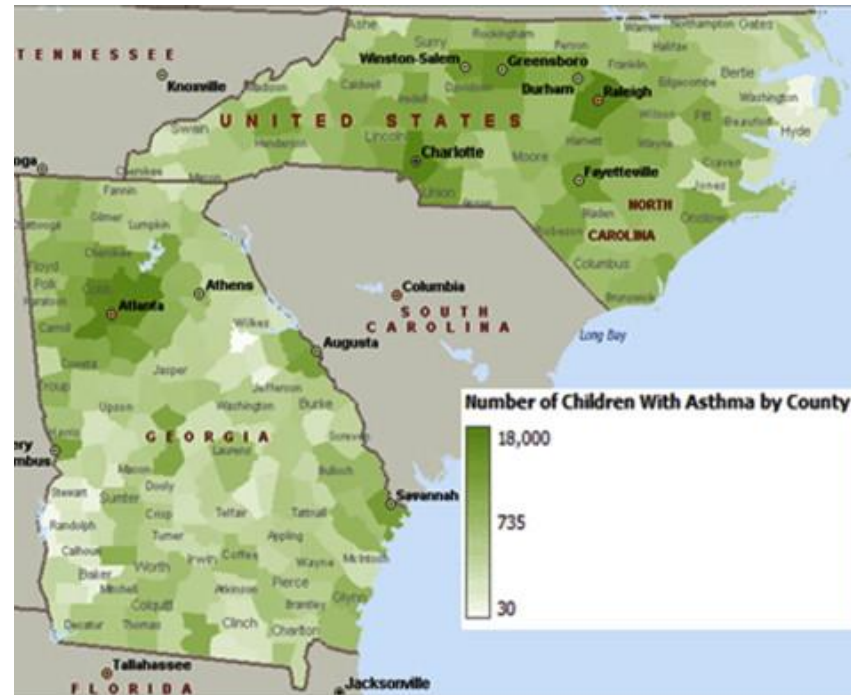


Fig E1

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Journal of Allergy and Clinical Immunology, 2015

<http://dx.doi.org/10.1016/j.jaci.2015.01.030>

$$\begin{aligned}
 & \text{Min } \sum_{j \in D} \sum_{i \in P} x_{ij} d_{ij} & (1) \\
 & \text{Subject To :} & (2) \\
 & \sum_{j \in D} x_{ij} \leq 1 & \forall i \in P & (1) \\
 & \sum_{j \in D} \sum_{i \in P} x_{ij} \leq |P| & (2) \\
 & \sum_{i \in P} x_{ij} \leq u_j & \forall j \in D & (3) \\
 & \sum_{j \in D} x_{ij} d_{ij} \leq m_i & \forall i \in P & (4) \\
 & \sum_{j \in D} \sum_{i \in P} x_{ij} \geq 0.9|P| & (5) \\
 & \sum_{j \in D_c} x_{ij} \leq g * Specialists_c & \forall c \in Counties & (6)
 \end{aligned}$$

Fig E2

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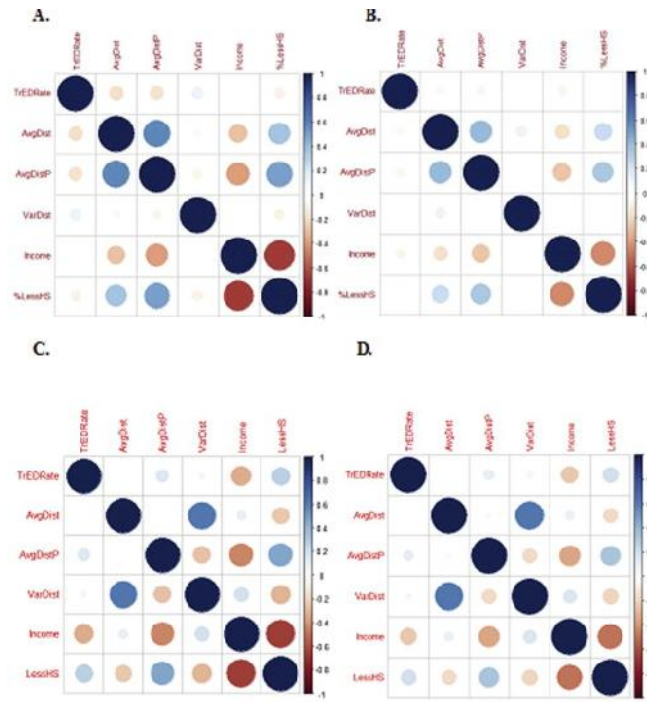


