EVALUATING ACCESS TO CARE AND UTILIZATION FOR CHRONIC PEDIATRIC CONDITIONS

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EVALUATING ACCESS TO CARE AND UTILIZATION FOR CHRONIC PEDIATRIC CONDITIONS

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To my mom, for her never-ending love and support.

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LIST OF SYMBOLS AND ABBREVIATIONS

AL	Alabama
AR	Arkansas
CA	California
CDC	Center for Disease Control
CMS	Centers for Medicare and Medicaid Services
CRG	Clinical Risk Group
DoPH	Department of Public Health
ED	Emergency Department
FL	Florida
GA	Georgia
HCUP	Health Care Utilization Project
ICD-9	International Classification of Diseases Code, ninth revision
IRB	Institutional Review Board
LA	Louisiana
MAX	Medicaid Analytic eXtract
MD	Non-Medicaid Primary Care
MDM	Medicaid Primary Care
MN	Minnesota
MS	Mississippi
NC	North Carolina
NCQA	National Committee for Quality Assurance
NDC	National Drug Code

NPI National Provider Index

NY New York

OASIS Online Analytical Statistical Information System

PA Pennsylvania

PPPM Per Patient Per Month

PPPY Per Patient Per Year

PS Psychological Service

RUCC Rural-Urban Continuum Code

RX Medication Received

S Non-Medicaid Specialist Care

SC South Carolina

SEDD State Emergency Department Database

SID State Inpatient Database

SM Medicaid Specialist Care

TN Tennessee

TX Texas

SID State Inpatient Database

SM Medicaid Specialist Care

TN Tennessee

TX Texas

SUMMARY

Physical and mental health can each have a huge impact on a child's daily life, and whether or not their medical conditions are properly treated can have a lifelong impact on their overall health. In this thesis, we focus on two chronic pediatric conditions, asthma (a physical health condition) and depression (a mental health condition). We aim to evaluate selected aspects of the current state of the health care system with respect to these conditions.

In Chapter 2, we first calculate the census tract level distance to receive asthma specialist care for children in fourteen states using a centralized optimization model to assign patients to providers. From these distances, we identify which states have better access to specialist care, and identify areas in which there is no access to care. For two states, we use this measure of access to care as a predictor in logistic regression models to determine the statistical significance of geographic access to asthma specialist care in estimating the rate of severe asthma outcomes (ED visits and hospitalizations).

In Chapter 3 we extend the optimization model to account for visits for asthma care that are met by both primary care and asthma specialist providers and divide the children with asthma into the Medicaid and non-Medicaid population. Using CMS MAX data, we determine the capacity for pediatric asthma visits for individual providers as well as for each provider type. We then compute the census tract level distance for Medicaid and non-Medicaid children to receive primary and specialist care from the optimization model output, as well as the percent of the need in each census tract that is unmet.

In Chapter 4 we establish a depression baseline for the Medicaid population using the CMS MAX data. The baseline includes treated prevalence and utilization for Medicaid children age 12-17 in twelve states from 2005 to 2012. The treated prevalence and utilization are presented at the state level and by patient stratifications within each state.

In Chapter 5 we use a matching procedure to create a data set of Medicaid children that simulates paired data. Each child with depression is matched to a child without depression but who otherwise has similar characteristics. Using these pairs of children, we compare the visits, prescription fills, and Medicaid charge amounts for non-depression related health care in 2010 and 2011 in order to quantify the differences in health care utilization and expenditure between the depression and non-depression populations.

CHAPTER 1. INTRODUCTION

Physical and mental health can each have a huge impact on a person's life, and this is true for children as well as adults. Children are a particularly vulnerable population, however, as they lack the ability and resources to manage their own treatment. In addition, whether or not their medical conditions are properly treated can have a lifelong impact on their overall health.

1.1 The Impact of Geographic Access on Severe Health Outcomes for Pediatric Asthma

Asthma is one of the most common chronic pediatric conditions in the United States, and it is an excellent candidate condition to study because many of the severe outcomes that it causes are preventable. In order for a child to have well managed asthma and avoid unnecessary health outcomes, he or she must be able to receive the medical care he needs. In the second chapter, we compute the estimated geographic access to specialist care for children in each census tract in Georgia and North Carolina, and then quantify the impact of geographic access to asthma specialist care on the rate of severe pediatric asthma outcomes. This analysis provides quantitative evidence for the importance of having asthma specialists that can be reached by people from every census tract. This may be used to inform policy concerning state level standards for spatial access to care or in the selection of interventions so that access can be improved in the counties where there is the greatest room for improvement.

1.2 Spatial and Seasonal Access to Primary and Specialist Pediatric Asthma Care

Knowing that geographic access to asthma care is a significant factor in estimating and predicting severe pediatric outcomes leads to further questions and provides justification for continued study of potential geographic access to care. In chapter 3 we extend the model from chapter two in three ways: (1) expanding to include seven southeastern states; (2) dividing the patients into the Medicaid and the non-Medicaid population; (3) including the estimation of access to asthma care to both primary care physicians and asthma specialists, both of which are the appropriate source of treatment for children with asthma of varying degrees of severity and control. It is well known that asthma is impacted by a wide variety of factors, including the weather and allergies, which often depend on the season. Using Medicaid claims data, we are able to confirm that there are seasonal trends in the number of office and emergency room visits that are due to asthma. We also compute the available capacity for pediatric asthma visits at primary and specialist providers that serve the Medicaid population and apply that provider type capacity to all of the primary and asthma specialist providers in each state. The second section addresses the questions of if there are significant differences in access to each type of care for Medicaid and non-Medicaid patients, and whether or not the variations in demand are large enough to cause a change in access to care across the seasons.

1.3 Healthcare Utilization Among Medicaid-Enrolled Adolescents Diagnosed with Depression

While depression is not as common in children as asthma is, it can impact not only a child's mental health but also his physical health outcomes (including those for asthma).

There is not a complete existing baseline analysis of the prevalence of pediatric depression, and so we begin by establishing a depression baseline in the Medicaid population that includes a detailed breakdown of the population by demographic factors including age, gender, race, overall health (measured with the clinical risk group score) and Medicaid eligibility code. This baseline includes summary information about the population with depression in 12 states, as well as the utilization of medical services for depression by state over the seven-year period 2005-2012.

1.4 Healthcare Outcome Measurements for Medicaid-Enrolled Children Diagnosed with Depression

After establishing the baseline, we create a data set of children with and without depression from the MAX files using a matching procedure that can be treated as paired samples for the remainder of the analysis. Using the pairs of children in each state, we conduct a comparison of the utilization and cost of health care per patient per month enrolled. In the analysis, we focus on the visits and charges for non-depression care so that we can quantify the impact of comorbid depression on other health outcomes. This comparison provides insight into the monetary value over time of being able to treat a child with depression so that he can be considered treated, or in remission with no expected relapse.

CHAPTER 2. THE IMPACT OF GEOGRAPHIC ACCESS ON SEVERE HEALTH OUTCOMES FOR PEDIATRIC ASTHMA

2.1 Introduction

Asthma is a common chronic childhood condition, with over 7.1 million American children having a current asthma diagnosis[1]. In addition to impairing quality of life, asthma contributes significant costs to the healthcare 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 healthcare[2]. In 2006 the asthma hospitalization rate for children living in a zip code with a median income below $37,000 was 76% higher than for other children[3]. African American and Hispanic children are more likely to have asthma and to experience a severe asthma outcome than White children[4-8].

Both the underlying severity of the disease and how well controlled the patient's asthma is contribute to the likelihood that he will have a severe outcome. Asthma control can be difficult to attain, and the importance of control is highlighted throughout the literature[9-11]. Unfortunately, many patients lack a correct understanding of what it means for their asthma to be controlled, and both patients and physicians alike often do not see control as defined by medical guidelines as attainable. [12]. Bianchi et al conclude that control is such an telling factor that hospitalizations are representative of uncontrolled, rather than particularly severe, asthma.[13] Improved adherence by the patients improves both asthma and control, and is the focus of multiple interventions[14-17].

Receiving proper medical treatment is critical to an asthmatic child's health. It is well documented in the literature that asthma control plays as large a role in severe outcomes as underlying severity, and that regular medical visits are required for most children to maintain control over their asthma. National guidelines recommend between two and twelve visits per year for asthma when a child has well controlled asthma, and even more frequent visits for those whose asthma is not well controlled. On average, children on Medicaid in Georgia only have office visits for asthma treatment twice per year, which is lower than we would anticipate since we do not expect that all children will have well controlled asthma. Therefore, it is likely that many children are not going to the doctor for asthma treatment as frequently as is recommended to maintain good control.

A key contributor to health and healthcare disparities for chronic conditions, particularly pediatric asthma, is the insufficient access to healthcare 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[18-22]. In this study, we focus specifically on geographic access. While 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 impact health care utilization and health outcomes[23-25] , 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[26]. Understanding the extent of this relationship will suggest interventions targeted to reduce severe outcomes.

Potential access is commonly used in place of realized access[27-38]. In this chapter, we study the link between potential geographic access and severe outcomes for pediatric asthma while controlling for other potentially contributing factors in Georgia (GA) and North Carolina (NC). Improving asthma outcomes is a priority for the Georgia Department of Public Health (DoPH), which leads the Georgia Asthma Control Program. Data availability, geographic proximity to GA, and a different distribution of distance to receive asthma specialist care contributed to choosing NC as the second state for analysis. We use mathematical 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.

2.2 Methods

2.2.1 Model Data Collection

The number of children with asthma is computed using the US 2010 Census and BRFSS survey prevalence estimates. Figure 1 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.

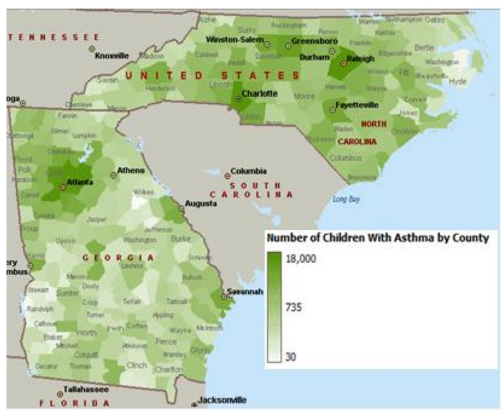

Figure 1. Number of children with a current asthma diagnosis per county in GA and NC

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. Table 1 below summarizes the annual number of appointments available for each specialist type.

Table 1. Annual appointments available to pediatric asthma patients for an individual asthma specialist by 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

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.

2.2.2 Study Population

The population under consideration consists of children ages 5 to 17 estimated to have a current diagnosis of asthma in GA and NC. The age group 0 to 4 is excluded because of the difficulty of diagnosing asthma for this age group. The percent of children who had a current diagnosis of asthma is reported by age group in Table C3 of the 2010 BRFSS survey for GA[39] and by the 2011 National Survey of Children's Health (NSCH) for NC[40]. The census tract population counts of children for each age group were obtained from the 2010 Census data Table B09001[41]. 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 percent 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 the estimates are aggregated at the county level, shown in Figure 1 above, for the regression analysis.

2.2.3 Overall Approach for Understanding Severe Outcomes

To predict severe outcomes, we consider covariates that fall into three categories: age indicator, health access (which is of primary interest) and socio-economics, to control for other factors over the network. For consistency, the values for all covariates are collected or aggregated at the county level. GA has 159 counties and NC has 100.

In this study, a severe outcome is defined as an ED visit or hospitalization that was 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 GA, ED visits and hospitalizations in 2010 were obtained from the online OASIS database[42]. For NC, the ED visits and hospitalizations for 2009 were obtained from the Healthcare Cost and Utilization Project state databases, which contain de-identified individual records from community hospitals[43, 44]. IRB approval was obtained for this research. Severe outcomes were extracted using the ICD9 codes for asthma and the criteria that at least one of the first two diagnosis codes is for asthma.

2.2.4 Covariates of Primary Interest: Travel Distances to Asthma Care Providers

There are three 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 intra-county variance of distance to specialist care ("VarSpecialistDistance"). We consider this third access measure because there can be a large variation across the census tract distances to specialist care. To control for mobility of the population across county lines for hospital care, the number of hospitals in each county is included as a potential predictor ("NumberHospitals")[45].

We calculate potential geographic access to primary and asthma specialist care using recent methodology to match supply and demand[31]. The approach accounts for constraints in the network (e.g., mobility) along with potential barriers to care (e.g., 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[31], we use distance as a primary criteria 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 an National Provider Identifier (NPI) classification of Pediatrics, Nurse Practitioner Pediatrics, Family Medicine, and Internal Medicine and obtained travel distances for GA and NC from the recent work of Gentilli et al[46].

For specialist asthma care, we extracted the locations of asthma specialists from the NPI Registry using the National Uniform Claim Committee's taxonomy codes[47]. Consistent with the identification of asthma specialists in analyses of the importance of specialist care in the literature, we considered allergists and pulmonologists as asthma specialists[48, 49]. The maximum caseload of visits for pediatric asthma care was adjusted depending on the specialty and whether or not the provider has a pediatric designation, and is shown in Table 1 above. 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[50].

The notation and full optimization model description for matching patients with providers are listed here, with the mathematical model shown in Figure 2.

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

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

Figure 2. Centralized optimization model to assign patients to specialists

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.

We examine the distribution of distances to care for each state along with the Pearson's correlation of the distances. Similarly to Nobles' work,[31] we estimate the spatial correlation on distance to care using Moran's I measure, used to evaluated systematic disparities in geographic access[51].

2.2.5 Other Model Covariates

All socioeconomic variables extracted from the 2010 Census data are restricted to data on households that have at least one child under the age of 18[41]. We include an indicator (0 or 1) variable ("AgeX-Y") for whether the response variable is for children in each of three age ranges (X to Y) [39, 40]. For income and education, we select among potential variables by investigating the strength of the association of these variables with the response variable. The variables selected are the median family income

(“MedianIncome”) and the percent of the adults with less than a high school diploma (“AdultEducation”).

2.2.6 *Statistical Model*

We quantify the impact of geographic access on severe outcomes using logistic regression with replications (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 2, we performed model selection using forward, backward and forward-backward stepwise regression. Of the three resulting models for each state and outcome pair (GA ED Visits, GA Hospitalizations, NC ED Visits, NC Hospitalizations), the one with the smallest AIC value was selected.

This process can be explained with the following algorithm:

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

S = S = {GA, NC}

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

Y = {ED, H}

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

R = R = {F, B, FB}

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

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

For each state s in S:

For each outcome y in Y:

For each selection method r in R:

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

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

The final set of main effect covariates considered in the model is defined in Table 2 below.

Table 2. The final set of main effect covariates included for consideration in the regression model. The final model also includes interaction terms between these covariates.

Variable Name	Description
AgeX-Y	Number of children that are X-Y years old For GA: 5-8,9-14,15-17 For NC: 5-9,10-14,15-17
SpecialistDistance	Within- county average distance to an asthma specialist
VarSpecialistDistance	Within- county variance of distance to an asthma specialist
PrimaryDistance	Within- county average distance to a primary care pediatrician
MedianIncome	Median family income households with children under age 18
AdultEducation	Percent of the adult population who have less than a high school diploma and live in a household with children under age 18
NumberHospitals	Number of hospitals

The regression analysis was implemented using the R statistical software. For model interpretation, we point 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 two 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.

The selected models with the estimated coefficients and their corresponding significance p-values are provided in the Table 4 for Georgia and Table 5 for North Carolina.

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 of 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.

We also use the results of the regression model to predict the reduction of 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 the predictors (including new distances where applicable) to obtain a predicted response. Using the predicted response, we take the inverse of the logit function to get the percent 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.

2.3 Results

2.3.1 Geographic Access to Primary and Specialist Asthma Care

Figure 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 in Figures 4 and 5 respectively, with summary statistics in Table 3. Overall, in GA there are more counties with longer travel distances to asthma care than in NC. Specifically, in NC, the maximum distance to receive asthma specialist care is 30 miles, and only 5 counties have an average distance greater than 15 miles. In contrast, the tract level specialist distances in GA are as high as 50 miles, with counties having an average distance greater than 30 miles. For primary care in GA, 56 counties travel further than 15 miles, while in NC, 11 counties travel further than 15 miles. Figure 6 shows the difference in access to primary and specialist care in both states.

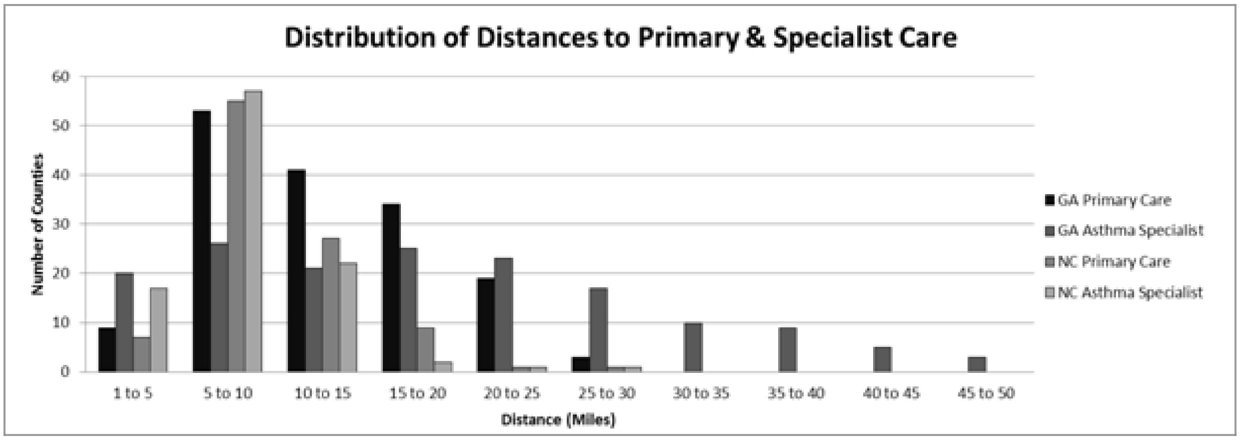

Figure 3. Comparing the distribution of geographic access measures for GA and NC.

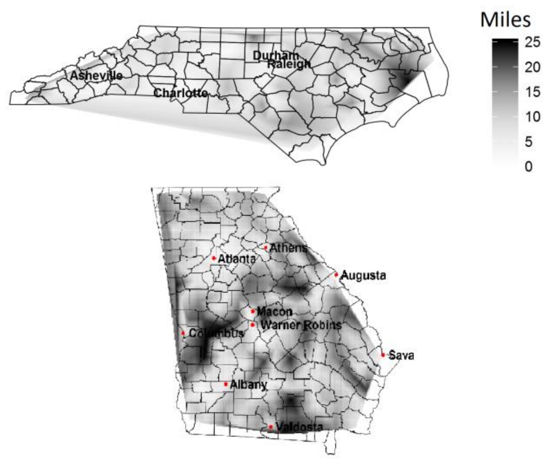

Figure 4. Maps of the census-tract level travel distances to primary for GA and NC.

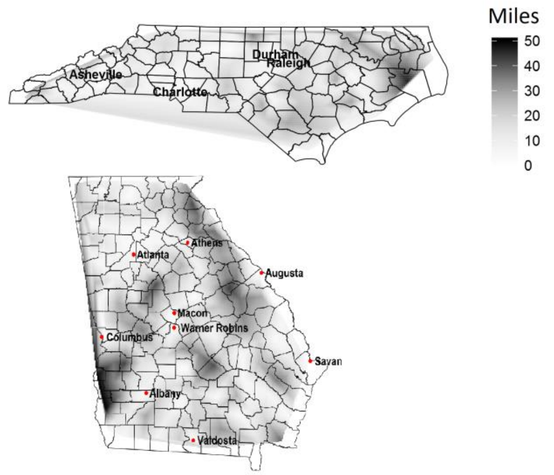

Figure 5. Maps of the census tract level travel distances to specialist care for GA and NC.

Table 3. Summary statistics for the three access variables at the county level in GA and 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	

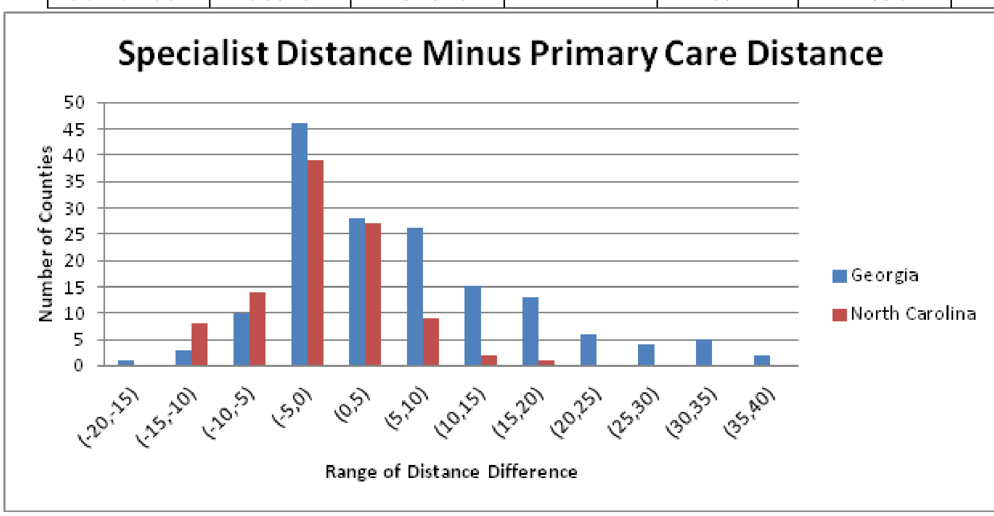

Figure 6. The difference in the county level distance to receive specialist and primary care in GA and NC.

The Pearson's correlation between the travel distances to primary and to specialist care in GA is 0.3898, while the correlation in NC is 0.0904, shown in Figure 7. Both GA and NC have significant spatial correlation for primary and specialist care, as indicated by significant z-values for the local Moran's I measure, shown in Figure 8.