Fig E3

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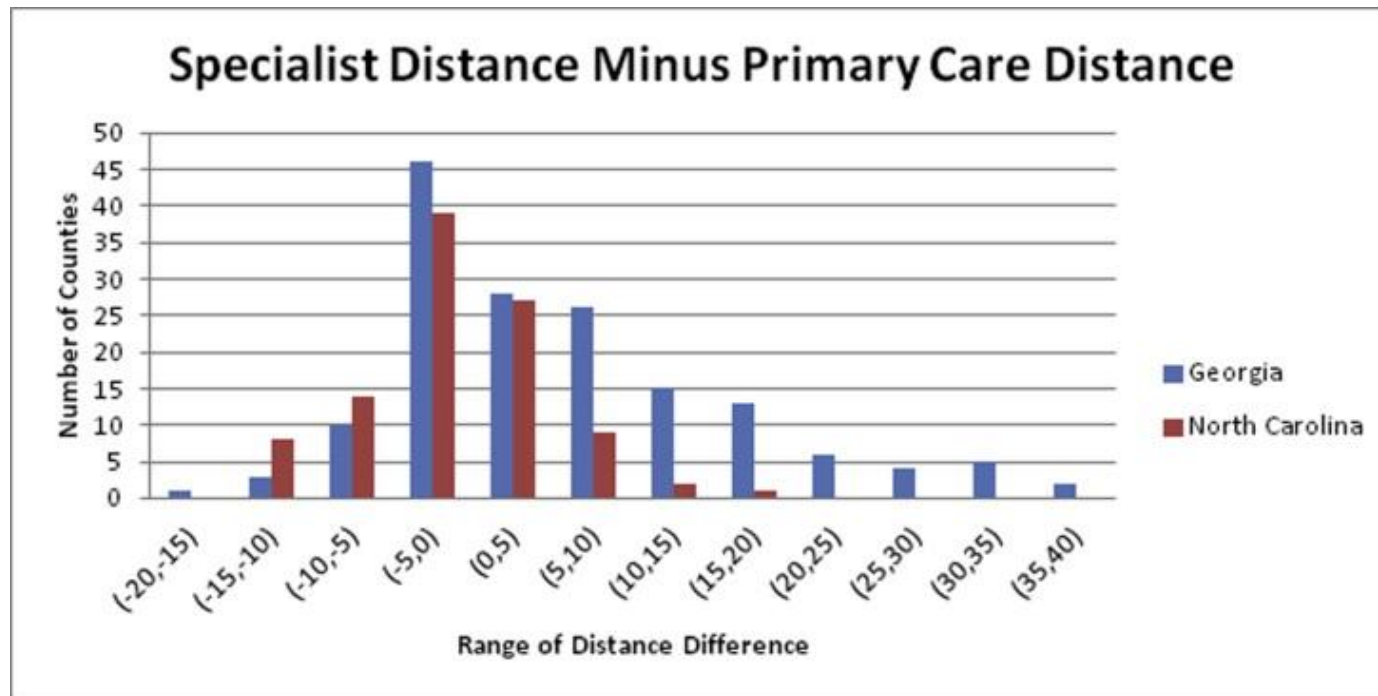


Fig E4

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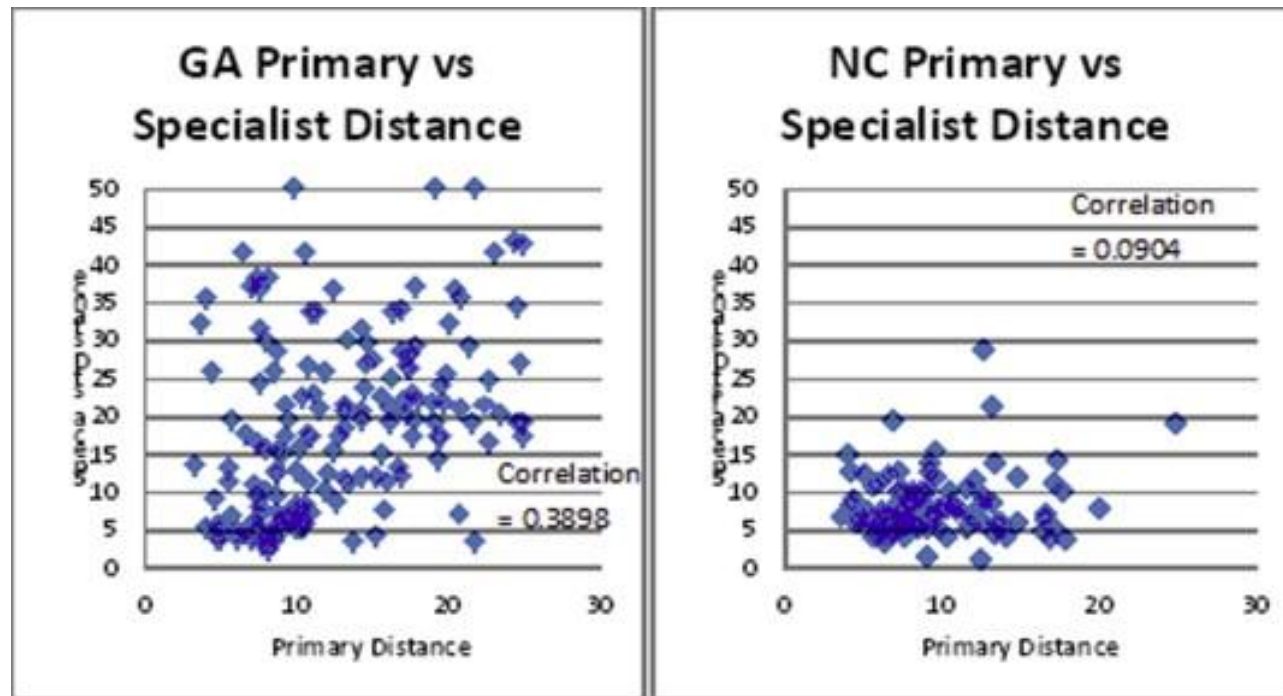


Fig E5

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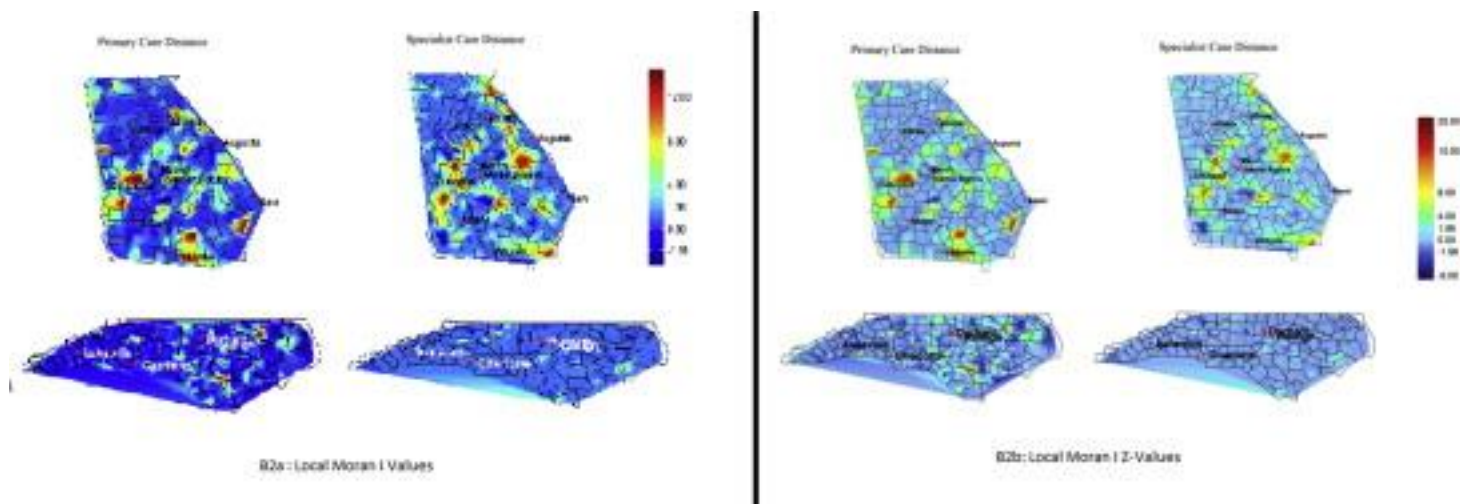


Fig E6

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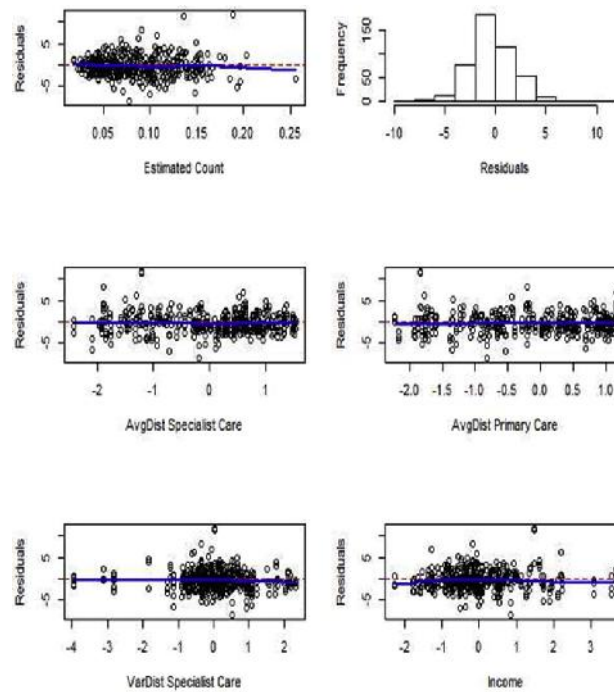


Fig E7

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