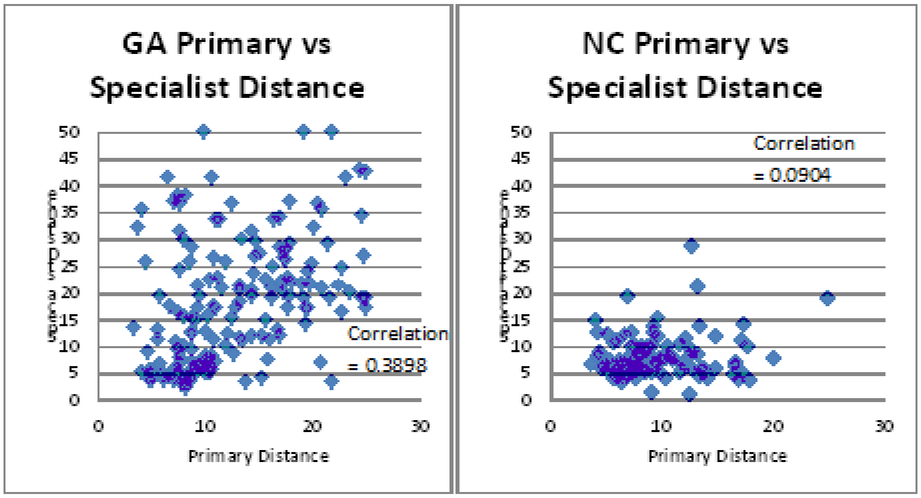

Figure 7. The scatter plots of primary vs specialist distance for GA and NC with linear trend lines and the Pearson correlation coefficient

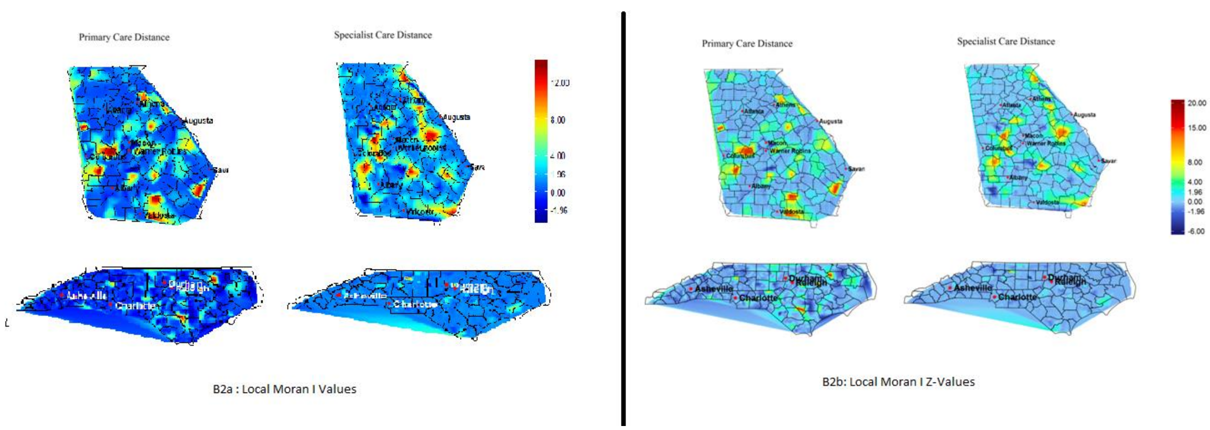

Figure 8. The values and z-values for the local Moran's I for spatial auto-correlation of distances to receive primary and asthma specialist care in Georgia and North Carolina.

2.3.2 Regression Results

The detailed results of the logistic regression for ED visit and hospitalization rates are shown in Appendix A. The results for Georgia are in Table 33. The results for North Carolina are in Table 34. In all models, geographic access is statistically significant, although through different access variables and in interaction with different factors. Model R-squared values are provided in Appendix A Table 35.

2.3.3 ED Visit Model: General Results

For explaining ED visits in GA, access to primary care 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 Figure 9.

In NC, all three 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 5-8.

2.3.4 Hospitalization Model: General Results

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

In NC, however, all three access variables are statistically significant. These access variables are also significant in more interaction terms than in the models for GA hospitalizations. Thus, the NC model is more complex than the GA hospitalization model.

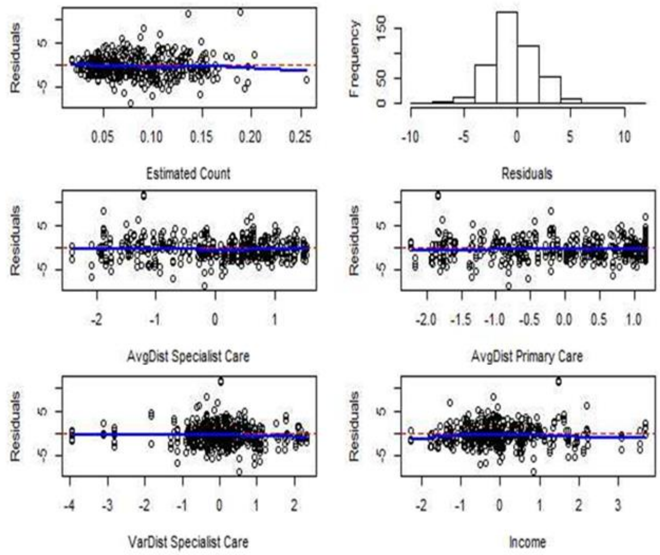

Figure 9. Deviance residual analysis for the ED visits model for Georgia.

2.3.5 Projecting Severe Outcome Reduction with Access Improvement

We use the fitted regression model to compute the predicted number of severe outcomes for each county and age group when the distance is reduced at the specified levels while keeping fixed all other predictors in the model.

Figure10 presents the number of county/age pairs in each state with a predicted reduction in the number of ED visits for each of the four distance interventions. For only improving specialist care to be no more than 15 miles, in NC 131 county-age pairs (out of 300) have a reduction in ED visits, and in GA 191 county-age pairs (out of 477) have a reduction in ED visits. The total reduction in ED visits is higher in NC, but both states have more than 30 county-age pairs where annual ED visits are reduced by more than 15.

Figure 11 shows the geographic distribution of locations with a positive improvement in outcome. For the intervention of specialist care, no more than 15 miles (figure far left), adding a reduction of primary care (third from left) only adds 1 new county in GA. In contrast, further reducing specialist care to no more than 5 miles (second from left) adds 10 additional counties although the additional improvement in ED visits is small for the counties that already had improvements from the 15-mile max distance intervention.

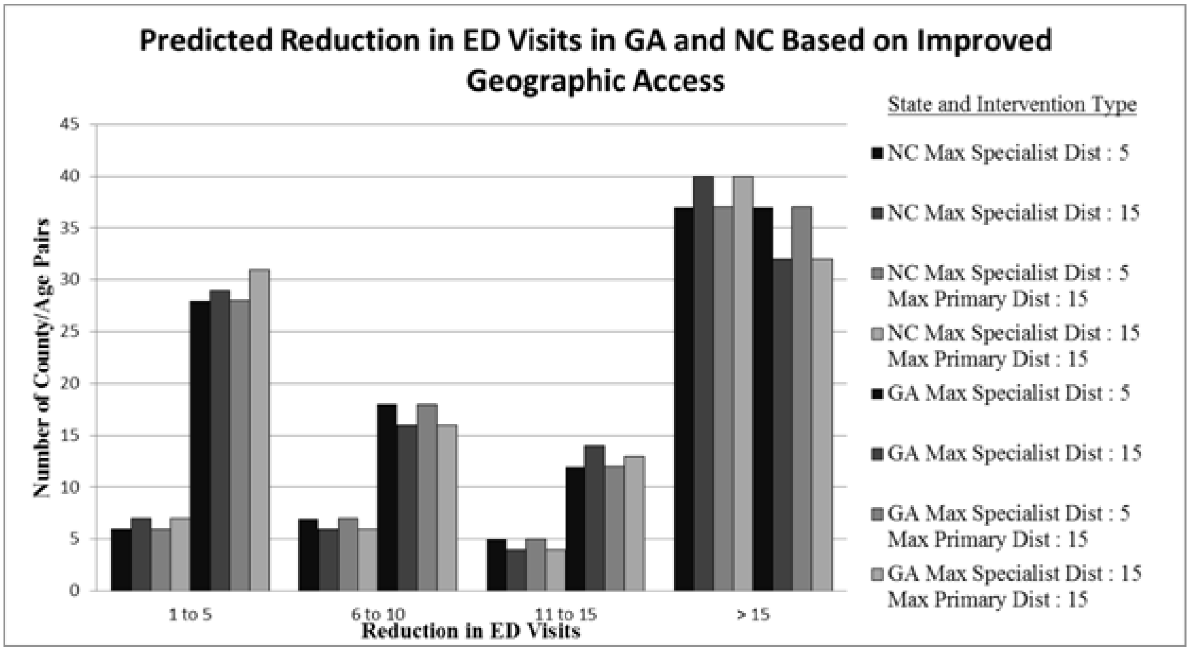

Figure 10. The graph shows the number of county-age pairs with an expected reduction in ED visits under four types of interventions on access. The interventions include reducing distance to specialist care to be no more than 5 or 15 miles, possibly in combination with reducing the distance to primary care to no more than 15 miles.

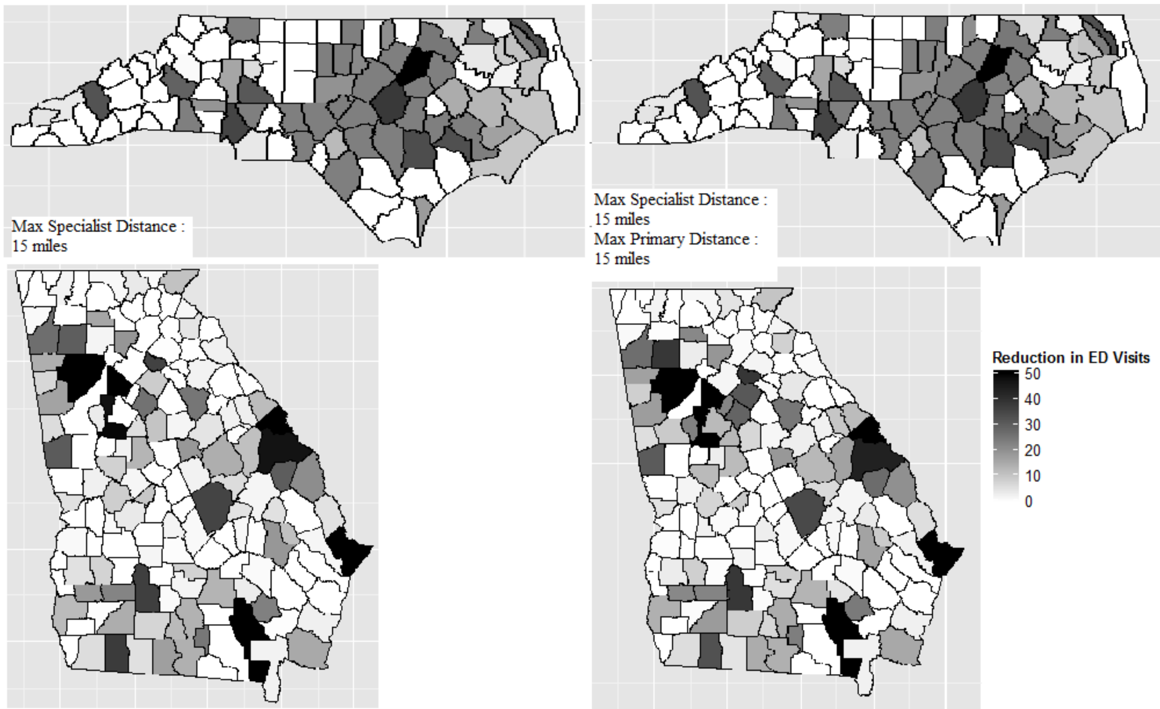

Figure 11. Reduction in ED visits when access to primary and specialist care is improved.

2.4 Discussion

Our study provides evidence for the association between severe pediatric asthma outcomes and estimated geographic access to healthcare while it underlines that this association is not uniformly impactful across geography or types of care. Existing literature has provided evidence for the association between asthma outcomes and a variety of socioeconomic and environmental variables, but not geographic access[3, 6, 24, 33, 52, 53]. Additionally, there is a relationship between race, lower utilization of asthma specialists, and the rate of severe asthma outcomes[54]. Mayer discussed the geographic proximity of children to a variety of pediatric specialists, but without any connection to health outcomes [55]. Other studies analyze the impact of distance on various health outcomes and resource utilization[56, 57], but the connection between geographic access to care and severe outcomes for pediatric asthma has not been investigated.

Geographic access can be quantified using methods such as distance to nearest service site[32], gravity-based model[33], or optimization-based models[31] which we use in this study. Although this approach requires more computational effort, it provides more accurate estimates than other methods, especially for dense healthcare networks[30]. The results showed that access to asthma care for pediatric patients varied widely between and within states. Interestingly, the correlation in primary and specialist care distances is smaller in NC than in GA. This indicates that children without good spatial access in Georgia are more likely to also have poor access to specialist care than the children with the same access in North Carolina.

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, ED visit versus hospitalization. For example, in GA 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 hospitalizations. Therefore, we would expect that improving access to primary care would have a greater impact on the hospitalization rate than the ED visit rate.

Moreover, a different set of access variables are associated with severe outcome rates when comparing GA to NC. For example, unlike in GA, the main effects of all three access variables are significant in the corresponding model for NC. Contrasting the models for hospitalizations, there are more significant interaction terms involving the access variables in NC 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 two states, in addition to those included in our model. Generally, NC scores higher in multiple state health rankings, both in general and with respect to the state Medicaid programs, where the analysis also covers differences related to policies [58, 59]. In addition, the overall population density in NC is higher than in GA, and the distribution of the population in the two states is different[60].

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

We also project the level of ED visits reduction when improving access (decreasing the distance to receive care to certain levels). We compared four interventions for improving access to specialist and primary care in GA. We find that there is a significant spatial trend in the ED visits 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, while the joint improvement of access to primary and specialist care does not lead to a noticeably greater impact 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, while a level of access similar to the comparative state of NC 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 the census tract level since many data sets only provide state or county level information. 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 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 percent of adults that smoke, the percent of children exposed to second hand smoke and indoor allergens[61, 62], air pollution and outdoor allergen measurements[53, 63-71], obesity[69, 71] and percent of children with insurance[72]. A second limitation is the simplicity of the calculation of the number of children with asthma, as described in the Methods. The age breakdowns used for each state are slightly different based on data availability. 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 chapter 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.

CHAPTER 3. SPATIAL AND SEASONAL ACCESS TO PRIMARY AND SPECIALIST PEDIATRIC ASTHMA CARE

3.1 Introduction

Asthma is a chronic condition that affects people of all ages. In addition to impacting patients' daily life, asthma can lead to severe health outcomes. Both underlying severity of the disease and how well controlled the patient's asthma is contribute to the likelihood of severe outcomes [9-11, 73].

Receiving proper medical treatment is critical to controlling asthma; regular medical visits are recommended for most children to maintain control over their asthma. Children who received specialist care for one year after diagnosis experienced a reduction in both asthma episodes and antibiotic use.[74] There is also a significant decrease in asthma symptoms and emergency visits for patients within one year after their first visit to a specialist [75].

National guidelines recommend 2 to 12 visits per-year for asthma care when a child has well controlled asthma, and even more frequent visits for those whose asthma is not well controlled [76]. However, recent research on longitudinal asthma care for about a million Medicaid-enrolled children diagnosed with persistent asthma found that the rate of physician office visits for asthma care is very low compared to the recommended care guidelines [77].

Access to asthma care is a major determinant of healthcare utilization. According to the Community Guide for Preventive Services, comprehensive multi-component, multi-trigger interventions for asthma care include appropriate access to clinical care [78]. Access to healthcare is associated with fewer disparities in health outcomes, reduced healthcare costs by preventing emergency care to treat preventable conditions, and improved quality of life [79, 80]. Prior research has showed that geographic access to specialist and primary care for asthma is a significant factor in estimating and predicting severe outcomes for pediatric asthma [81].

The aim of this chapter is to measure and make inference on accessibility and availability of pediatric asthma care at the community level, with comparison across multiple states. A*vailability* is the opportunity patients have to choose among different providers of healthcare services, varying in the service quality and patient accommodation [82]. A*ccessibility* is the time and/or distance barriers that patients experience in reaching their providers [82]. *Spatial access,* referring to availability and accessibility together [83-85], is critical to manage chronic disease care such as pediatric asthma.

Specific research questions include:

- What healthcare providers provide pediatric asthma healthcare and what is their capacity devoted to asthma?
- Are there seasonal differences in spatial access to pediatric care?
- Are there systematic disparities in spatial access to pediatric asthma care between-states?
- Are there systematic disparities between children eligible for Medicaid/CHIP versus other children?

The states piloted in this analysis include seven southeastern states (Alabama, Arkansas, Georgia, Louisiana, Mississippi, North Carolina, and Tennessee). The selected states vary significantly in implementation of Medicaid/CHIP programs, as well as in population size, population distribution, and demographics but they share geographic proximity.

3.2 Methods

The data sources include 2005-2012 Medicaid Analytic eXtract (MAX) data files acquired from the Centers for Medicare and Medicaid Services (CMS), the National Plan and Provider Enumeration System (NPPES), Census Bureau and American Community Survey among others. This study was approved by CMS (Data Use Agreement #23621) and by the Institutional Review Board of Georgia Tech (protocol #H11287).

3.2.1 Study Population

The study population consists of children ages 5 to 17 in the seven states. Children age 4 or younger are excluded from this analysis because of the difficulties in obtaining an accurate asthma diagnosis in young children. We divide the child population into age groups: 5-9, 10-14, 15-17. Children are also divided into groups based on insurance type. For ease of presentation, children that meet the eligibility criteria for public insurance (Medicaid/CHIP) are referred as Medicaid, and children that are not eligible for Medicaid/CHIP are referred as non-Medicaid.

3.2.2 Demand Estimation

For this project, we make the simplifying assumption that all of the population in a census tract is located at the centroid of the census tract. Grouping patient locations by census tract ensures that the optimization model remains small enough to be solved directly using Cplex. The latitude and longitude coordinates for the centroid of each census tract based on the 2010 census are downloaded from the US Census Bureau website [86]. The *demand* is the number of appointments for asthma care demanded for children in each census tract. Demand is differentiated into Medicaid and non-Medicaid visits, as well as primary and specialist care visits.

The number of children in each age group is multiplied by the current asthma prevalence estimates from the Behavioral Risk Factor Surveillance System (BRFSS)[39] by the Centers for Disease Prevention and Control (CDC) to estimate the number of children with asthma in each census tract.

3.2.2.1 <u>Number of children with asthma per census tract</u>

We estimate the number of children with asthma in each census tract by combining publicly available data from the US Census with the Behavioral Risk Factor Surveillance System (BRFSS) survey data published by the Centers for Disease Control (CDC).

For each state, census data table B09001 contains the number of children by age (5, 6-8, 9-11, 12-14, 15-17) in each census tract and is downloaded from the US Census factfinder website [41].

Table C3 of the BRFSS Child Asthma Prevalence Tables provides the breakdown of lifetime and current asthma prevalence for each state by age (5-9,10-14,15-17) and is downloaded from the CDC website [39].

The age groups used by the US Census and the CDC do not line up exactly, thus we adjust the breakdown of the census data to line up with the CDC age groups. We add together the number of children in each tract belonging to age groups 5 and 6-8, and one third of the children in age group 9-11 to obtain the number of children age 5-9. We add together two-thirds of the children in age group 9-11 with the number of children age 12-14 to obtain the number of children age 10-14. All values are rounded up to the nearest integer number of children. The number of children age 15-17 does not need to be adjusted. We multiply the current asthma prevalence for a particular age group by the number of children of that age in each census tract to estimate the number of children with asthma per age group per census tract. Finally, we take the sum across the three age groups to get the final estimate for the number of children with asthma per census tract. An example for one census tract, 9501, in Georgia is given below, with BRFSS data in Table 4, census population data in Table 5, and the estimates for the number of children with asthma in Table 6.

Table 4: BRFSS Table C3: 2010 Current Asthma Prevalence for Georgia by age group

% Kids 5-9	% Kids 10-14	% Kids 15-17
13.7%	6.0%	10.9%

Table 5: Population in Tract 9501 from Census Table B09001 and then aggregated to match BRFSS data age groups.

# Kids 5	# Kids 6-8	# Kids 9-11	# Kids 12-14	# Kids 15-17	# Kids 5-9	# Kids 10-14	# Kids 15-17
40	247	181	90	97	348	211	97

Kids 5-9 = 40 + 247 + (1/3)*181

Kids 10-14 = (2/3)*181 + 90

Kids with Asthma 5-9 = 348*0.137

Kids with Asthma 10-14 = 211*0.06

Kids with Asthma 15-17 = 97 * 0.109

Table 6: Number of Children with Asthma in Georgia Tract 9501

# Kids 5-9	# Kids 10-14	# Kids 15-17	# Kids 5-17
46	13	11	72

3.2.2.2 <u>Number of visits needed in each census tract per season</u>

Asthma care guidelines state that children with well-controlled asthma should have a minimum of 2 visits per year for maintenance of their asthma management plan, and children with more severe or uncontrolled asthma should go to a physician up to twice a month until their asthma is considered to be well-controlled [73]. In the literature, however, many studies indicate that asthma is undertreated [13, 87-89].

Using the Medicaid MAX files, we determine the average number of asthma visits per year for children with asthma. For each child in the population with asthma, we count the number of asthma (primary or secondary diagnosis code) visits he has each year. The average number of asthma visits across all children with asthma in the seven states is 2.16 visits per year. It follows that for each census tract, we thus assume the number of asthma visits required each year to be 2 visits per child with asthma. While this is lower than we would expect based strictly on the asthma care guidelines, it is consistent with the understanding in the literature that many children receive insufficient care for their asthma.

To divide the yearly visits by season, we use the Medicaid MAX files as defined below. The percent of the annual visits that occur in each season is multiplied by the number of visits needed in each census tract, and the result is rounded up to the nearest visit. For example, we estimate that there are 72 children in Georgia census tract 9501 with asthma, each of which needs on average 2 visits per year for asthma care. In Georgia, 47%

of asthma visits occur in the fall, 29% occur in the spring and 24% occur in the summer. The calculations for the number of visits needed per season are shown in full below.

Fall Visits = 72 Children * 2 visits per year * $47 \frac{Visits\ in\ the\ fall}{100\ visits\ per\ year}$ = 68 visits in the fall

Spring Visits = 72 Children * 2 visits per year * $29 \frac{Visits\ in\ the\ fall}{100\ visits\ per\ year}$ = 42 visits in the spring

Summer Visits = 72 Children * 2 visits per year * $24 \frac{Visits\ in\ the\ fall}{100\ visits\ per\ year}$ = 35 visits in the summer

3.2.2.3 Percent of children on Medicaid per census tract

Census tracts are uniquely contained within county boundaries, so the county level percent of children on Medicaid can be applied to each census tract contained in that county. We used the county level percentages from the Kids Count data center[90]. Because we have assumed that each child demands the same number of asthma visits, the percent of children on Medicaid can be assumed to be the percent of visits for asthma care that are demanded by Medicaid patients. For the model input, we then multiply the number of visits in each tract by the percent of the children in the tract that are on Medicaid. This number is subtracted from the total visits needed to give the number of non-Medicaid visits per tract.

3.2.2.4 Medicaid Asthma Visits Per Child

From the 2005-2012 MAX claims data, we identify the Medicaid population that has asthma by selecting the patients with two or more claims with an ICD-9 code for asthma

(493.X). For each Medicaid patient, we count the number of asthma care visits per-year. We assume that the average number of asthma visits per-year per Medicaid child is the same as the average number of asthma visits per-year per non-Medicaid child with asthma. The resulting Medicaid average of 2.16 asthma visits per-year is multiplied by the number of children with asthma in each census tract to obtain the number of asthma visits per-tract per-year. This is a lower bound because asthma care guidelines recommend at least two visits per year for children with controlled asthma, and more for children with severe or uncontrolled asthma [73].

We also compute the percent of Medicaid pediatric asthma visits occurring in each of the three seasons defined by the primary education academic calendar, Fall, Spring, and Summer. These percentages are multiplied by the number of annual visits per-tract to obtain the number of pediatric asthma visits per-tract per-season. The same number of visits per-year and percent of visits occurring in each season are used for all of the states. Appendix Table 1 contains additional data about the start and end times of each season.

The demand for pediatric asthma visits is further split into demand for primary care visits and demand for asthma specialist visits. We assume that 25% of children should be referred to an asthma specialist for care based on the prevalence of severe or uncontrolled asthma [91, 92] and expert opinion.

3.2.3 Supply Estimation

We consider two different categories of providers, primary care providers and asthma specialists. The primary care providers include Pediatricians, Pediatric Nurse Practitioners, and Family Practice or Internal Medicine. The group of specialist providers includes (Pediatric) Allergists and (Pediatric) Pulmonologists. The exact NPPES taxonomy codes included are in Appendix A Table 37.

3.2.3.1 Location of providers

A complete list of medical providers in the United States is available in the National Provider Index files that are published each year through the National Plan and Provider Enumeration System (NPPES)[93] and contain each provider's street address and taxonomy codes. The set of providers with taxonomy codes for primary care and asthma specialists are extracted from the NPI files. The street addresses of these providers are submitted to the Texas A&M Geoservices Batch Geocoding website [94] to obtain the corresponding latitude and longitude coordinates.

3.2.3.2 Medicaid Acceptance

Each asthma provider that has claims in the MAX database is marked as accepting Medicaid. We assume that an individual provider either accepts Medicaid or not, and if a provider accepts public insurance then he will not reject any Medicaid patients unless his capacity is full. This assumption may overestimate access to pediatric asthma care for this sub-population.

Each claim in the Other Therapy (OT) MAX files includes data elements that identify the billing and service providers, PRVDR_ID, NPI (corresponding to the PRVDR_ID) and SRVC_PRVDR_ID. We extract the list of unique providers (we take the unique combination of PRVDR_ID, NPI, and SRVC_PRVDR_ID) that have any Medicaid claims with a primary or secondary diagnosis for pediatric asthma. This set of providers is independent from the provider list that is identified using the NPI and NUCC Taxonomy codes.

There are many records that have missing or unknown values for the provider ID or different billing and service provider IDs, there is not a 1-1 matching of billing and service providers, and there is not a column in the database for the NPI corresponding to the service provider id directly. In order to obtain the NPI for each service provider, we query the database using the values of SRVC_PRVDR_ID as the PRVDR_ID and extract the corresponding NPI value. Unfortunately, there is not always a unique NPI for each service provider ID. For the service providers that have two unique NPI values in the database but one is a code for an unknown NPI, the known NPI value is selected. For providers with two or more distinct NPI codes that are not for an unknown NPI, we are unable to identify which NPI is correct.

We add the NPI corresponding to each service provider, where available, to the asthma provider information so we have PRVDR_ID, NPI (for PRVDR_ID), SRVC_PRVDR_ID, NPI (for SRVC_PRVDR_ID). For each line of provider information, we choose which NPI will be used to represent that row. When the NPI for the service provider is available, it is selected, otherwise the NPI for the billing provider is used. There are many providers with no NPI information for either the billing or service provider, these are labeled as “Unknown”. This final list of NPIs is the set of providers that accept Medicaid for pediatric asthma visits.

For each provider in the set of primary care and specialist physician identified using the NPI and NUCC Taxonomy codes, we check if their NPI is in the list of NPIs accepting asthma patients in the MAX files. In addition to the primary and asthma specialist providers that we know accept Medicaid patients, we select a random subset of additional primary and asthma specialist providers that we will allow to accept Medicaid to account for the Medicaid providers with an "Unknown" NPI. For each state, we have P primary care providers that we know accept Medicaid, S specialist providers that we know accept Medicaid, and U Medicaid providers with an "Unknown" NPI value. We randomly select PM additional primary care providers and SM specialist providers to accept Medicaid. where PM = 0.5*U*P/(P+S) and SM = 0.5*U*S/(P+S). The number of providers selected to accept Medicaid is U/2 instead of U because in each state, many of the providers with an "Unknown" NPI have a taxonomy code that identifies them as labs, dentists, or other providers that would not qualify to provide pediatric asthma treatment, even though they see patients that also have pediatric asthma. For the final data files, the number of randomly selected additional providers to accept Medicaid ranges from 54 (Arkansas) and 520 (Mississippi).

It is at this stage of the analysis that South Carolina was removed from consideration because of incomplete provider data in the MAX files. The majority of asthma records did not have usable provider data (mostly missing NPI values) and so accurate provider capacity data could not be obtained.

3.2.3.3 Caseload

There are no standard values for what a physician's maximum caseload is because this measure is dependent on so many factors. Based on the caseload ranges in the literature, the Kaiser-Permanente average caseload for primary care and expert opinion, this paper uses a caseload for primary care physicians of 1700 patients per-year and for specialists of 1200 patients per-year [95-97].

We assume that each provider has a maximum percentage of his total visits that are used for pediatric asthma. To estimate caseload for asthma, we use the 2012 MAX data to compute the percent of the Medicaid claims visits that were for pediatric asthma. These provider-level capacitates are further aggregated by provider type. We then assume that the percent of Medicaid visits that is for pediatric asthma is the same as the percentage of a provider's visit capacity that is for pediatric asthma. In order to account for variation between providers, we added a buffer to each individual provider's capacity. The additional percent of each provider's capacity that is added is computed by sampling from the empirical distribution of provider capacities across all of the states, split by primary and specialist providers and into high (above the median) and low (below the median) capacities for asthma care. 10% of the sampled value is added to the physician's percent capacity for asthma care.

We assume that the capacity at each provider is uniformly distributed across the calendar year, so we compute the provider capacity in a particular season as the percent of their total capacity that occurs within the fraction of the year that belongs to that season. For example, there are 18 weeks in the fall season, so 18/52 = 34.6% of a provider's annual capacity for asthma visits is available for asthma visits that occur in the spring.

3.2.4 Access Optimization Model

To estimate geographic access to asthma care, we use a centralized optimization model with a similar structure to the ones used by Nobles et al and Gentili et al. [31, 98].

Our mathematical formulation differs from the one presented by Gentilli et al. by including assignment to asthma specialists in addition to primary care providers, using a smoothing term in the objective function like the one presented by Zheng et al. [99] instead of balancing distance with provider congestion, and determining which patients will not receive care because of limited provider capacity instead of enforcing that a given percentage of visits will be assigned.

The assignment decision variables represent the number of patient visits in each census tract, separated by whether or not they are in the Medicaid system, that are assigned to each primary or asthma specialist office. These are x_{ij} and y_{ij} for non-Medicaid and Medicaid patients where i is a census tract and j is a provider. We also have variables to track the percent of appointments that should ideally be assigned to a specialist but are instead assigned to a primary care provider for non-Medicaid visits (v_i) and Medicaid visits (w_i) for each census tract i. Finally, we have variables to track with percent of appointments are not assigned at all (g_i^t) for each census tract i and physician type t (MD – primary care non-Medicaid, MDM – primary care Medicaid, S – specialist non-Medicaid, SM – specialist Medicaid).

The objective function, shown in Figure 12, minimizes the sum of the total distance for the assignments that are made, the penalties for not assigning needed visits to a provider, and the weighted smoothing terms between each pair of census tracts. The second term is necessary because there are places where there is insufficient provider capacity to meet the demand.

$$\min \sum_{i\in T}\sum_{j\in D}(x_{ij}+y_{ij})d_{ij}+\sum_{i\in T}(v_i+w_i)p+\sum_{i\in T}\sum_{t\in D_{type}}(g_i^t)p^a+\sum_{t\in D_{type}}\sum_{i\in T}\sum_{k\in T}\frac{n_{ik}(d_i^t-d_k^t)^2}{nr(a_i^n+a_k^n)}$$

Figure 12: Optimization model objective function

The smoothing terms are a practical restriction on the system to prevent children in neighboring census tracts to have dramatically different assignments or average distances to care. Two census tracts are considered to be neighbors if the distance between their centroids is less than 10 miles. In the optimization model, we penalize differences in the average distance per visit to a particular provider type between neighboring census tracts. Without this smoothing term, it is possible for the model to assign all of the children in one census tract to a provider and none of the children in a neighboring tract, where the more realistic outcome would be that half of the children in each tract would visit the provider.

Some children with asthma should receive asthma care from a specialist instead of solely relying on a primary care provider, and so we include a separate sets of decision variables for the assignment of patient visits to primary and asthma specialist providers. The capacity at each provider location for asthma visits depends on the provider type and number of physicians, as described in the supply section. For this subset of asthmatic children that should receive specialist care, it is possible that they receive some, or all, of their treatment from primary care providers and so we allow for the assignment of these visits to primary care providers with a penalty to account for the preference that the visits be made to a specialist. For every non-Medicaid visit that is assigned to a primary care provider instead of a preferred specialist, there is a penalty of 15 miles added to the assignment distance, and for Medicaid patients the penalty is 20 miles. We impose a higher penalty for Medicaid patients because this population is already underserved and faces greater transportation restrictions, so are less likely to be able to travel farther to receive specialist care than non-Medicaid patients. With these penalties, a patient would have no preference between a specialist that is 50 miles and a primary care provider that is 35 miles away. This accounts for patient preference to have a closer provider, and allows children who do not have access to a specialist at all to be assigned to a primary care provider.

Another practical constraint that we add to the model is that for each census tract the average distance for visits to a particular provider type that are by children on Medicaid cannot be lower than the average distance for non-Medicaid visits in the same tract. This ensures that we do not assign only the Medicaid patients when there is insufficient capacity.

This model is solved for each of the three seasons for each state. This allows the results to be compared across the seasons for each state, and between the states. The list of sets and parameters are given in Table 6 and Table 7, and the constraint set for the mathematical model is given in Figure 13 below.

Table 7: Set notation and descriptions

Set	Description
D	The set of all providers
D^P	The set of primary care providers
D^S	The set of specialist providers
D_{type}	The set of physician types (MD, MDM, S, SM)
T	The set of census tracts

Table 8: Parameter notation and descriptions

Parameter	Description
a_i^n	the number of non-Medicaid appointments needed in tract i
a_i^m	the number of Medicaid appointments needed in tract i
r	the percent of appointments that should be met by a specialist
rMin	the percent of appointments that should be met by a specialist that must be met by a specialist
nr	the percent of appointments that should be met by primary care physicians (1-r)
d_{ij}	the distance (miles) from the centroid of census tract i to provider j

Parameter	Description
q_{ij}	binary value for if provider j accepts Medicaid patients
u_{ij}	the capacity, in appointments, of provider j
p	the penalty, in miles, for not assigning 1 appointment to a provider at all
p^a	binary value for if census tracts k and j are neighbors or not
n_{ik}	the distance, in miles, between the centroids of tracts i and k
d_i^t	the average distance for appointments to physician type t in tract i

$$\left.\begin{aligned}
\sum_{j \in D} x_{ij} + g_i^{MD} + g_i^S &= a_i^n && \forall i \in T \\
\sum_{j \in D} y_{ij} * q_j + g_i^{MDM} + g_i^{SM} &= a_i^m && \forall i \in T
\end{aligned}\right\} \text{Meet Total Demand}$$

$$\left.\begin{aligned}
\sum_{j \in D^S} x_{ij} + g_i^S &\geq r * rMin * a_i^n && \forall i \in T \\
\sum_{j \in D^S} y_{ij} * q_j + g_i^{SM} &\geq r * rMin * a_i^m && \forall i \in T \\
\sum_{j \in D^P} x_{ij} + g_i^{MD} &\geq nr * a_i^n && \forall i \in T \\
\sum_{j \in D^P} y_{ij} * q_j + g_i^{MDM} &\geq nr * a_i^m && \forall i \in T
\end{aligned}\right\} \text{Meet Demand by Visit Type}$$

$$\left.\begin{aligned}
v_i &= r - \sum_{j \in D^S} x_{ij} && \forall i \in T \\
w_i &= r - \sum_{j \in D^S} y_{ij} * q_j && \forall i \in T
\end{aligned}\right\} \text{Track Specialist Appts Assigned to Primary Care}$$

$$\left.\begin{aligned}
\sum_{i \in T} x_{ij} + y_{ij} * q_j &\leq u_j && \forall j \in D
\end{aligned}\right\} \text{Physician Capacity}$$

$$\left.\begin{aligned}
\sum_{j \in D} x_{ij} * d_{ij} &\leq \sum_{j \in D} y_{ij} * q_j * d_{ij} && \forall i \in T \\
\sum_{j \in D} x_{ij} * d_{ij} &= d_i^t && \forall i \in T, \forall t \in D_{type}
\end{aligned}\right\} \text{Tract Distance Restriction and Tracking}$$

Figure 13: Optimization model constraints

3.2.5 Access Measures

(1) The *travel distanc*e measured as the average distance to receive care;

(2) The *unmet need for asthma specialists* measured as the percent of visits that are assigned to primary instead of specialist care; and

(3) The *unmet need* for asthma care measured as the percent of visits that cannot be assigned to a provider within the Georgia access standards (30 miles in urban and 45 miles in rural communities).

The access measures are computed for the four provider categories (MD, MDM, S, SM) at the census tract level.

The measure for unmet need includes those visits that cannot be assigned by the optimization model because there is insufficient provider capacity in the state as well as the visits that are assigned to a provider that is more than 30 or 45 miles away for urban and rural children. We use the same access standards for all seven states for consistency in the analysis. Alabama, Arkansas, Louisiana, and North Carolina do not have access guidelines, and the distance cut-offs for Georgia, Mississippi and Tennessee range from 8 to 30 miles for urban primary care and 45 to 90 miles for rural specialist care [100]; see Appendix A Table 38.

3.2.6 Statistical Analysis

The primary statistical tests are one-way ANOVA to determine if we can reject the null hypothesis that the mean of a given measure is the same in all states or seasons, and the pairwise Tukey's Test to identify which of the pairs are different. These tests are applied to the available provider capacity, the distance to receive care, and the unmet need.

To compare the results of the optimization model across the seasons, we use the null hypothesis of equal means in all three seasons. This test is used for each state and provider type for the Medicaid and non-Medicaid population to determine if there are seasonal differences in the access measures. In addition, we test the null hypothesis that the distance to receive a particular type of care (MD, MDM, S, SM) is the same across all states in the fall season.

We compare the unmet need in each state using the null hypothesis that the unmet need in each state is the same to determine if there are significant differences in the number and percent of children that are not able to receive any asthma care.

In order to determine the significance of the difference in access to the different types of care within each state, paired t-tests are used to compare the distance to receive care between pairs of provider types (MD-MDM, S-SM, MD-S and MDM-SM). We repeat these tests for the null hypothesis of equal means and then for a difference in means of 2, 5, and 10 miles.

3.3 Results

3.3.1 Supply Estimation: Pediatric Asthma Caseload by Provider Type

Only a fraction of each physician's total caseload will be dedicated to pediatric asthma visits. For each provider in the OT MAX files that accepts Medicaid patients, we extract their caseload summary. We count the number of distinct patients that they serve each year, the number of distinct children with asthma that they serve each year (see demand section for more details on this population), the total number of visits (where claims occurring at the same place of service on the same day are counted as one visit) that are recorded each year, and the total number of visits where the primary or secondary diagnosis code is for asthma and the patient is a child age 5-17. The percent of the provider's caseload for pediatric asthma is the number of distinct asthma children divided by the total number of patients, and the percent of their visits that are for pediatric asthma is the number of pediatric asthma visits divided by the total number of visits.

The average percent of the provider's caseload and the average percent of visits that are for pediatric asthma are computed for each provider type (Pediatrician, Pediatric Nurse Practitioner, Family and Internal Medicine, Pulmonologist, Allergist, Pediatric Pulmonologist, Pediatric Allergist) using the same formulas as those for individual providers. Figure 14 below shows the boxplots of the percent of provider visits that are for pediatric asthma by provider type and states.

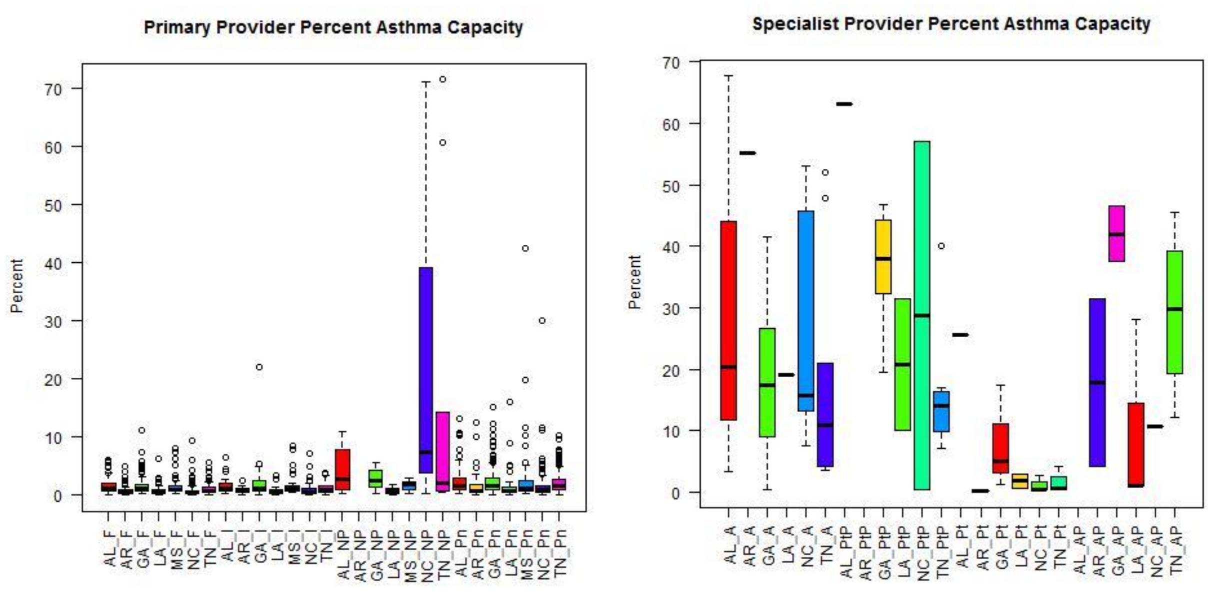

Figure 14: Distribution of the assigned tract level distance to primary and asthma specialist care for Medicaid and non-Medicaid patients in each state for the fall season with clearly increasing trend by provider type. For the provider type abbreviations, we have non-Medicaid and Medicaid primary care (MD & MDM) and non-Medicaid and Medicaid specialist care (S & SM)

The percent of a provider's visits in each state summarized by provider type is in Table 9. The percent of the Medicaid caseload for primary care physicians for children with asthma is consistent across all of the states. Between 2 and 5% of patients at a pediatrician's office have asthma, between 1 and 3.5% of patients have asthma at both family practices and internal medicine providers, and between 3 and 8.3% of patients that see a pediatric Nurse Practitioner have asthma.

In Alabama, pediatric pulmonologists have the highest percentage (54.7%) of pediatric asthma patients, followed by non-pediatric allergists and pulmonologists (19% and 18%). In Arkansas, the only provider category with more than 7% of their panel belonging to children with asthma is non-pediatric allergists, who have on average 46% pediatric asthma patients.

Table 9: Percent of provider visits in the MAX claims files that are allocated for pediatric asthma by state and provider type

State/ Provider Category	Unknown	PEDIATRICIAN	NP_ PEDIATRIC	FAMILY	INTERNAL	Combined Family& Internal	PULMONOLOGIST	PEDIATRIC_ PULMONOLOGIST	ALLERGIST	PEDIATRIC_ ALLERGIST	Specialist Unknown
AL	1.5%	2.4%	4.6%	1.4%	1.9%	1.6%	25.7%	63.2%	19.9%	--	25.8%
AR	0.7%	1.3%	--	0.5%	0.7%	0.5%	0.2%	--	55.1%	8.3%	7.6%
GA	1.0%	1.6%	2.6%	1.2%	1.4%	1.3%	2.6%	34.8%	14.2%	42.6%	18.2%
LA	0.8%	0.75%	0.8%	0.6%	0.6%	0.6%	0.7%	26.5%	19.2%	1.1%	1.3%
MS	0.8%	1.7%	1.9%	1.2%	1.1%	1.2%	--	--	--	--	--
NC	0.8%	1.1%	4.1%	0.5%	0.7%	0.6%	0.5%	1.2%	21.0%	10.7%	3.5%
TN	0.9%	1.2%	4.5%	0.9%	0.8%	0.9%	0.7%	17.1%	7.5%	22.7%	5.3%

To account for the variation in provider capacity and percent of their caseload and visits that are used for pediatric asthma, we add a random, non-negative buffer capacity to the percent of their caseload and visits that are available for pediatric asthma. For every provider, we add a buffer capacity that is based on the empirical distributions of the percent of patients and visits that are used for pediatric asthma among the Medicaid providers. The data for all seven states is combined into one set for this analysis. Among primary care providers, the percent of the caseload and visits for pediatric asthma are very similar across the states, so combining the states data does not have a significant impact on the distributions. For specialist providers, we need to take all of the states and providers together in order to have a sufficiently large group of providers to create a distribution to sample from.

This sampling is done separately for primary care, specialist care, percent of the patient caseload and percent of the patient visits that are for pediatric asthma. The process is described below for the percent of the patient caseload at primary care providers, and is repeated for the three other cases.

Using the R statistical software package, we compute the summary statistics for the percent of the patient caseload that is for asthma patients at primary care providers and then split the data set into two groups. The High Capacity group contains the data for providers whose percent of the caseload is greater than the median percent (M%), and the Low Capacity group contains the data for providers whose percent of the caseload is less than the median percent. We fit an empirical distribution to the percent of the caseload for the high and low capacity groups separately.

For each primary care provider in the set identified using the NPI and NUCC Taxonomy codes, we classify the provider as high or low capacity by comparing their baseline percent of the patient caseload to the median percent, M% as identified above. There are NP_H primary care providers that are high capacity and NP_L primary care providers that are low capacity. We take NP_H samples (s_i^H with i from 1 to NP_H), with replacement, from the High Capacity distribution and NP_L samples (s_j^L with j from 1 to NP_L), with replacement, from the Low Capacity distribution. For each high capacity primary care provider i (with i from 1 to NP_H) we add s_i^H*0.1 to their baseline capacity, and for each low capacity primary care provider j (with j from 1 to NP_L) we add s_j^L*0.1 to their baseline capacity. The distribution of the percent of visits for pediatric asthma for high and low acceptance primary care and specialist physicians are shown in Figure 15.

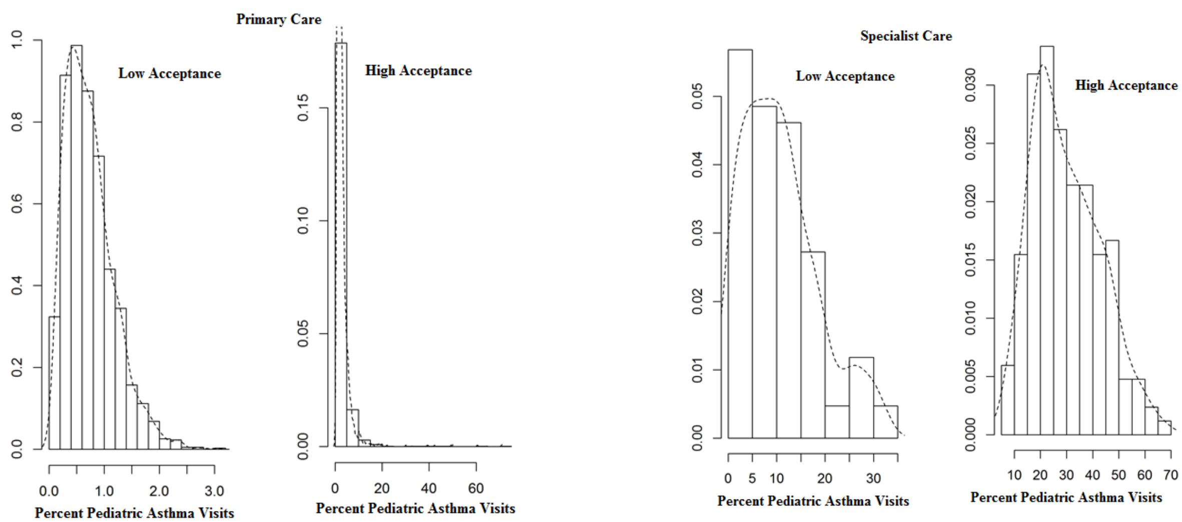

Figure 15: Distributions of the percent of asthma visits each provider allocates for pediatric asthma by provider type

In the optimization model, Family Practice and Internal Medicine are treated as one provider type. This does not result in a loss of input data accuracy because the percent of a provider's caseload and visits that are for pediatric asthma are very similar for these two provider types. For example, in Georgia the percent of the Medicaid caseload for children with asthma is 2.45% and 2.79% for Family and Internal Medicine respectively, and their percentage of visits that are for pediatric asthma are 1.23% and 1.4%.

This consistency is not seen in the patient caseload of specialists. In most states, non-pediatric pulmonologists do not have a large percentage of children with asthma in their panel (between 1 and 5%), but in Alabama almost 20% of the total Medicaid patients in a non-pediatric pulmonologist's office are children with asthma. For pediatric pulmonologists, North Carolina has an unusually low percentage, less than 2%, most of the states have 20-30%, and AL again has the highest rates with almost 55% of the patient panel being comprised of children with asthma. In four of the states, 15-20% of allergist patients have pediatric asthma, two states have roughly 27%, and Arkansas stands out with 40% of the panel being pediatric asthma patients. Pediatric allergists have more variation in the percent of the panel that is children with asthma, with Arkansas having only 6.4% while Georgia has 43.4%.

We assume that the percent of a provider's non-Medicaid caseload that is for pediatric asthma visits is the same as the percent of that provider's Medicaid caseload that is for pediatric asthma. For primary care and specialist providers that we know accept Medicaid, we use their exact percent of Medicaid patients and visits that are for pediatric asthma as their base acceptance. Since not all providers can be matched to one that accepts Medicaid patients, the average percent for each provider type (based on the Medicaid claims) is used as the percent of their visits that are available for pediatric asthma.

3.3.2 Geographic Variations in Supply

There is significant geographic variation in the supply of primary and specialist visits both within each state and between the states. The highest concentration of available visits occurs in urban areas, with fewer visits available in rural areas. Every state has more zip codes with available primary care visits than zip codes with available specialist care visits. Arkansas has the lowest percent of zip codes with available primary care visits (33%) and specialist care visits (5%). Georgia and North Carolina have the highest percent of zip codes with available primary care visits (59% and 60%), and Georgia, Mississippi and North Carolina have the highest percent of zip codes with available specialist care visits (14%, 15%, and 15%). Mississippi has the largest variance in the number of available primary care visits at the zip code level in one state, and Tennessee has the largest variance in the number of available specialist visits at the zip code level in one state. Table 10 below shows the number of zip codes in each state that have any primary and specialist care visits available.

Table 10: Number of zip codes in each state with any available primary or asthma specialist visits

State	Total Number of Zip Codes	Zip Codes with Available Primary Care Visits	Zip Codes with Available Specialist Visits
AL	645	315	80
AR	596	199	30
GA	735	437	100
LA	516	251	45
MS	424	202	64
NC	808	485	121
TN	631	327	65

The number of visits for primary and specialist care differ significantly from state to state. Table 11 contains the summary statistics for the number of primary and specialist visits available in each state, and Figure 16 shows the number of visits per zip code in each state. Using ANOVA, we reject the null hypothesis that the number of appointments at the zip code level is the same in all seven states for both primary care and specialist visits ($p < 0.01$ for both provider categories). The differences in available tract level primary care visits between Mississippi and each of the other six states are all statistically significant (Tukey's Test p-value < 0.01), while for specialist care visits the only state with which Mississippi differs significantly is Louisiana. Tennessee has the only other significant differences in the number of specialist visits in the pairwise comparison with four states: Alabama, Georgia, Louisiana and North Carolina.

Table 11: Summary statistics for the number of annual available visits for primary and specialist care across the zip codes in which there is at least one provider (either primary or specialist) by state

	Available Primary Care Visits				Available Specialist Visits			
	Min.	Mean	Max.	Stdev	Min	Mean	Max	Stdev
AL	3022	76,970	2427000	175559	0	26930	2033000	138439
AR	0	34070	636900	72828	0	31580	2259000	193675
GA	0	64850	2229000	156234	0	30430	1269000	99677
LA	0	54040	2259000	153206	0	3096	152700	14456
MS	0	147800	1748000	238760	0	59460	2154000	199244
NC	1984	62170	1425000	134034	0	30960	1441000	131500
TN	2055	85220	2526000	193821	0	63260	3002000	228700

Available Primary Care Visits by Zip Code

Available Specialist Visits by Zip Code

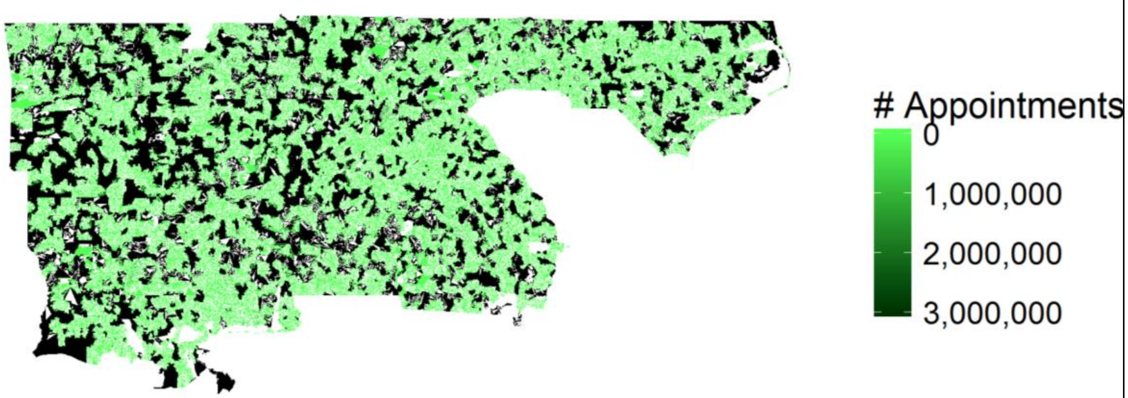

Figure 16: Number of specialist visits available for primary and specialist care in each zip code. Zip codes that are shaded in black have no providers.

3.3.3 Access Measures: Travel Distance

Figure 17 shows the boxplots of the tract-level travel distance to receive care for all states and provider types, for the Medicaid and Non-Medicaid population, in the Fall season. The county level assigned distance to receive care is shown in the maps in Figure 18.

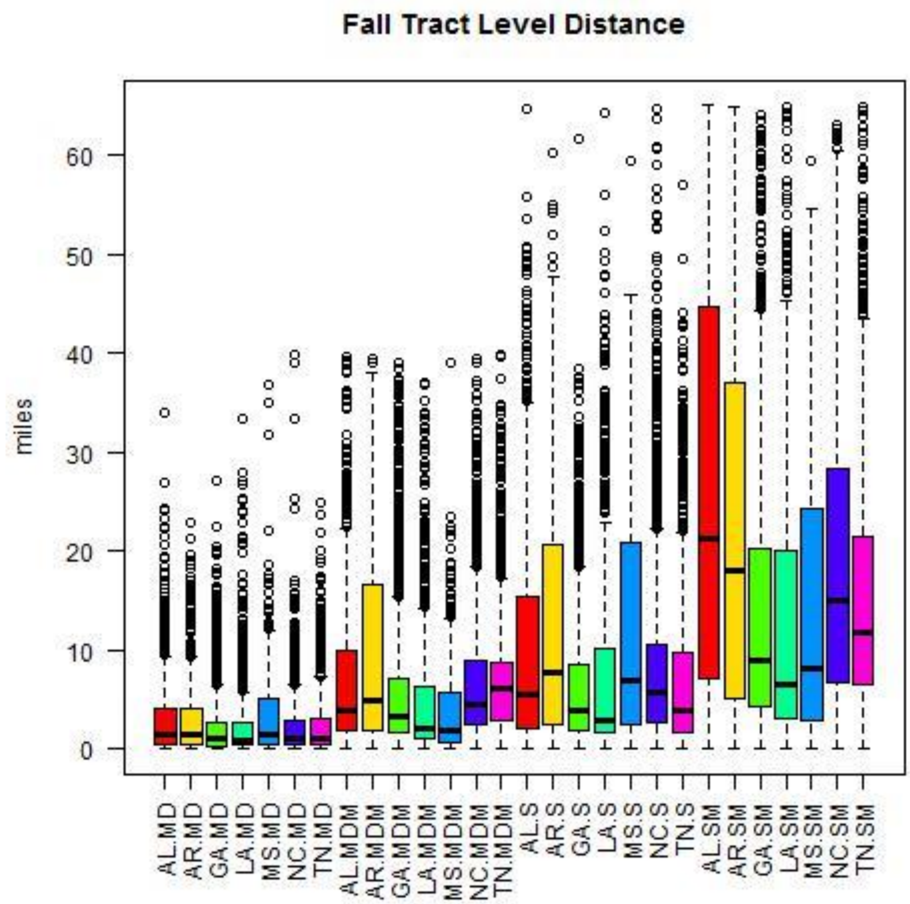

Figure 17: Distribution of the assigned tract level distance to primary and asthma specialist care for Medicaid and non-Medicaid patients in each state for the fall season with clearly increasing trend by provider type.

For all states except Tennessee, the MD median tract-level distance is the lowest, followed by the distance for MDM visits, followed by distance to S visits, with the largest distances being for SM visits. In Tennessee, the order is inverted for MDM and S median distances.

The distribution of the tract-level distances for MD visits are similar across all of the states, with the differences in distance between the states being more pronounced for MDM visits. There is more variation in the distance to asthma specialists than to primary care providers, and the greatest differences between the states occur when considering the driving distance for SM visits.

The median distance to specialist care is at least twice as high for the Medicaid population as it is for the non-Medicaid population in every state. In addition, the inter-quartile range of the tract-level distance to care is larger for SM visits than for any other type of care in all states.

Based on the ANOVA results, the difference in the distance to receive care in the different seasons is not statistically significant (p-value < 0.05) for most states and provider types. The cases where the travel distances to receive care are statistically different are for the Medicaid/CHIP-enrolled children for access to primary care in North Carolina and Tennessee, and to specialist care in Tennessee.

ANOVA confirms that the distance to receive each type of care is not the same in all of the states. The differences between the tract-level distances between the states are significant with p <2e-16 for all four provider types. From the Tukey's Test results we see that only 12 of the 21 state pairs have significant differences in distance to MD visits, and 17 pairs have significant differences in distance to MDM visits. For specialist care there are 17 and 18 pairs with significant differences in the distance for S and SM visits respectively. contains the mean difference in distance and the p-values for each provider type between each pair of states. The full test results are in Table 12 below.

Table 12: Tukey's Test results comparing the mean tract level distance, in miles, between each pair of states to receive each of 4 types of care

	MD		MDM		S		SM	
State Pair	Difference	P-Value	Difference	P-Value	Difference	P-Value	Difference	P-Value
AR-AL	-0.05	1.0000	2.83	0.0000	2.75	0.0000	-3.65	0.0005
GA-AL	-0.84	0.0000	-1.26	0.0000	-3.53	0.0000	-12.05	0.0000
LA-AL	-0.65	0.0007	-1.98	0.0000	-2.13	0.0000	-13.05	0.0000
MS-AL	0.06	0.9999	-3.34	0.0000	1.82	0.0018	-12.53	0.0000
NC-AL	-1.00	0.0000	-0.41	0.6563	-1.80	0.0000	-7.34	0.0000
TN-AL	-0.70	0.0000	0.12	0.9994	-2.79	0.0000	-10.46	0.0000
GA-AR	-0.79	0.0000	-4.09	0.0000	-6.28	0.0000	-8.40	0.0000
LA-AR	-0.60	0.0177	-4.81	0.0000	-4.88	0.0000	-9.40	0.0000
MS-AR	0.11	0.9983	-6.17	0.0000	-0.93	0.5787	-8.88	0.0000
NC-AR	-0.95	0.0000	-3.25	0.0000	-4.56	0.0000	-3.69	0.0001
TN-AR	-0.65	0.0023	-2.71	0.0000	-5.54	0.0000	-6.81	0.0000
LA-GA	0.19	0.8097	-0.72	0.1060	1.40	0.0030	-1.00	0.5918
MS-GA	0.90	0.0000	-2.08	0.0000	5.35	0.0000	-0.49	0.9901
NC-GA	-0.15	0.8176	0.85	0.0018	1.73	0.0000	4.71	0.0000
TN-GA	0.14	0.9261	1.38	0.0000	0.74	0.2675	1.59	0.0286
MS-LA	0.70	0.0022	-1.36	0.0018	3.95	0.0000	0.51	0.9929
NC-LA	-0.35	0.1516	1.56	0.0000	0.33	0.9741	5.71	0.0000
TN-LA	-0.06	0.9998	2.10	0.0000	-0.66	0.6283	2.59	0.0004
NC-MS	-1.05	0.0000	2.92	0.0000	-3.63	0.0000	5.19	0.0000
TN-MS	-0.76	0.0002	3.46	0.0000	-4.61	0.0000	2.08	0.0399
TN-NC	0.29	0.2034	0.54	0.2475	-0.98	0.0383	-3.12	0.0000

Within each state, we have significant differences in the distances to receive different types of care. For each state, we perform paired t-tests to compare the tract level distance to receive each type of care within the state and determine at which threshold (unequal means, difference of 2 miles, 5 miles, or 10 miles) is the difference in the distance care is significant. Table 13 below gives the maximum distance threshold (0 miles, 2 miles, 5 miles or 10 miles) at which the difference between the distance to different types of care is significant. Table 14 below contains the mean difference in the distance to care for each pair of provider types in each state, as well as the p-values indicating the significance, or lack thereof, of the difference in distance for provider types at each threshold.

Table 13: Maximum distance at which the difference between the distance to two types of care is significant. The distance to the provider type listed second in each pair is the greater distance. Ex: MD-MDM tests if the MDM distance is greater than the MD distance by the threshold distance value.

State/Provider Types	MD-MDM	S-SM	MD-S	MDM-SM
AL	2	10	5	10
AR	5	10	5	10
GA	5	5	2	5
LA	2	2	2	5
MS	0	0	5	5
NC	2	10	5	10
TN	2	5	2	5

Table 14: Mean difference in distance to receive care to selected pairs of provider types and p-values for paired t-tests indicating if the difference in distance to care is significant at the given threshold.

	AL	AR	GA	LA	MS	NC	TN
MD-MDM Diff Mean Value	*-4.01*	*-6.94*	*-3.46*	*-5.23*	*-1.52*	*-4.51*	*-4.72*
MD-MDM Diff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MD-MDM Diff > 2	0.0000	0.0000	0.0000	0.0002	1	0.0000	0.0000
MD-MDM Diff > 5	1	0.0000	1	1	1	1	0.9762
MD-MDM > 10	1	1	1	1	1	1	1
S-SM Diff Mean Value	*-17.67*	*-11.86*	*-7.55*	*-5.04*	*-8.46*	*-10.94*	*-8.59*
S-SM Diff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
S-SM Diff > 2	0.0000	0.0000	0.0000	0.0000	0.9931	0.0000	0.0000
S-SM Diff > 5	0.0000	0.0000	0.0000	0.2092	1	0.0000	0.0000
S-SM Diff > 10	0.0000	0.0061	1	1	1	0.0003	1
MD-S Diff Mean Value	*-6.81*	*-9.39*	*-4.23*	*-7.54*	*-8.46*	*-5.91*	*-4.68*
MD-S Diff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MD-S Diff > 2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MD-S Diff > 5	0.0000	0.0000	1	0.4346	0.0000	0.0000	0.9517
MD-S Diff > 10	1	0.9090	1	1	0.9998	1	1
MDM-SM Diff Mean Value	*-19.62*	*-12.71*	*-8.25*	*-0.57*	*-9.44*	*-11.88*	*-4.68*
MDM-SM Diff	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MDM-SM Diff > 2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MDM-SM Diff > 5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MDM - SM Diff > 10	0.0000	0.0004	1	1	0.8971	0.0000	1

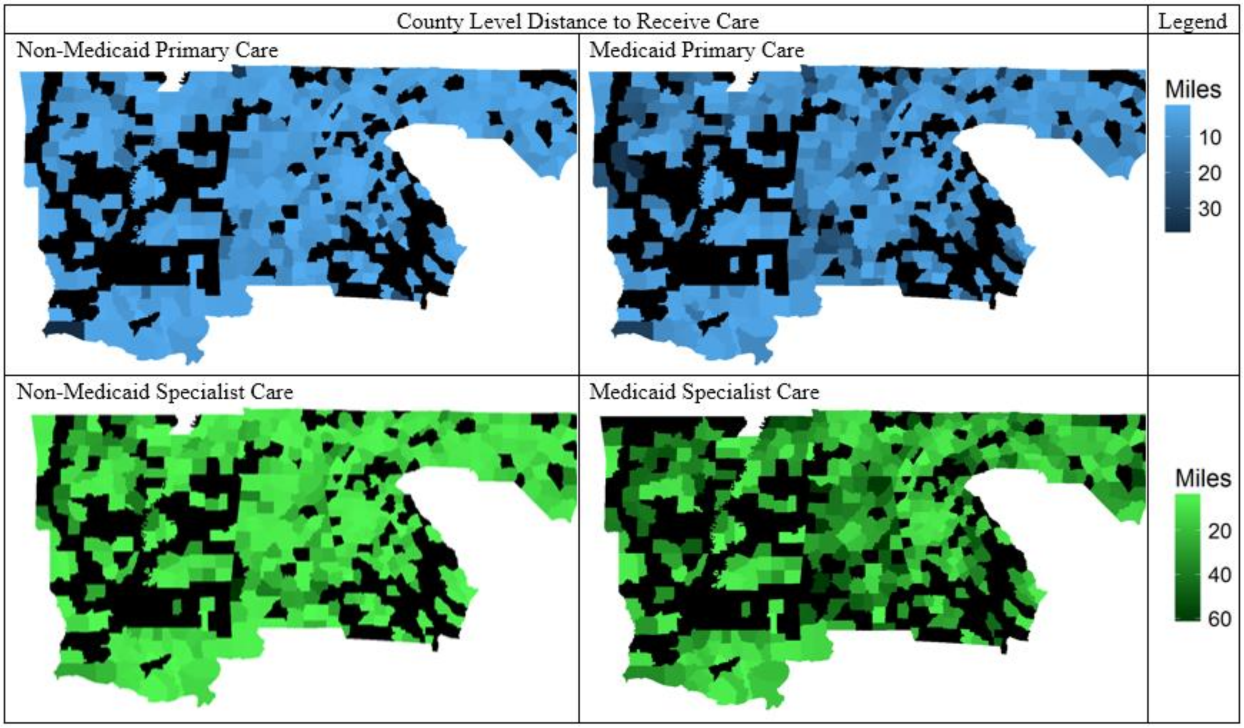

Figure 18: County level distance for primary and specialist appointments for Medicaid and non-Medicaid patients. Counties shaded with black have no met need (the optimization model is unable to assign any visits to providers in these counties).

3.3.4 Access Measures: Unmet Need for Specialist Care

In every state and season, the percent of appointments that were assigned to primary care providers instead of specialist providers is higher among the Medicaid population than the non-Medicaid population. The maximum percent of visits in an individual tract that are assigned to primary instead of specialist care is higher for the Medicaid population in every state except for North Carolina.

Table 15 provides the number of tracts where all of the specialist appointments are met by primary care providers in each state. For example, in Arkansas, over 20% of the census tracts (149 of the 686 tracts) have all of the appointments that were allocated for SM care assigned instead to MDM providers; for the non-Medicaid population, there are only 9 tracts where the entire demand for specialist appointments is assigned to primary care providers.

Table 15: Number of census tracts in which all specialist appointments are met instead by primary care providers for both the Medicaid and non-Medicaid population

State	# Census Tracts	# Tracts All S visits assigned to MD providers	# Tracts All SM visits assigned to MDM providers
AL	1181	1	138
AR	686	9	149
GA	1969	0	10
LA	1148	7	20
MS	664	0	0
NC	2195	4	60
TN	1497	1	16

3.3.5 Access Measures: Unmet Need

The percent of the need that is unmet in each season is almost the same; this means there is more unmet need in terms of visit number in the fall than in either the spring or the summer for both primary and specialist care in every state. In Alabama, for example, there are over 1100 more visits that cannot be assigned to a Medicaid specialist provider in the fall than in the summer out of the 17000 more visits (for all provider types) that are demanded. In Arkansas, 630 of the additional 11000 visits for Medicaid patients to receive asthma specialist care that are needed in the fall cannot be assigned and are therefore unmet need.

Table 16: Unmet need in each state reported as the number and percent of visits that cannot be assigned to a provider within the 30 and 45 miles for urban and rural children

	Rural Non-Medicaid		Rural Medicaid		Urban Non-Medicaid		Urban Medicaid Unassigned	
State	#	%	#	%	#	%	#	%
AL	244	5.5%	181	8.5%	1283	1.8%	2629	7.8%
AR	225	4.8%	275	5.2%	341	2.1%	1825	10.3%
GA	44	0.7%	360	4.9%	206	0.1%	3514	3.2%
LA	56	5.4%	88	5.6%	648	1.9%	2711	4.6%
MS	141	2.8%	73	2.7%	1056	2.1%	757	3.1%
NC	327	5.5%	394	8.6%	844	1.0%	3256	5.2%
TN	30	1.7%	191	10.3%	517	0.8%	1648	3.3%

Table 16 shows a lower bound for the unmet need for each state in the Fall season divided by the urban and rural population. The results for the spring and summer are similar. Children on Medicaid have from 1.7 (Arkansas) to 5 (Mississippi) times as much unmet need for specialist care as for primary care. There is more variation in the difference in unmet need for specialist care between the Medicaid population and the non-Medicaid population, ranging from Mississippi, which has slightly more unmet need in the non-Medicaid population, to Georgia, where there is 20 times as much unmet need in the Medicaid population. Table 17 summarizes the unmet need by provider type for the seven states and shows the ratio of unmet need between selected provider type pairs.

In at least 1% of the census tracts in each state, all of the need for primary care, specialist care, or both, is unmet. Arkansas has the worst access for Medicaid children requiring specialist care, with all of the need being unmet in 40% of the tracts. This is distantly followed by 23% and 17% of tracts in Alabama and Louisiana having entirely unmet need for Medicaid specialist visits. Arkansas is also only one of two states, Louisiana being the other, where none of the need for children on Medicaid for primary care is met in more than 10% of the census tracts.

The unmet need for non-Medicaid visits in rural areas is the highest in Alabama, Louisiana and Mississippi with over 5.4%. For rural Medicaid children, Tennessee has the highest unmet need with 10.3% of the visits being unassigned under 45 miles. In urban areas, the greatest unmet need occurs in Arkansas and Mississippi where 2.1% of non-Medicaid visits cannot be assigned. As in rural areas, access is worse for the Medicaid population in urban areas, and with unmet need reaching 10.3% in Arkansas. For both urban and rural areas, Georgia has the lowest unmet need for children that are not part of the Medicaid population, and is second lowest for unmet need for Medicaid visits.

Table 17: Unmet need by provider type in each state and the ratio of unmet need for selected service types (ex: SM/S is the ratio of unmet need (as visits) for Medicaid specialist care to non-Medicaid specialist care)

Number of Visits	MD	MDM	S	SM	ALL MEDICAID	ALL NON-MEDICAID
AL	406	714	524	2494	3208	930
AR	172	960	153	1647	2607	326
GA	133	1309	182	3788	5097	315
LA	107	474	380	2164	2638	488
MS	312	134	831	670	804	1142
NC	365	953	433	3088	4041	798
TN	118	398	334	1640	2038	453
Ratios	**MDM/MD**	**SM/S**	**SM/MDM**	**S/MD**	**MEDICAID/NON-MEDICAID**	
AL	1.76	4.76	3.49	1.29	3.45	
AR	5.57	10.74	1.72	0.89	8.01	
GA	9.87	20.80	2.90	1.37	16.19	
LA	4.41	5.69	4.57	3.54	5.41	
MS	0.43	0.81	4.99	2.67	0.70	
NC	2.61	7.14	3.24	1.19	5.07	
TN	3.36	4.91	4.12	2.82	4.50	

Using ANOVA, we fail to reject the null hypothesis that the mean tract-level unmet need for rural primary care for both Medicaid and non-Medicaid is the same in all states. The full ANOVA output is in Table 18 below. We do reject the null hypothesis of equal means for unmet need for rural specialist care and to both primary and specialist care for Medicaid and non-Medicaid patients in urban areas (F-Statistic <0.01).

Table 18: ANOVA Results for percent of visits that cannot be assigned to a provider within an acceptable distance

		Df	Sum Sq	Mean Sq	F value	Pr(>F)
MD Urban	State	6	5.95	0.99	69.00	<2e-16
	Residuals	8639	124.15	0.01		
MDM Urban	State	6	6.19	1.03	51.21	<2e-16
	Residuals	8639	174.04	0.02		
S Urban	State	6	2.44	0.41	29.52	<2e-16
	Residuals	8639	118.91	0.01		
SM Urban	State	6	7.14	1.19	55.66	<2e-16
	Residuals	8639	184.73	0.02		
MD Rural	State	6	0.23	0.04	1.94	0.0717
	Residuals	687	13.29	0.02		
MDM Rural	State	6	0.10	0.02	2.00	0.064
	Residuals	687	5.93	0.01		
S Rural	State	6	0.51	0.09	5.29	2.38E-05
	Residuals	687	11.07	0.02		
SM Rural	State	6	1.53	0.26	4.66	0.0001
	Residuals	687	37.67	0.05		

Because there are statistically significant differences between the states, we use Tukey's Test to identify which pairs of states have significant differences. Appendix B.5 provides the results of the statistical tests to determine for which pairs of states the difference in unmet need is significantly different for each provider type in rural and urban settings. Significant differences have p-values that are highlighted in green.

For rural non-Medicaid specialist care, the only significant differences between states are for Georgia when compared to Alabama and Arkansas. For rural Medicaid specialist care, Alabama differs significantly from Georgia, Louisiana, and Mississippi. 11 of the 21 pairs of states differ significantly in unmet need for urban Medicaid and non-Medicaid primary care. For urban specialist care, there are 9 pairs that differ significantly for both Medicaid and non-Medicaid unmet need, and 3 additional pairs having different unmet need for non-Medicaid care, and 7 pairs with significantly different unmet need for Medicaid specialist care.

3.4 Discussion

This paper focuses on measuring and evaluating access to pediatric asthma care with comparison across multiple states. In contrast to prior models for measuring spatial access to pediatric asthma care that focus on one aspect of access such as travel time to a hospital[101] or provider to population ratio [25] or are based on interviews[102], or have a more limited constraint set [81], the measurement and inference approach in this study takes into account multiple aspects of the pediatric asthma healthcare: (1) Demand for asthma care is not constant over the course of a year; (2) Not all providers accept public (Medicaid/CHIP) insurance; (3) Pediatric asthma healthcare is provided by both specialized and primary care providers; and (4) A proportion of children have severe asthma and thus they need access to specialist care in order to control their condition.

The capacity allocated to pediatric asthma among primary care physicians is consistent, with only small variations across providers and states. Thus, the assumption that the capacity for non-Medicaid children with asthma among primary care physicians is similar to that for Medicaid population is reasonable.

However, there is more variation in the percent of providers' capacity for pediatric asthma among the specialists as inferred from the Medicaid claims. In some cases, there are no providers or only one provider of a particular type that accept Medicaid in an entire state. For example, in Alabama there are no Medicaid-accepting pediatric allergists, and only one adult pulmonologist and one pediatric pulmonologist. The caseloads for the adult (allergist and pulmonologist) and pediatric specialists are over 20% and 60% respectively, which may be because these providers have high asthma caseloads to meet the demand. In Arkansas, on the other hand, it is the regular allergists with the larger asthma caseload of 55%, while the pediatric allergists take less than 10% and the one pulmonologist accepting Medicaid has less than 1% of their visits for pediatric asthma. These differences highlight that the asthma caseload is not strictly dependent on the number of specialists in a state nor the provider type. While our constraints account for this variation by building in buffer capacity based on regional averages for the supply at each provider, they could be improved if caseload data for the non-Medicaid population at each provider location could be obtained. There are many factors that may contribute to the variation in this capacity across provider types and states including prevalence of other conditions and number of providers available for both the Medicaid and non-Medicaid populations.

There are not significant differences in spatial access to care between the seasons in spite of the variations in demand from one season to the next. This means that in the areas where there is access to care, it is available all year long and that the capacity is high enough to handle the seasonal variations in demand. On the other hand, there is unmet need even during the lower demand seasons indicating that in some areas, the reduced access to care is primarily driven by the lack of providers rather than the lack of provider availability as during busier times of the year. These results suggest that seasonal interventions such as school based programs may not be sufficient to provide access to asthma care, because more permanent and year-long interventions, such as adding to the care network additional asthma specialized providers, are needed for children to receive the treatment they need.

There is not one state that has the highest or lowest median distance to receive care in all four categories (Louisiana is the closest, with one of the lowest median distances in every category). This indicates that there is not one state that is entirely the best or the worst place to receive asthma care in terms of travel distance. Rather each state has different areas with the greatest potential for improvement. For example, Arkansas has one of the highest median distances to care for all categories, exceeded only by the median distance for Medicaid Specialist care in Alabama. Therefore, we expect that Arkansas has one of the greatest potentials for improved access to care if the capacity for asthma visits were increased.

Consistently across all of the states, the distance to receive care is the highest for the Medicaid population requiring specialist care. This group also has the greatest variance in their distance to receive care within each state.

Within each state, the assigned distances for specialist and Medicaid visits are higher than for primary care and non-Medicaid visits. When comparing the distance to MD and MDM visits, the paired t-tests show that for every state except Mississippi the difference is either 2 or 5 miles farther for Medicaid than non-Medicaid visits. The results are similar for the difference in the distance to MD and S appointments, with all state having a significant difference of 2 or 5 miles. Georgia is the only state for which the difference in distance between MD and S visits is smaller than that between MD and MDM visits. There are greater disparities when considering the distance to S and SM visits and MDM and SM visits. In Alabama, Arkansas, and North Carolina the difference between these two pairs of visit types is at least 10 miles, and no state has less than a 5-mile difference in assigned distance to MDM and SM appointments. This indicates that the distance travelled by the

Medicaid population to receive specialist care is significantly higher than the distance to receive any other type of care. For the Medicaid population, having to travel an additional 10 miles to receive specialist care may be a greater barrier to receive care than the same distance would be for a patient in the non-Medicaid population due to other financial and transportation restrictions.

Tukey's test shows that there is not a statistically significant difference in the average unmet need between any pair of states for rural MD or MDM visits, and the difference between S and SM unmet need is only significant for 3 and 4 pairs of states respectively. This means that the need for improvement in the availability of providers is, at a state level, similar for rural areas in all states. In urban areas, on the other hand, there are significant differences for every pair of states in the unmet need for at least one provider type, with the exception of Tennessee and Mississippi who have no significant differences in unmet need.

Georgia has the lowest percent of unmet need for non-Medicaid visits out of all of the states, with less than 1% of the need being unmet in both urban and rural areas. For the Medicaid population, Mississippi has the lowest percent of unmet need in both rural and urban areas, with Georgia and Tennessee having similarly low values in urban areas (within only 0.2% of the unmet need observed in Mississippi).

The percent of unmet need for non-Medicaid visits is greater in rural areas than urban areas in all seven states. For Medicaid visits, the percent of unmet need is greater in rural areas than urban areas for five states, while Arkansas and Mississippi have greater unmet need in urban areas. The difference in unmet need between the urban and rural Medicaid populations in Arkansas is the greatest difference between geographic areas in any state, with 5.2% of the need being unmet in rural areas and 10.3% being unmet in urban areas. This indicates a shortage of Medicaid-accepting providers even in the larger cities in Arkansas.

This shortage of Medicaid accepting providers in Arkansas' urban areas is highlighted again when comparing the percent of unmet need in urban areas between the Medicaid and the non-Medicaid populations. In Arkansas, this difference is the largest across all of the states, with over 8% more need being unmet for the urban Medicaid population than the urban non-Medicaid population and the next largest difference is only 6%, which is observed in Alabama. Mississippi has the smallest difference, with only 1% more unmet need for Medicaid than non-Medicaid visits in urban areas.

For children in rural areas, the percent of unmet need is greater in the Medicaid population than the non-Medicaid population for every state except Mississippi, where the unmet need for non-Medicaid visits is 0.1% higher than the unmet need for Medicaid visits. The largest difference is in Tennessee, where only 1.7% of the need for non-Medicaid visits is unmet in rural areas, but 10.3% of the Medicaid need is unmet. Because the unmet need for non-Medicaid visits is so low in Tennessee, increasing the percent of providers that accept Medicaid in some rural areas may be sufficient to improve access to Medicaid specialist care without needing to increase the absolute number of providers. Further analysis on the provider capacity would be necessary to determine if allocating any excess capacity for non-Medicaid visits to Medicaid visits would be sufficient to significantly reduce the unmet need for rural Medicaid visits. In addition, potential incentives to providers to accept Medicaid patients should be evaluated.

While the unmet need is similar across the seasons in terms of the percent of visits that are unassigned, the absolute number of visits that are unmet is worth addressing. The number of visits needed in the fall is higher than in the spring or summer, so if the same percent of need in each season is unmet, there will be more unmet need in terms of visits in the fall. For example, in Alabama the percent of unmet need is the same in all three seasons, but there are 1100 more visits that cannot be assigned in the fall than in spring or summer. This means that there are roughly 1100 more children who are not receiving the necessary asthma care in the fall. Inadequate care is known to result in worse asthma outcomes, and in some cases these outcomes may be severe or require more expensive care [103].

The interventions that might be implemented in across communities and states may differ; not all will have the same potential impact on the number of children served. Any intervention should be evaluated in terms of the additional number of children served as well as the geographic coverage of the children served because an urban intervention may impact a large number of children in a small geographic space while a rural intervention may impact all of the children in multiple census tracts that previously had no access to care.

Limitations

Important limitations of this study are related to the data. There are many providers in the Medicaid database that record asthma visit claims but are not classified as primary or asthma care providers, and it is not possible to determine why these claims are recorded or the exact type of service provided. In addition, we are estimating the demand for asthma visits using tract level population and state level prevalence values that are broken down by gender. It would be advantageous to be have more granular prevalence estimates that combined multiple demographic factors, such as prevalence by both age and race together, rather than one or the other. While assuming that all of the population in a census tract is located at the centroid for the optimization model is computationally efficient, this aggregation may be problematic in 5-10% of census tracts[28]. This assumption means that the individual driving distance for patients within a tract may vary from the estimate by a few miles, the significance of which depends on many additional factors that are individual to each child. A key assumption that we make is that the capacity for asthma visits is the same for Medicaid and non-Medicaid children at each provider location. Comparisons with other data sources that include the non-Medicaid population would be needed to determine for which states or provider types this assumption should be adjusted.

Other limitations are related to the model assumptions. We assume that the time to receive an appointment is not a significant factor so long as there is capacity within the given season, which is a multiple month time period. It is possible that some children may not be able to receive an appointment within the needed time frame even though there is capacity in the season as a whole. In addition, everything in the model is computed in terms of driving distance, including the penalty for receiving primary instead of specialist care. For children with the most severe asthma cases, this uniform distance penalty may not be an accurate representation of their preference.

In spite of these limitations, this study provides details about the availability of asthma care and the capacity of providers that is allocated to pediatric asthma visits, and it identifies areas of improvement for access to asthma car in each state.

CHAPTER 4. HEALTHCARE UTILIZATION AMONG MEDICAID-ENROLLED ADOLESCENTS DIAGNOSED WITH DEPRESSION

4.1 Introduction

According to the National Institute of Mental Health, depression currently affects between 7-15% of adolescents ages 12 to 17 in the United States[104, 105]. Conservative estimates of the underlying epidemiological prevalence of depression for adolescents give a lower bound of 4% to 8%[106, 107] while 18% of adolescents in one study showed symptoms of depression[108]. Other studies find that major depressive disorder, which is just one sub-category included in depression diagnoses, affect 7.5% of adolescents and that 10.7% have at least one major depressive episode each year[109, 110] Depression has a significant impact on the lives of affected youth, and can compound the effects and costs of other conditions acquired over the course of their lifetime. For example, major depression among youth can cause a two-point increase in average adult BMI[111], and teenage depression increases the risk of becoming obese later in life [112, 113]. Depression has been found to be undertreated, with prevalence rates varying with gender, race, age, and income[105, 108]. If left untreated, depression can cause lifelong health complications and increased healthcare costs, especially if other mental and physical health comorbidities are present[114, 115].

To assess the prevalence of diagnosis and/or treatment of depression and other conditions, the Centers for Disease Prevention and Control (CDC) has published survey results for the general child and adolescent population derived from self-reported surveys[107]. The estimates derived from these surveys, however, are not available for pediatric subpopulations such as Medicaid-insured children, a vulnerable population facing many access barriers to care including the low rates of acceptance of public insurance among healthcare providers, and lack of education about depression and the importance of evidence-based treatment[116-118]. Moreover, Medicaid is the largest insurance program for children in the U.S., with more than 27 million children enrolled nationally. Understanding healthcare utilization for treating depression in the Medicaid-enrolled adolescent population is important in assessing whether state Medicaid programs provide appropriate behavioral and mental healthcare, with comparisons across states[119, 120]. Some studies in the literature have provided an analysis for a limited time frame, geographic region (often a single state) or set of treatment options[108, 121-123].

This study provides the largest and most comprehensive analysis of the receipt of treatment for depression among Medicaid-enrolled youth. Specifically, this study provides critical information about the treated prevalence of depression 12 states, as well as the types of services received for depression. The 12 states vary in the management mental and behavioral health of the Medicaid enrollees, including managed care (Georgia, Louisiana, Minnesota, South Carolina, Tennessee, Texas), fee for service (Alabama, Arkansas, New York), carve-out (Florida), and local management (North Carolina) [124]. The findings from this study provide much needed baseline information about treatment for depression among Medicaid-enrolled youth across states and over time.

4.2 Methods

4.2.1 Data Source

The primary data source is the Medicaid Analytic eXtract (MAX) files, consisting of identifiable individual-level claims data with information on service utilization and expenditures for all Medicaid-enrolled beneficiaries. The states in this study are Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), Minnesota (MN), North Carolina (NC), New York (NY), South Carolina (SC), Tennessee (TN), and Texas (TX).

We obtained the Institutional Review Board (IRB) approval from Georgia Tech University for this study.

Extremely low prevalence and utilization rates in CA and PA led us to investigate the health care reporting policies in those states. They elected to exclude or "carve-out" mental and behavioral health services from managed care programs[124], and thus data on such services are not completely reported to the state Medicaid program. For this reason, these two states have been removed from the analysis.

The study population consists of all Medicaid-enrolled adolescents age 12 to 17, with claims having a primary or secondary diagnosis code pertaining to depression. This includes major depression, dysthymia, and depression not otherwise specified (identified using International Classification of Diseases Code ninth revision (ICD-9) codes 296.2X, 296.3X, 300.4, and 311[125]). Although depression can be diagnosed at any age and medication recommendations begin at the age of 6, the healthcare community widely uses age 12 as the lower bound for research on pediatric depression because of the significant increase in the rates of depression at that age[104, 126, 127]. We included adolescents in the study population if they had at least two recorded healthcare visits with a depression diagnosis at different time points over the entire time period in order to exclude patients with a misdiagnosis or single improperly coded visit.

We extracted claims data from the Other Services Record (OT) and the Drug Record (RX) MAX files to determine per-patient and overall service utilization summaries for the study sample. Included for each claim from the OT files were data entries specifying the date of service, the patient identification number, the ICD-9 code, the procedure code, and the type and place of service codes.

We extracted a comprehensive list of approved drugs for treating major depression, excluding bipolar depression, from the National Committee for Quality Assurance (NCQA)[128].

4.2.2 Treated Prevalence Estimation

Using claims data, we capture *treated prevalence* defined as the proportion of children diagnosed and treated for depression. We estimated treated prevalence of depression in each state by dividing the total number of Medicaid eligible months for each child in the study population by the total number of Medicaid eligible months of all adolescents in the study population for the corresponding state and year.

We extracted the following variables from the MAX other therapy table: patient_id, STATE_CD, MAX_YR_DT, EL_DOB, EL_SEX_CD, EL_RACE _ETHNCY_CD,

MSIS_TOS, PLC_OF_SRVC_CD, PRCDR_CD, SRVC_BGN_DT, NPI, DIAG_CD_1, and DIAG_CD_2. We extracted the EL_ELGBLTY_MO_CNT and EL_RSDNC_CNTY_CD_LTST variables from the MAX personal summary table.

The patient_id was used to keep track of each patient throughout the study. We used the STATE_CD to group the overall population into subpopulations by state. The MAX_YR_DT and EL_DOB were used to calculate the age of the patient when the claim was submitted. The EL_SEX _CD and RACE_ETHNCY _CD were used to classify each claim by strata (either male or female and either white, black, or other). The PRCDR_CD, PLC_OF_SRVC_CD, and MSIS_TOS were used to determine the type of claim (either behavioral therapy, emergency room, or other depression). DIAG_CD_1 and DIAG_CD_2 were used to determine if the claim was depression related. The EL_ELGBLTY _MO_CNT was used to calculate the total number of eligible months for all patients in the population in order to calculate per member per year statistics. The EL_RSDNC_CNTY_CD_LTST was used to determine the urbanity of the patient using the rural-urban continuum codes (RUCC).

We extracted the following variables from the MAX prescription drug table: patient_id, STATE_CD, MAX_YR_DT, and NDC. We only extracted RX claims for patients from the population from the OT table. The STATE_CD and MAX_YR_DT were used to categorize each RX claim by state and year, and the NDC was used to determine if the drug was used to treat depression.

Our final step was to aggregate the claims into visits. Multiple non-prescription claims in a single day (determined by SRVC_BGN_DT) for the same patient (determined by patient_id) and same provider (determined by NPI) were considered as a single visit.

Table 19:Selected MAX files data elements to identify the depression baseline

Variable	Description
DIAG_CD_1	The First ICD-9-CM Diagnosis Code for the Record
DIAG_CD_2	The Second ICD-9-CM Diagnosis Code for the Record
EL_DOB	Birth Date of the Medicaid Eligible
EL_ELGBLTY_MO_CNT	Total Number of Months the Individual Was Eligible for Medicaid During the Calendar Year
EL_RACE_ETHNCY_CD	Race/Ethnicity of The Medicaid Eligible
EL_RSDNC_CNTY_CD_LTST	Federal Information Processing Standard (FIPS) Code Indicating the Eligible's County of Residence
EL_SEX_CD	Code Indicating the Gender of the Medicaid Eligible
MAX_YR_DT	Calendar Year Covered by the Max Personal Summary File
MSIS_TOS	Code Indicating the Medicaid Statistical Information System (MSIS) Type of Service
NDC	National Drug Code (NDC) for the Service
NPI	National Provider Identifier of the Provider Who Treated the Recipient (As Opposed to the Provider Billing for the Service)
patient_id	Unique Identification Number Used to Identify a Medicaid Eligible in the Medicaid Statistical Information System Across Multiple Years
PLC_OF_SRVC_CD	Code Indicating the Place Where the Service Was Performed
PRCDR_CD	Procedure (Service) Provided
SRVC_BGN_DT	The Beginning Date of Service for the Claim
STATE_CD	U. S. Postal Service 2-Character Abbreviation for the State Medicaid Agency Submitting the Data

4.2.3 Outcome Measures

We considered multiple claims for the same type of care in a single day as one *healthcare utilization event* or *visit*. We classified each of the events with a depression diagnosis as psychotherapy and other psychosocial services (PS), medication (re)filled (RX) scaled to a 30-day supply, or emergency department visit (ED). We determined if a given care event was a PS event based on the place and type of service for the visit as well as whether or not the procedure code was a PS code. We classified an event as an ED event based on the place of service code.

We derived two utilization outcome measures for each service:

1. *Treatment exposure rate* estimated as the percentage of youth in the study population who have had at least one psychological service, medication (re)fill, or ED visit.
2. *Utilization rate* estimated as the per-patient per-year (PPPY) rates for each service, specifically, aggregated counts for the service divided by the total enrollment months for all the adolescents diagnosed with depression who received the service and multiplied by 12.

We stratified our key outcome variables by several child characteristics including: age, race, gender, the residential urbanicity level given by the Rural-Urban Continuum Codes, Medicaid eligibility criteria, and clinical risk grouping (CRG) derived using the 3M Clinical Risk Grouping software.

We categorized the age variable as 12 -14 or 15-17. We considered three categories for the race category: white, black, and other (American Indian, Asian, Hispanic with no race information given, Hispanic and one or more races, Pacific Islander, More than One, Other). Each patient's county code was identified from the personal summary table, and we used the rural-urban continuum codes (RUCCs – shown in Table 20 below)[129] to determine whether that county was urban (1,2,3), suburban (4,5,6), or rural (7,8,9).

Counties are assigned an RUCC by the Economic Research Service division at the U.S. Department of Agriculture. Medicaid eligibility is grouped into disabled, foster, or other.

Table 20: Rural Urban Continuum Code (RUCC) definitions

Code	Description
Metro counties:	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Non-metro counties:	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area

To assess the total severity of each person, we derived the CRGs using the 3M™ Core Grouping Software version 2014.3.2 with the Clinical Risk Groups version 1.12. While the CRGs by 3M have multiple levels of granularity (summarized in Table 21 below with additional details in Appendix B), we grouped patient CRGs as either low-risk (CRG 1 to CRG 5a) or medium-to-high-risk (CRG 5b to CRG 9). We grouped the medium and high risk CRGs together because there were few high-risk patients (patients with a clinical risk group of 8 or 9) within the study population.

Table 21: Clinical Risk Group (CRG) category definitions

CRG	Description
1	Healthy
2	Recent History of Significant Acute Disease
3	Single Minor Chronic Disease
4	Minor Chronic Disease in Multiple Organ Systems
5a	Single Moderate Chronic Disease
5b	Single Dominant Chronic Disease
6	Significant Chronic Disease in Multiple Organ Systems
7	Dominant Chronic Disease in Three or More Organ Systems
8	Dominant, Metastic, and Complicated Malignancies
9	Catastrophic Conditions

4.2.4 Statistical Analysis

To compare utilization across states, the 2012 county level PPPY for each state and treatment type were used. For each of the three visit types, Analysis of Variance (ANOVA) was used to test the null hypothesis that the average utilization in all 12 states is the same. Pairwise comparison was then applied for the analysis of each pair of states.

4.3 Results

4.3.1 Study Population

The total population for each state consisted of the number of unique adolescents across the eight years of the study. A summary of the population over the entire horizon of 2005 to 2012 is in Table 22.

Table 22: Depression Patients by Demographics from 2005 to 2012

	State	AL	AR	FL	GA	LA	MN	MS	NC	NY	SC	TN	TX
Age	12 to 14	35	37	38	39	36	34	37	37	38	34	32	40
	15 to 17	65	63	62	61	64	66	63	63	62	66	68	60
Race	White	59	66	40	50	55	64	45	51	35	57	74	28
	Black	36	22	24	41	40	14	46	38	20	34	19	15
	Other	5	13	36	9	6	22	9	11	45	9	7	57
Gender	M	39	42	41	43	41	42	42	42	39	39	41	43
	F	61	58	59	57	59	58	58	58	61	61	59	57
Long/Short Term	LT	46	56	36	42	44	55	49	49	45	46	47	44
	ST	54	44	64	58	56	45	51	51	55	54	53	56
Urbanicity	Urban	69	57	93	77	79	68	38	73	90	81	69	85
	Suburban	25	24	7	16	18	20	36	22	9	18	24	12
	Rural	5	19	0	6	3	12	24	5	1	1	7	3
Eligibility	Other	75	82	66	67	80	82	75	77	76	79	77	66
	Foster	7	6	16	21	7	8	6	10	8	12	14	20
	Disabled	18	12	18	12	13	10	19	13	16	9	9	14
CRG	Low Risk	8	6	16	8	9	14	4	7	14	14	10	8
	High Risk	93	94	85	93	91	86	96	93	87	86	90	92

Table 23 includes the percent of adolescents from the study population that have depression in each stratum subcategory by state for 2012. The size of the study population ranges from 14,846 children with depression in MS (3,058 in 2012) to 87,757 children in TX (19,639 in 2012).

Table 23:2012 Sample Characteristics Among Medicaid-Enrolled Youth with Depression Diagnosis Across 12 States

Sample Characteristics	AL	AR	FL	GA	LA	MN	MS	NC	NY	SC	TN	TX
Population												
Number of Children with Depression	3901	5974	9753	8294	6918	8865	3058	8386	16048	4040	6940	19639
Treated Prevalence	2.84%	4.9%	2.0%	3.3%	3.3%	8.3%	3.2%	3.5%	3.2%	2.7%	3.7%	2.8%
Age Group												
12 to 14	46%	48%	45%	50%	47%	48%	49%	49%	45%	43%	45%	50%
15 to 17	54%	52%	55%	50%	53%	52%	51%	51%	55%	57%	55%	50%
Race/Ethnicity												
White	59%	64%	39%	49%	53%	63%	47%	50%	38%	57%	73%	25%
Black	35%	19%	22%	39%	41%	13%	45%	36%	19%	32%	18%	13%
Other	6%	17%	39%	12%	5%	24%	8%	14%	44%	11%	8%	62%
Urban/Rural Setting												
Rural	5%	18%	0%	5%	3%	12%	21%	3%	1%	1%	7	3%
Suburban	26%	22%	6%	16%	17%	19%	34%	20%	10%	16%	23%	11%
Urban	68%	61%	94%	79%	80%	69%	43%	77%	89%	83%	70%	86%
Clinical Risk Grouping (CRG)												
Low	7%	6%	13%	5%	12%	11%	5%	5%	11%	13%	8%	6%
Medium/high risk	93%	94%	87%	95%	88%	89%	95%	95%	89%	87%	92%	94%

In all 12 states, there were more depression-diagnosed adolescents aging from 15 to 17 than depression-diagnosed adolescents aging from 12 to 14, more females than males, more from urban areas than from suburban or rural areas, more from the "other" eligibility class than disabled or foster children, and more in medium-to-high risk CRGs than in low-risk CRGs. There were more depression-diagnosed white children than of any other race in all states except MS, NY, and TX.

Between 20% (in SC) and 52% (in LA) of the depression related claims extracted in each state had either a primary or secondary diagnosis code for major depression (codes 296.2X and 296.3X). The complete breakdown of the percent of visits by state for each ICD9 code is provided in Table 24 below.

Table 24: Percent of Depression Visits By Diagnosis Code

	Total Visits	ICD9 : 296.2X	ICD9 : 296.3X	ICD9 : 300.4X	ICD9 : 311.X	Major Depression
AL	318,705	18.9%	19.1%	8.6%	54.2%	37.9%
AR	1,416,605	11.1%	17.8%	10.7%	60.9%	28.8%
FL	977,245	14.4%	19.0%	21.4%	45.4%	33.3%
GA	725,724	18.8%	27.7%	12.8%	41.0%	46.4%
LA	608,369	22.4%	29.7%	3.1%	45.0%	52.0%
MN	1,094,646	16.7%	21.8%	18.9%	43.7%	38.4%
MS	397,655	15.3%	14.1%	8.3%	62.5%	29.3%
NC	2,170,799	20.0%	25.1%	14.5%	41.0%	44.0%
NY	1,365,456	12.8%	16.4%	19.4%	51.5%	29.2%
SC	465,889	11.1%	9.1%	7.6%	72.3%	20.1%
TN	541,402	14.6%	20.3%	7.2%	58.2%	34.8%
TX	1,447,385	25.8%	25.3%	9.5%	39.6%	51.1%

4.3.2 Treated Prevalence Estimation

Figure 19 shows the treated prevalence of depression for each state and year in the study, with corresponding data values in Table 25. The percentages were calculated by dividing the total number of Medicaid eligible months for each depression population in each state and year by the total number of Medicaid eligible months of the total number of Medicaid patients aging from 12 to 17 for the corresponding state and year. The total population for each state consists of the number of unique patients across the eight years of the study.

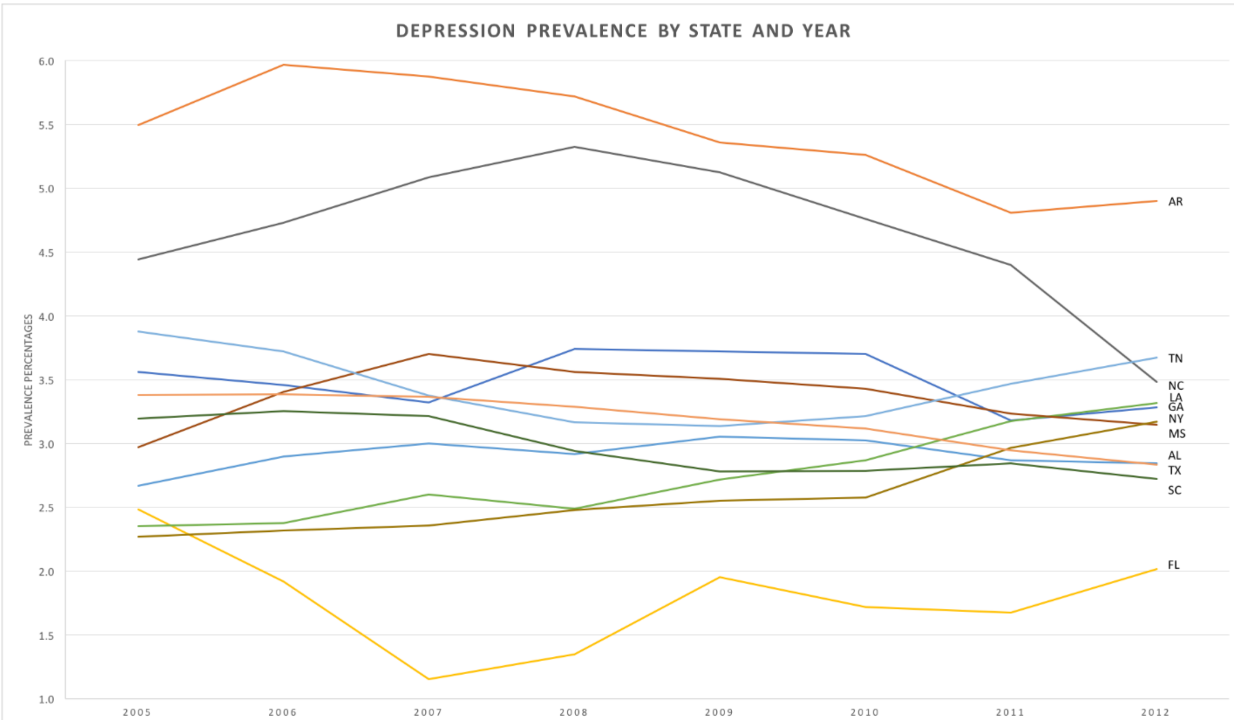

Figure 19: Treated Prevalence of Depression among Medicaid-Enrolled Youth (age 12-17), by state from 2005-2012

Table 25: Depression Prevalence by State and Year

State	Total Population	2005	2006	2007	2008	2009	2010	2011	2012
AL	12,245	2.67%	2.90%	3.00%	2.92%	3.05%	3.02%	2.87%	2.84%
AR	20,550	5.50%	5.97%	5.88%	5.72%	5.36%	5.26%	4.81%	4.90%
FL	25,829	2.48%	1.92%	1.16%	1.35%	1.95%	1.72%	1.68%	2.02%
GA	26,994	3.56%	3.46%	3.33%	3.74%	3.72%	3.70%	3.18%	3.28%
LA	18,553	2.35%	2.38%	2.60%	2.49%	2.72%	2.87%	3.18%	3.32%
MN	21,048	7.08%	7.37%	7.44%	7.11%	7.43%	7.81%	7.88%	8.25%
MS	13,218	2.97%	3.41%	3.70%	3.56%	3.51%	3.43%	3.24%	3.15%
NC	37,518	4.44%	4.73%	5.09%	5.32%	5.13%	4.76%	4.40%	3.48%
NY	41,875	2.27%	2.32%	2.36%	2.48%	2.55%	2.58%	2.97%	3.17%
SC	9,815	3.20%	3.25%	3.22%	2.94%	2.78%	2.79%	2.85%	2.72%
TN	25,482	3.88%	3.72%	3.38%	3.17%	3.14%	3.21%	3.47%	3.67%
TX	73,957	3.38%	3.39%	3.36%	3.29%	3.19%	3.12%	2.95%	2.84%

From 2005 to 2012, half of the states have an overall increase in treated prevalence of pediatric depression, while half have an overall decrease. The change in the treated prevalence is no more than 1.2% in either direction. MN had the highest overall treated prevalence of depression across all years and the largest increase over time, reaching 8.3% in 2012. FL has the lowest treated prevalence from 2006-2012, reaching just 2%.

4.3.3 Population Outcome Measures

Treatment exposure rates and utilization rates (PPPY utilization) in 2012 for each treatment type are shown in Table 26.

Table 26: 2012 Depression Service Utilization (as percent and Per Patient Per Year - PPPY) Among Medicaid-Enrolled Youth with Depression Diagnosis Across 12 States

Service Utilization	AL	AR	FL	GA	LA	MN	MS	NC	NY	SC	TN	TX
Total Number of Depression Visits (PPPY)	10.7	18.1	8.7	12.7	5.4	11.2	13.6	4.9	10.1	7.7	7.5	3.3
Any Psychological Service Utilization (%)	49%	66%	40%	61%	13%	45%	54%	9%	24%	38%	49%	37%
# Psychological Service Visits (PPPY)	4.8	12.8	4.3	8.1	0.6	4.6	8.9	0.6	1.8	3.8	3.8	2.1
Any Medication Prescription (%)	62%	59%	47%	53%	67%	61%	58%	52%	38%	61%	53%	60%
# Medications Filled (PPPY)	4.18	3.73	2.71	3.68	3.67	4.77	3.11	3.40	2.26	3.64	3.29	4.05
Any ED Visit (%)	33%	43%	34%	22%	32%	35%	29%	20%	71%	14%	17%	26%
# ED Visits (PPPY)	1.75	1.56	1.70	0.93	1.17	1.85	2.38	0.98	5.96	0.28	0.39	1.18

The treatment exposure rate for PS ranges from 9% in NC and 13% in LA to 61% in GA and 66% in AR. For ED visits, SC and TN have the lowest treatment exposure rates with only 14% and 17% respectively, and NY has the highest with 71% of children with depression going to the ED at least once in 2012. There is the least variation across the states for RX treatment exposure, ranging from 38% in NY to 67% in LA.

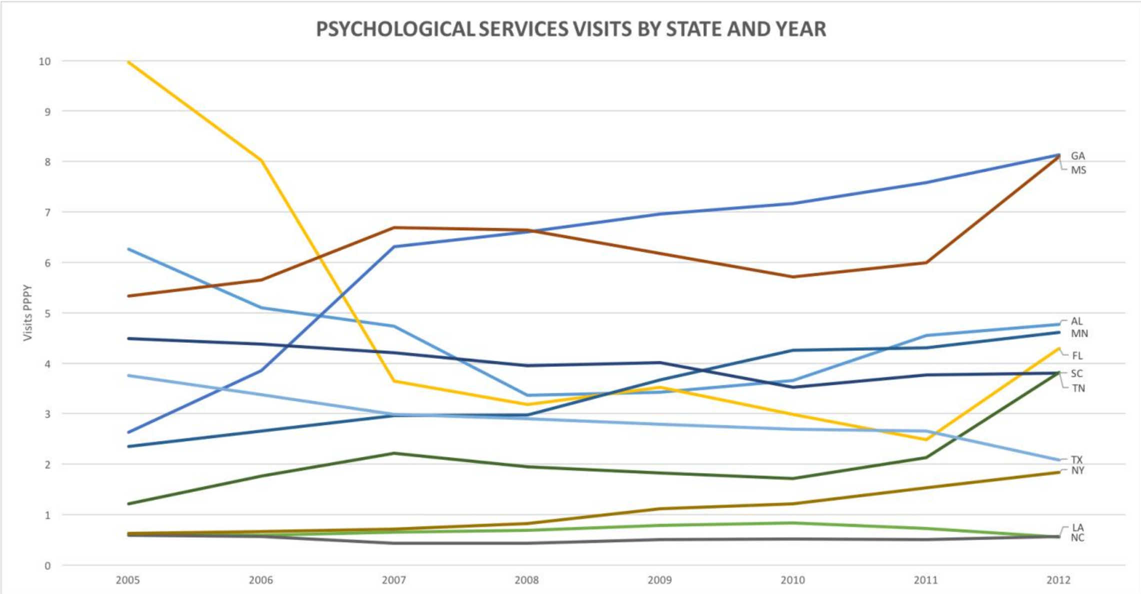

Figure 20 shows the PS utilization rates across eight years for 12 of the states in the study, AR had the highest, while LA and NC had the lowest average PS utilization rate across all years of the study with 12.78 and less than 1 visits PPPY respectively. FL had the largest decrease in PS utilization rate over time, dropping from 9.96 visits PPPY in 2005 to 4.29 visits PPPY in 2012. AL, SC and TX each decrease by at least one visit PPPY. GA has the largest increase over time, rising from 2.63 PS events PPPY in 2005 to 9.13 PS events PPPY in 2012. AR, MN, MS and TN also increase by at least 2 visits PPPY. The remaining states, LA, NC, and NY have little change in utilization rates over time.

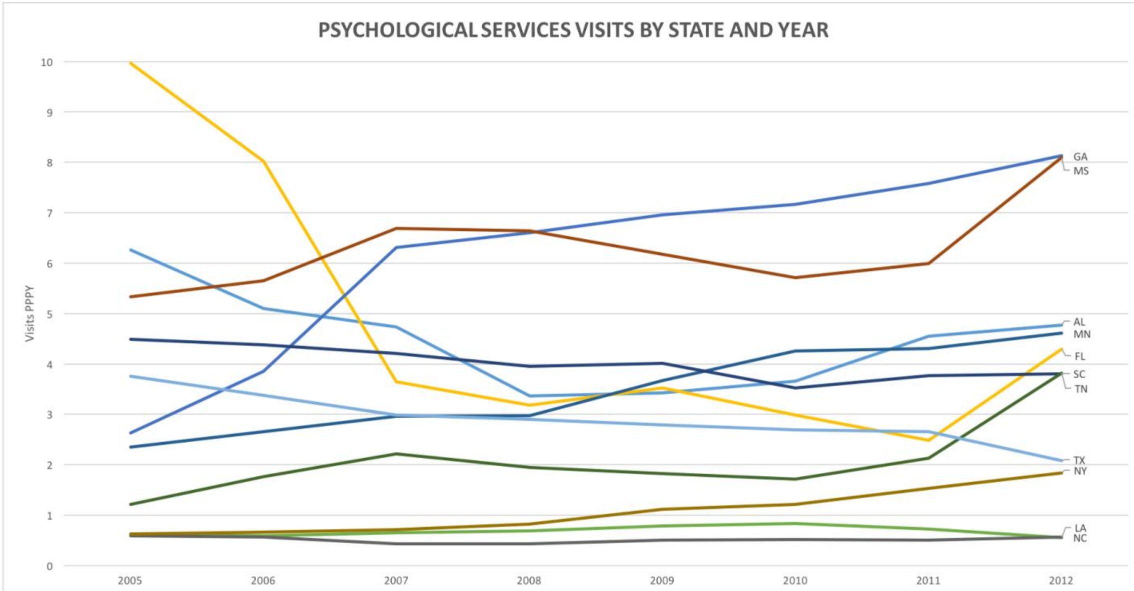

Figure 20: Psychological Service Utilization (Assessed by Number of PS Visits Per Patient Per Year), by State from 2005 to 2012. Note: PPPY is calculated as the aggregated count for PS events divided by the total number of enrollment months for all the adolescents with those services multiplied by 12.

Figure 21 shows the PPPY utilization of ED services from 2005-2012. The majority of the states had steady ED utilization rates over time, changing by less than 0.5 visits PPPY. FL and MN had overall increasing trends in ED utilization, while AL, NC, and NY had decreasing utilization by over 2.5 visits PPPY over the time horizon.

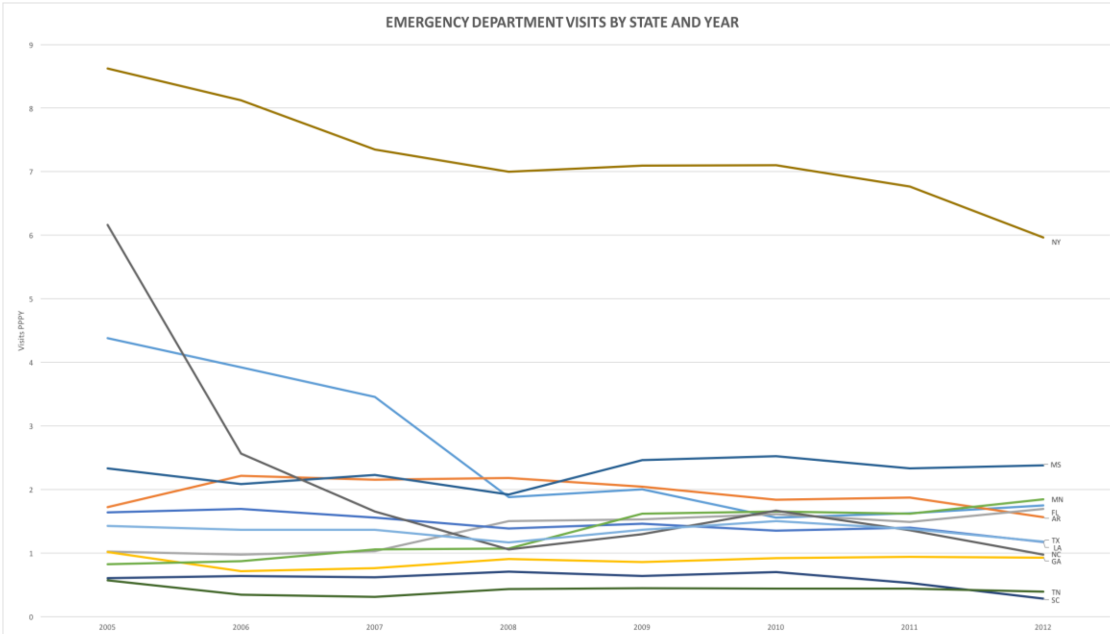

Figure 21: Emergency Department Utilization (Assessed by Number of ED Visits Per Patient Per Year), by State from 2005 to 2012. Note: PPPY is calculated as the aggregated count for ED events divided by the total number of enrollment months for all the adolescents with those services multiplied by 12.

Figure 22 shows the distribution of RX utilization rates across eight years for all of the states in the study, except for MN in 2010 and LA in 2011 which are not available because of data incompleteness. All of the states have an overall increase in RX utilization rates over time. The weighted average utilization rate of RX across all states and years is 3.08 RX fills PPPY. MN has the highest average RX utilization rate across all years of the study with 3.97 fills PPPY, and NY has the lowest average RX utilization rated across all years of the study with 1.89 fills PPPY. In 2012 MN has highest RX utilization rate, with 4.77 depression-related RX fills per patient, followed closely by AL and TX that also have over 4 RX fills PPPY. The average increase in RX utilization rates from the first year to the last year of the study across all of the states is 1.22 RX fills PPPY, with a high of a 1.87 increase for MN and a low of a 0.7 increase in AL.

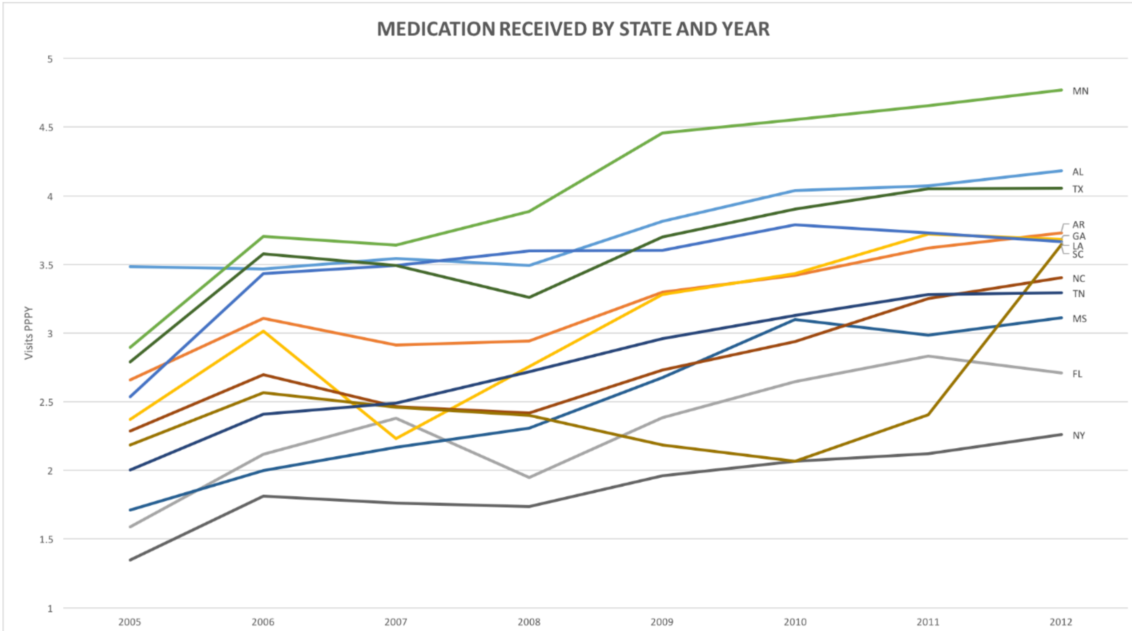

Figure 22: Medication Utilization (Assessed by Number of Visits Per Patient Per Year), By State from 2005 to 2012. Note: PPPY is calculated as the aggregated count for RX events divided by the total number of enrollment months for all the adolescents with those services multiplied by 12.

Table 27 contains the number of per patient per year (PPPY) visits for three different depression events (psychological service, emergency department, or medication received) by state from 2005 to 2012 for each state in the depression study.

Table 27: PPPY Visits by State, Event, and Year

State	Event Type	2005	2006	2007	2008	2009	2010	2011	2012
AL	ED	4.38	3.92	3.45	1.88	2.00	1.56	1.63	1.75
AR	ED	1.72	2.21	2.15	2.18	2.04	1.84	1.87	1.56
FL	ED	1.02	0.98	1.03	1.50	1.53	1.61	1.49	1.70
GA	ED	1.02	0.72	0.76	0.91	0.86	0.92	0.94	0.93
LA	ED	1.64	1.69	1.56	1.39	1.46	1.35	1.40	1.17
MN	ED	0.82	0.87	1.06	1.07	1.62	1.66	1.62	1.85
MS	ED	2.33	2.09	2.23	1.92	2.46	2.52	2.33	2.38
NC	ED	6.16	2.56	1.65	1.06	1.29	1.67	1.36	0.98
NY	ED	8.62	8.12	7.35	7.00	7.10	7.10	6.77	5.96
SC	ED	0.61	0.64	0.62	0.71	0.64	0.70	0.53	0.28
TN	ED	0.57	0.34	0.31	0.43	0.45	0.44	0.44	0.39
TX	ED	1.43	1.37	1.36	1.17	1.37	1.50	1.38	1.18
AL	PS	6.26	5.10	4.74	3.36	3.43	3.66	4.55	4.77
AR	PS	9.52	9.28	9.56	9.81	12.49	13.10	13.18	12.78
FL	PS	9.96	8.02	3.65	3.19	3.53	2.99	2.48	4.29
GA	PS	2.63	3.86	6.31	6.60	6.96	7.17	7.58	8.13
LA	PS	0.63	0.59	0.65	0.69	0.79	0.84	0.72	0.56
MN	PS	2.35	2.66	2.97	2.98	3.67	4.25	4.30	4.61
MS	PS	5.34	5.66	6.69	6.64	6.18	5.71	5.99	8.09
NC	PS	0.60	0.57	0.44	0.43	0.50	0.51	0.51	0.57
NY	PS	0.63	0.66	0.71	0.82	1.11	1.21	1.53	1.84
SC	PS	4.49	4.37	4.20	3.95	4.01	3.52	3.77	3.81
TN	PS	1.21	1.76	2.21	1.95	1.83	1.71	2.13	3.81
TX	PS	3.76	3.38	2.98	2.89	2.79	2.69	2.66	2.08
AL	RX	3.48	3.47	3.54	3.49	3.81	4.04	4.07	4.18
AR	RX	2.66	3.11	2.91	2.94	3.30	3.42	3.62	3.73
FL	RX	1.59	2.12	2.38	1.95	2.39	2.65	2.83	2.71
GA	RX	2.37	3.01	2.23	2.76	3.28	3.43	3.72	3.68
LA	RX	2.54	3.43	3.49	3.60	3.60	3.79	7.61	3.67
MN	RX	2.90	3.70	3.64	3.89	4.46	8.98	4.66	4.77
MS	RX	1.71	2.00	2.17	2.31	2.67	3.10	2.98	3.11
NC	RX	2.29	2.70	2.46	2.42	2.73	2.94	3.25	3.40
NY	RX	1.35	1.81	1.76	1.74	1.96	2.07	2.12	2.26
SC	RX	2.18	2.57	2.46	2.40	2.19	2.06	2.41	3.64
TN	RX	2.00	2.41	2.49	2.72	2.96	3.13	3.28	3.29
TX	RX	2.79	3.58	3.49	3.26	3.70	3.90	4.05	4.05

4.3.4 Stratified Outcome Measures

The number of depression-related events PPPY varied across the states, but there were some clear utilization patterns within the strata. Utilization rate is higher for female and medium/high clinical risk children than for male and low clinical risk children in 10 states. In 2/3 of the states, older children and children in foster care have higher utilizations than the other sub-groups, and in a majority of the states, children living in urban areas have the most visits PPPY. The greatest variation between the states is in the utilization patterns by race, with black children having the highest utilization in 2 states while white and other race children have the highest utilization rates in 5 states each.

While children in foster care have the highest PPPY utilization in 9 states, the largest percent of total visits in every state is made by children with an income-based eligibility criterion (neither disabled or in foster care). Similarly, the largest percent of visits in all states are made by children living in urban areas, even though in 5 states they do not have the highest utilization rates. In every state medium/high clinical risk children are responsible for at least 90% of the total visits, and in all states except MS and TX white children receive the most visits.

Table 28 provides the percentage of depression-related visits per patient per year utilized by each stratum subcategory for each state in 2012. An example of how to read

Table 28 is as follows: for Alabama in 2012, 45% of depression related visits were attended by patients aging from 12 to 14, 59% of depression related visits were attended by white patients, and 12% of depression related visits were attended by foster children.

Table 28: Depression Visits by Strata

State	Age 12 to 14	Age 15 to 17	Black	Other Race	White	Male	Female	LT	ST	Rural	Suburban	Urban	Disabled	Foster	Other Eligibility	Low Risk	Medium/ High Risk
AL	45%	55%	36%	6%	59%	37%	63%	68%	32%	4%	24%	72%	20%	12%	68%	4%	96%
AR	49%	51%	21%	20%	59%	43%	57%	81%	19%	17%	21%	62%	19%	8%	73%	4%	96%
FL	44%	56%	21%	41%	38%	36%	64%	62%	38%	0%	4%	96%	19%	18%	63%	11%	89%
GA	46%	54%	42%	15%	43%	39%	61%	72%	28%	4%	13%	83%	22%	36%	42%	3%	97%
LA	47%	53%	34%	6%	60%	37%	63%	63%	37%	2%	16%	82%	15%	8%	77%	8%	92%
MN	46%	54%	11%	22%	67%	37%	63%	77%	23%	10%	20%	70%	10%	8%	82%	9%	91%
MS	51%	49%	53%	9%	38%	38%	62%	74%	26%	22%	33%	43%	21%	9%	71%	4%	96%
NC	47%	53%	27%	11%	61%	36%	64%	67%	33%	2%	21%	76%	14%	14%	73%	4%	96%
NY	45%	55%	17%	43%	39%	35%	65%	74%	26%	1%	9%	90%	18%	6%	76%	9%	91%
SC	44%	56%	29%	14%	57%	37%	63%	75%	25%	1%	13%	86%	12%	10%	78%	11%	89%
TN	41%	59%	18%	8%	74%	40%	60%	70%	30%	6%	24%	70%	8%	21%	71%	8%	92%
TX	52%	48%	12%	60%	29%	39%	61%	62%	38%	3%	11%	86%	18%	26%	55%	5%	95%

Bar charts with the stratified percent of visits made by children in each category can be found in Appendix C.1.

4.3.5 State Level Utilization Differences

For all three visit types, we reject the null hypothesis that the mean utilization in all states is the same (p-value <2e-16). Five pairs of states do not have significantly different means for PS, ED, or RX, and 12 pairs of states have different means for all three visit types. MS has the least in common with the other states. It has significantly different utilization rates for all three service types in 6 of its 11 pairwise comparisons and statistically different utilization for 2 of the 3 service types in the other 5 comparisons.

4.4 Discussion

Using Medicaid data from multiple states, this study derives the largest, most comprehensive sample to describe the overall treated prevalence for depression and the levels of mental and behavioral health services received by those with a diagnosis of depression. We find that: (1) the overall treated prevalence of depression is very low in this population; (2) the overall receipt of psychological services for depression is also very low (given that this is often the first-line treatment for depression according to recommended care guidelines[130]; (3) there is statistically significant variation in receipt of services across states; and (4) there are important trends over time across all states.

This study shows that the overall treated prevalence of depression is lower than expected in the Medicaid population. The treated prevalence across the states studied ranges from 2% to 8.3% in 2012. Only AR and MN had treated prevalence in each year close to reported depression prevalence (4-8% from self-reported surveys[107], 7.5% with major depressive disorder[109], or 10.7% with at least one major depressive episode each year[110]). The treated prevalence in NC drops below 4% in 2012, and all of the other states have treated prevalence that is below 4% for the entire study period. This is particularly noteworthy considering the fact that these are low-income youth with even greater risk factors for depression[131]. Thus, the data suggest that under-diagnosis of depression is of concern for Medicaid-enrolled youth. The fact that the vast majority of the sample were in the medium to high risk CRG category provides some evidence to suggest that those who are actually being treated for depression have multiple/complex chronic conditions. Therefore, it is possible that other co-morbid mental health or physical health problems that are the motivating factor that brings them into services, rather than just having depression in and of itself.

The overall use of psychological services for depression is also highly variable and in many states, very low. The percentage of children with depression that received any psychological service in a particular state is between 9% in NC and 66% in AR. PPPY visits have a similar span, ranging from 0.56 visits PPPY in LA to over 12 visits PPPY in AR. However, the gap from between PPPY utilization in AR and the next highest state (8.13 PPPY in GA) is much larger than the gap in the percent of children receiving any psychological service, which is 61% in GA. This finding is especially concerning because psychotherapy services are supposed to be the first-line treatment for youth with depression per the AACAP clinical guidelines. Medication is only supposed to be used for those whose depression does not improve after receiving these services in part because of the potentially severe side effects[127, 130, 132]. Furthermore, the average number of psychological services visits is especially low. Although there is no specific cutoff for how many psychotherapy visits should be received for youth with depression, prior studies have used thresholds of 4 visits and 8 visits to characterize whether someone received minimally adequate psychotherapy[133, 134]. Thus, with 6 states having fewer than 4 and 9 states having fewer than 8 visits PPPY, our findings suggest that most of those who do receive PS may not receive enough visits to receive minimally adequate treatment with psychotherapy and other psychosocial services.

By using data from multiple states, we identify important variation in how depression is treated among Medicaid-enrolled youth from one state to another. To compare utilization across states, the county level PPPM for each state and treatment type were used. ANOVA confirms that the mean number of visits for each treatment type across all states are not the same. While the difference in utilization rates between most pairs of states are significant, there are cases where the difference is not significant. Further research is needed to understand the key sources of the variation in both the utilization of depression medication and the likelihood that a youth receives first-line psychosocial/psychotherapy services.

There are trends over time across all states as well. The PPPY medication filled increased over time in most states, while the treated prevalence only increases in half of the states. While PS utilization only increases in five states, these trends are overall consistent with other research for the general population that show an increase in mental health diagnoses and office visit utilization from 1995 to 2010[135, 136].

One limitation of this study was reliance on claims data to infer healthcare outcome measures. The MAX files only include claims that have been submitted for reimbursement. Therefore, estimates on the healthcare utilization may be biased where certain subgroups have difficulty in maintaining Medicaid coverage, lack of access, or are susceptible to particularly disparate utilization [137]. Furthermore, Medicaid MAX files can have data quality issues, especially for states with large populations on managed care[138, 139]. Based on the standards in the Mathematica Policy Brief, the data quality for three states in our sample did not meet the quality standards. These are Florida in 2008 and 2009, Minnesota in 2007, 2008 and 2009, and New York in 2010 for the Drug Record [25,26.] Another limitation is in the estimation of utilization rates for psychological services and medication. Procedure codes for psychological services have been only uniformly used after 2005, with some states being slower adopters of the uniform coding system. Also, some of the medications prescribed for depression are also used to treat other co-morbid mental health conditions, thus there could potentially be over estimation of the medication utilization.

In spite of these limitations, this study provides the most comprehensive examination of depression treatment among Medicaid-enrolled adolescents. We find that treated prevalence and service utilization are lower for the Medicaid population than has been reported in other studies and reports for the general population. This indicates that depression is likely under-diagnosed in this vulnerable population and that even those adolescents who are diagnosed may not be receiving adequate care.

CHAPTER 5. HEALTHCARE OUTCOME MEASUREMENTS FOR MEDICAID-ENROLLED CHILDREN DIAGNOSED WITH DEPRESSION

5.1 Introduction

Depression is frequently undertreated, with many adolescents and adults not receiving minimally adequate treatment [133, 134]. In the Medicaid population specifically, treated prevalence rates are lower than expected (see chapter 4), only 59% of youth with a new diagnosis of depression receive adequate psychotherapy and only 13% receive adequate medication [120]. Studies have shown that delaying treatment for adolescent depression can result in higher rates of severe health outcomes and overall higher treatment costs [140]. For adults, remission rates are higher for patients whose depression remains untreated for more than six months after diagnosis[141].

There are many studies in the literature that demonstrate the impact of depression on health outcomes and healthcare expenditure for comorbid health conditions. Individuals, especially adolescent girls, with depression are more likely to become obese [113]. The relationship between childhood depression and obesity is well documented [142], and the duration of the pediatric depression is also a significant predictor of elevated adult BMI [111]. Worse health outcomes and higher costs occur when depression is combined with other health conditions including epilepsy[114], diabetes[143-145], adolescent cystic fibrosis[146], fibromyalgia [147] and mental health conditions like anxiety and ADHD[148-150] in the general population[151]. This is in part because treatment adherence for comorbid conditions is frequently lower among the depressed population, particularly when there is inadequate depression treatment [152] [153]) . By comparison, depressed adults are less likely to have regular primary care visits[154] and individuals with chronic physical health conditions and depression are more likely to use urgent healthcare[155, 156].

The health outcomes for adults with depression cannot be ignored when considering the impact of pediatric depression. If children with depression are able to receive appropriate treatment, then they would not be expected to have the same comorbid effects and complications as depressed adults.

In this work, we quantify and compare the healthcare utilization and expenditure for Medicaid-enrolled adolescents (age 12-17) with and without major depression. Our analysis determines if the differences in utilization and expenditure for non-depression related visits between the two populations are statically significant. We use CMS eXtract files from 2010-2011 for 14 states (Alabama, Arkansas, California, Florida, Georgia, Louisiana, Minnesota, Mississippi, North Carolina, New York, Pennsylvania, South Carolina, Tennessee, Texas) for the analysis.

5.2 Methods

5.2.1 Data Sources

The primary data source is the Medicaid Analytic eXtract (MAX) files, consisting of identifiable individual-level claims data with information on service utilization and expenditures for all Medicaid-enrolled beneficiaries. We used data from 2010–2012 for the following fourteen states: Alabama (AL), Arkansas (AR), California (CA), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), Minnesota (MN), North Carolina (NC), New York (NY), Pennsylvania (PA), South Carolina (SC), Tennessee (TN), and Texas (TX). This study was approved by CMS (Data Use Agreement #23621) and by the Institutional Review Board of Georgia Tech (protocol #H11287).

5.2.2 Study Population

The study population consists of all Medicaid-enrolled adolescents age 12 to 17. We differentiate among children with and without depression. Children with depression are those with claims having a primary or secondary diagnosis code pertaining to major depression, , dysthymia, and depression not otherwise specified (identified using International Classification of Diseases Code ninth revision (ICD-9) codes 296.2X, 296.3X, 300.4, and 311[125]). Although depression can be diagnosed at any age and medication recommendations begin at the age of 6, the healthcare community widely uses the age of 12 as the lower bound for research on pediatric depression because of the significant increase in the rates of depression at that age [104, 126, 127]. We included adolescents in the study population if they had at least two recorded healthcare visits over the entire time period with a depression diagnosis in order to exclude patients with a misdiagnosis or single improperly coded visit.

We select a comparison population of children without depression in order to compare the utilization and expenditure of healthcare for the two populations as provided in the next section.

5.2.3 Patient Matching

We add the number of months that each child in the depression baseline was enrolled in the Medicaid system from 2010-2011 to the depression baseline data.

For each state, we identify the non-depressed population of children age 12-17 that are enrolled in the Medicaid system in 2010-2011. For each child in this set, we extract the demographic information that was used in the depression baseline analysis (age group, gender, race, urbanicity, clinical risk group and Medicaid eligibility criteria) as well as the number of months that they were enrolled over the two-year period.

In order to compare the utilization and expenditures for the population of children with and without depression, it is necessary to create a data set that can be treated as though the samples are paired even though the data are from an observational data set. Patient matching is a common technique that is implemented in multiple ways in the literature[157-159] and we use the following steps to create a matched set of children where one member of the pair has depression and one does not.

For each child in the population of children with a depression diagnosis, we first attempt to find another child in the population with the exact same characteristics but without a depression diagnosis. Because enrollment can bias utilization, we match depression vs non-depression populations assuming that there can be up to a six-month difference in the months of enrollment between the children in the matched pair.

For every child with depression not yet matched using exact matching features, we relax one characteristic, the CRG score. A first relaxation of CRG is that it can be +/- 1 from the score of the child with depression or further, it can be within a CRG group defined by low risk (CRG scores 1-5a) or medium-high risk (CRG scores 5b-9). The second relaxation is to allow the urbanicity to vary by one level, so a child in an urban area can be matched with one in a suburban area, and a child in a rural area can be matched with a child in a suburban area. These relaxations are added as needed for each state.

This is similar to a breadth first search for matches because we try to match as many children as possible with a given criteria before relaxing any of the conditions. The alternative would be a depth first search where we would try to find a match for the current child and would relax the criteria one at a time until a match for that particular child (if available) is found. Then the process would start over again with the search for an exact match for the next child. Using the breadth first approach ensures that we do not use an exact match for depressed child D1 as a relaxed match for depressed child D2 when there is not another available exact match for depressed child D1. This ensures that we have as many exact matches as possible

5.2.4 Utilization Outcome Measures

For each child in the matched set, we extract the utilization and expenditure data for all non-depression claims from the MAX data in the Inpatient Table (IP), the Other Therapy Table (OT) and the Prescription Table (RX). Children who are enrolled in the Medicaid system for a longer period of time are expected to have higher utilization, thus we scale the utilization and expenditure by the number of enrollment months for comparison between children.

We consider six types of care. The IP visits are all classified as hospitalizations. The RX table provides second type of care, medication. We finally divide the OT visits into four subgroups based on the place of service: ambulatory or urgent care related visits, emergency department, physician office and other visits. The third group consists of inpatient visits all visits that occur in hospitals (location code 22), inpatient stays (21), ambulances (41-42), ambulatory surgery centers (location code 24) and urgent care facilities (location code 20). The fourth group is emergency department visits (location code 23) and the fifth group is office visits (location code 11). The sixth group is 'other', and includes all other visits in the OT table.

For the IP table, we use the following data elements: MDCD_PYMT_AMT, DIAG_CD_1.

For the RX table, we use the data elements: CHRG_AMT, MDCD_PYMT_AMT, NDC, QTY_SRVC_UNITS.

For the OT table, we use the following data elements: PLC_OF_SRVC_CD, CHRG_AMT, MDCD_PYMT_AMT, DIAG_CD_1.

We are only interested in comparing the utilization of health care services for non-depression related services, thus only the visits in the IP and OT tables that do not have a diagnosis code for depression are extracted, and only those claims in the RX table that are not for a depression medication are extracted. The excluded medications are the ones used in the depression baseline analysis. We extract the number of prescription units rather than the number of prescriptions that are filled to account for variations in the days of supply for each prescription fill.

The scaled measures are the number of visits per-enrollment-month for the IP and OT claims, and the number of prescription units per-patient-per-month-enrolled for the RX claims.

5.2.5 Expenditure Outcome Measures

In the Medicaid system, expenditure is reported differently with the *Type of Claims*. The claims directly billed and paid by Medicaid, for example, claims from fee-for-service or state-coordinated care plans, will have records for both the *Charge Amount* (CHRG), specifying the total amount of charges submitted by the care provider, and the *Medicaid payments* (MED), specifying the amount reimbursed by Medicaid. Other claims that are from prepaid plans or third-party managed care plans called *encounters* have records for CHRG but not for MED. Because most states included in our analysis are primarily under managed care, we have complete data on healthcare expenditure in the charge amount only; thus, charge amount is used in the derivation of the expenditure outcomes.

The expenditure outcome measures are the total expenditure per-enrollment-month, and the average expenditure per-visit or prescription unit.

5.2.6 Statistical Analysis

We use paired Wilcoxon rank test to compare the utilization and expenditure for children with and without depression in each state and for each outcome measure. Because we are conducting 14 independent tests, the Bonferroni correction is used to ensure that we do not falsely identify significant differences. The initial alpha value is 0.1, and there are 14 states to the corrected alpha value to determine significance is 0.0071.

It is also of interest to compare the results among the states. For each pair of children, we compute the difference in the number of monthly visits as well as the average cost per visit for each type of care. We use ANOVA and Tukey's Test to determine if these utilization and cost differences vary between the states.

All of the statistical tests were conducted using the R statistical software[160].

5.3 Results

5.3.1 Study Population and Patient Matching

Table 29 contains the number of children with and without depression enrolled between 2010 and 2012 with claims in the CMS database. There are between 4 and 26 non-depressed children available to be matched to each child with depression in each state.

Table 29: Number of children with and without depression in each state that are eligible to be matched and the number of pairs that are created through the matching heuristic

State	# Children With Depression	# Children Without Depression	Ratio Non-Depressed/ Depressed Children
AL	14200	178109	12.5
AR	22403	146895	6.6
CA	140795	1800178	12.8
FL	31776	650225	20.5
GA	30106	339210	11.3
LA	22552	247132	11.0
MN	27383	131481	4.8
MS	11666	133622	11.5
NC	37072	309375	8.3
NY	53564	651853	12.2
PA	15591	397760	25.5
SC	14864	179981	12.1
TN	26872	249154	9.3
TX	71528	995392	13.9

Table 30:Number of matches made with each relaxation and the total number of matches per state

State	Number of Matches With Exact Criteria	Number of Matches With Relaxed CRG +/- 1	Number of Matches With CRG Relaxed to Groups	Number of Matches With Relaxed Urbanicity	Total Number of Matches	Percent of Children With Depression That Are Matched
AL	7083	3562	151	68	10864	77%
AR	6419	7505	275	13	14212	63%
CA	87904	23234	169	--	111308	79%
FL	19675	6593	117	--	26389	83%
GA	11455	9238	171	32	20896	69%
LA	10744	3928	475	23	15170	67%
MN	7516	9577	232	86	17411	64%
MS	6192	2307	151	21	8671	74%
NC	5375	10257	263	154	16049	43%
NY	20408	23109	298	205	44020	82%
PA	5869	5990	62	--	11930	77%
SC	4124	6972	219	61	11376	77%
TN	2544	6095	174	127	8940	33%
TX	19865	22018	601	62	42546	60%

The percent of children with depression that can be matched to a child without depression using the matching features exactly tis highly variable, as is the number that can be matched at all. In Tennessee, only 33% of children with depression have a match, and North Carolina is the second lowest with only 43% matched. No other states have a match percentage that is less than 50%. The best results are in New York and Florida, where 82% and 83% of children with depression are matched.

Table 30 contains the number of children that are matched exactly and with each relaxation in each state.

Because there are many children without an exact match in some states, we need to identify which criteria are the limiting factors. Table 31 below contains a simple summary of the children that cannot be matched, and a more detailed breakdown can be found in Appendix D.1 Table 42. In every state, there are more females that cannot be matched than males and (except for MS) more unmatched children in urban areas than suburban or rural areas. In all of the states there are more children age 15-17 that cannot be matched than children age 12-14, and in 9 of the states there are no unmatched 12-14-year-old children. The race with the most unmatched children varies by state; 9 states have the most unmatched white children; two states have the most unmatched black children and three states have the most unmatched other race children. Across all of the states together there are more white children that are unmatched than any other race.

Table 31: Number of children with depression that are unable to be matched by gender, race, age, and urbanicity

	Gender		Race			Age Group		Urbanicity		
State	F	M	White	Black	Other	15 to 17	12 to 14	Urban	Suburban	Rural
AL	2272	1035	1801	1401	105	3307	0	2325	753	186
AR	5873	2312	5606	1768	811	8185	0	4533	2029	1623
CA	17909	11563	11266	5314	12892	29472	0	28592	735	145
FL	3563	1805	1630	1880	1858	5368	0	5061	307	0
GA	6013	3160	4201	3961	1011	9142	31	6895	1583	678
LA	5480	1884	3920	3122	322	7364	0	5749	1388	227
MN	6414	3532	6720	1287	1939	9946	0	7891	1235	820
MS	1982	995	1055	1543	379	2953	24	1061	1164	637
NC	13614	7403	10607	8550	1860	18437	2580	18076	2813	128
NY	6689	2823	3795	1779	3938	9512	0	8940	540	0
PA	2543	1095	2691	668	279	3638	0	2704	710	224
SC	2612	866	1873	1224	381	3478	0	3225	253	0
TN	11573	6337	12633	4194	1083	16305	1605	13234	3965	711
TX	18525	10420	7706	5416	15823	26216	2729	26569	2224	152
Total	105062	55230	75504	42107	42681	153323	6969	134855	19699	5531

5.3.2 Utilization and Expenditure Comparison

Table 32 shows the median difference in utilization and expenditure between the depression and non-depression populations in all three major categories as well as for the total charges per patient per month enrolled in every state. The median values for the depression (Table 47) and non-depression (Table 48) populations individually are presented in Appendix D.

Table 32: Median of the difference in the number of visits (or units for RX) and charge amounts per patient per month enrolled between the depression and the non-depression population.

State	OT Visits	OT Charges	IP Visits	IP Charges	RX Units	RX Charges	Total Charges
AL	-4.1	-$718.20	0.00299	$76.73	-0.2	$37.09	-$604.40
AR	-7.0	-$900.10	0.00439	$25.82	20.3	$65.79	-$808.50
CA	-0.8	-$157.80	0.00608	$154.60	1.4	$16.90	$13.60
FL	-4.1	-$760.10	0.00417	-$102.50	11.7	$34.49	-$828.10
GA	-4.4	-$583.30	-0.00212	-$44.50	3.5	$15.31	-$612.50
LA	-6.1	-$985.00	0.00423	$6.80	17.0	$60.80	-$917.00
MN	-6.2	-$360.80	0.00382	$17.50	18.1	-$28.50	-$371.80
MS	-3.7	-$480.50	0.00474	$104.80	-30.8	$23.50	-$352.30
NC	-4.8	-$418.50	0.00049	$24.54	4.0	$37.76	-$356.20
NY	-4.6	-$415.90	0.00510	$1.68	452.5	$1,300.00	$885.90
PA	-4.7	-$390.20	0.00247	$54.53	9.1	$43.97	-$291.70
SC	-3.8	-$553.10	0.00241	$37.65	10.3	$30.11	-$485.30
TN	-5.2	-$221.20	0.00358	$19.11	6.3	$30.41	-$171.70
TX	-11.9	-$1,131.00	-0.00090	-$57.90	7.9	$128.40	-$1,060.00

Appendix D Table 49 contains the number of pairs of children in each state where at least one child in the pair has IP visits as well as p-values for the one-sided Wilcoxon tests with an alternative hypothesis that the utilization/charge for the depression population is greater than the utilization/charge for the non-depression population. After using the Bonferroni correction with an initial $\alpha = 0.1$ for multiple hypothesis testing, our new alpha value is $\alpha = 0.0071$. Even with this conservative alpha value, there are significantly more IP visits made by children in the depression population than by children without depression in every state. The charge per-patient per-month for IP visits is also significantly higher for children with depression in all 14 states.

Similarly, the utilization in units per patient per month enrolled and charge amounts per unit of prescription medication are higher for children with depression than for children without depression in every state. The p-values for the one-sided Wilcoxon test are included in Appendix D Table 49.

The number of pairs of children with each type of OT visits as well as the significance of the difference in utilization and charge amounts are presented in Appendix D Table 50 and Appendix D Table 51 . For Hospital/Urgent Care/Ambulance claims, children with depression in every state have significantly more visits and higher charges than children without depression. The opposite is true for ED and Other claims; there are significantly more visits and higher charges for children without depression than for those with depression in all fourteen states. For Office visits, the results vary by state. In Alabama, there are significantly more visits for children with depression, but the charges are not significantly higher. The number of visits is not greater but the charge amount is in Mississippi, New York, and Tennessee. Finally, in Arkansas, Minnesota, South Carolina and Texas, neither the utilization nor the charge amount for Office visits is significantly greater for children with depression.

For the combined OT visits per patient per month enrolled, the median of the differences in utilization and expenditures between the depression and non-depression population are negative in every state (indicating that the non-depression population generally has more visits and higher charges). The magnitude of the differences in utilization has limited variation across the states (11 of the 14 states have a difference between -3 and -6 visits). There are greater differences in the charge amounts. California has the smallest difference and Texas has the largest in both the visits (-0.795 and -11 visits per patient per month enrolled) and the charge amount (-$157 and -$1131 per patient per month enrolled).

Based on the Wilcoxon test, the total charge amount per patient per month enrolled is significantly different between the depression and non-depression populations in every state. The charges are significantly higher for the depression population in California, Florida, New York, and Pennsylvania. The largest median difference is in New York ($885) and California is the lowest ($13).

Using the Kruskall-Wallis test, we reject the null hypothesis (p-value $< 2.2e-16$) that the median utilization and expenditure for each type of service are the same in all of the states. Similarly, ANOVA rejects the null hypothesis, in tests for each type of service, that the mean utilization and cost is the same across all of the states. The number of pairs of states in which the difference is statistically significant varies by visit type. There are 91 pairs of states that are compared using Tukey's Test. For IP claims, there are significant differences in the per-patient monthly visits in 37 pairs of states, but only 5 pairs of states with significantly different charge amounts (California is different from Florida, Georgia, Louisiana, New York and Texas). New York is significantly different from every other state for both the number of units and the charge amounts for prescription medication, and no other pairs of states have significant differences. When comparing total OT utilization and expenditures, there are 64 states with differences in utilization and 37 with differing charge amounts. The full Tukey's Test results are shown in Appendix D Table 52.

5.4 Discussion

In every state, there are at least 4 children in the non-depression baseline population per child in the depression baseline population, with the majority of the states having between 10 and 20 non-depression children available to be matched with each child with depression. However, there are still thousands of children with depression that we are unable to match to a similar child without depression using the specified matching criteria. The percent of children that we are able to match in each state is not strongly correlated with the number of available matches per child with depression (correlation = 0.49). This indicates that the total number of children available for matching is not the limiting factor in whether or not we are able to identify suitable matches.

In Tennessee and North Carolina in particular, we have over 50% of the depression population that remains unmatched and is therefore excluded from this comparison analysis. The largest unmatched group in Tennessee (44% of the unmatched children) is white children age 15-17 in urban and areas. In North Carolina, 44% of the unmatched children with depression are black and white females age 15-17 living in urban areas, with an additional 22% of the unmatched children being males with the same characteristics. Because of the population density of urban areas, it is not surprising that in terms of absolute numbers that is where the largest percent of unmatched children live.

While the average differences in IP utilization are significant for all of the states except for North Carolina and the median difference is significant in all of the states, the magnitude is relatively small and children with depression have less than 0.65 additional inpatient stay per year on average than their non-depression counterparts. When we consider the difference over six years to account for the age range we consider (12-17), however, the seemingly small differences in utilization adds up and in 7 of the 14 states there would be on average approximately 2 more inpatient visits per child with depression.

The median charge for inpatient visits in every state is also higher for children with depression. With both a higher median utilization and charge amount, the total cost for inpatient care for children with depression is higher than that for children without depression.

Based on the paired Wilcoxon test, there are significantly more RX units and fills in every state for the depression population than for the non-depression population. Based on the paired t-test, however, children with depression only have significantly more prescriptions units filled than children without depression in half of the states even though the number of fills is significantly higher in every state. Because the number of time depression children had prescriptions filled is significantly higher even when the units of medication is not, we can determine that the units per prescription fill is lower on average in the states without significant differences in the number of units. This could mean that children have to have prescriptions for medications that they need filled more frequently, which is less convenient and may lead to missed medication days[161] if there is a gap between when one prescription runs out and when the refill can be picked up.

The average difference in prescription units for the depression and non-depression populations in 13 of the states ranges from 1.7 (California) to 21 (Arkansas) additional units per month for children with depression, which is less than one additional unit per day. The extremely high difference in New York of 512 units per month is approximately 16 units per day different for each child with depression. Further study would be needed to understand why the average difference is so high in New York alone, because the number of prescriptions fills is not disproportionality large in New York. In addition, as shown in chapter 4, RX utilization for depression treatment is lower in New York from 2005-2012 than in almost any other state.

Children with depression have significantly higher severe outcome rates that require outpatient services at hospitals, in ambulances, and in urgent care centers in all 14 states. California, Louisiana and Minnesota have the greatest differences with at least one additional visit per month on average. These same three states have the highest difference in ED utilization as well, averaging more than two additional visits per depression patient per month. Having such high utilization of outpatient hospitals, urgent care facilities, and emergency departments indicates that these children are likely not receiving adequate preventative care. The costs per patient per month for these severe outcome treatments are also higher.

Utilization of office visits and “Other” OT visits are also significantly larger on average for the depression population for all states except for Pennsylvania (office only) and Texas. Even though the average utilization is not significantly higher for depression children in those two states, the median utilization is.

Overall, we see that there is higher utilization of health care services for children with depression. Even in the cases where the average utilization is not significantly larger, the median utilization is significantly larger for the depression population. The magnitude of the difference in utilization between the depression and non-depression populations varies across the states, which could be the result of state level health care policies or in part because of the effectiveness of depression treatment. The same is true for the expenditures in every state. The Medicaid charge amounts are consistently higher per patient per month enrollment among the population with depression.

These utilization and expenditure differences confirm that, separate from their depression treatment, children with depression require more frequent and more costly care. Therefore, it would be advantageous from both a health and a cost perspective for as many as children as possible to receive an early diagnosis and treatment to increase the likelihood of entering remission.

Limitations

The primary limitation in this study is the reduction of the sample size due to the number of children with depression that cannot be matched to a child without depression given the matching constraints. In addition, the scope of the study is limited to two years. With additional years of data, a longitudinal approach to track patients from age 12 to 17, or a longer-term analysis where a larger percent of the children may be enrolled for multiple years could be conducted. Finally, it is possible that there are children in the non-depression population that have mental health conditions other than major depression, dysthymia or depression not otherwise specified. Anxiety, bipolar disorder, and other mental health conditions are not included and thus could be present in the rest of the population.

CHAPTER 6. CONCLUSION

Asthma and depression are two of the most prevalent chronic pediatric health conditions in the United States and adequate treatment of these conditions is a critical factor in improving the health outcomes of the children who are affected by them. This thesis serves two purposes: to quantify spatial access to pediatric asthma care and to analyze the differences in healthcare utilization between children with and without depression among the Medicaid population.

We began by computing the spatial access to pediatric asthma specialist care. By using an optimization model to assign patients to providers, we are able to account for practical system constraints and obtain the average driving distance using the US highway network for children in each tract to receive asthma specialist care. This access measure is more accurate than measures obtained using other common methods, and is also straightforward to understand. We find that there is significant variation in the distribution of the access to care both within individual states and between the states in the study. Therefore, while access to asthma specialist care is, overall, better in some states than others, there is room for improvement in every state. After computing the estimates of spatial access to asthma specialist care, we use them in regression models for two states to demonstrate and quantify the significance of that access on the rate of severe health outcomes. We find that access to specialist care is statistically significant when estimating both ED and Hospitalization rates, and that the variation of the distance to receive care within each county as well as geographic access to primary care are also significant. These spatial access measures are significant on their own and in their interactions with other predictors. Therefore, a state by state analysis of potential interventions will be necessary because the improvements to one type of access or another will not have a uniform impact on the children in different areas.

After establishing the significance of geographic access to both primary and specialist care, we expand the optimization assignment model to conduct a seasonal analysis that includes both primary and specialist providers and also divides the patient population into children with Medicaid and children who are not on Medicaid. Among primary care providers in every state, there is very little variation in the percent of each provider's caseload that is allocated to pediatric asthma visits. The same is not true for asthma specialist providers. The percent of each specialist's caseload allocated to pediatric asthma ranges from less than 2% to almost 70%.

The unexpected result from the model is that there are no significant seasonal variations in access to either primary or specialist care in spite of the seasonality of the demand for asthma visits. Where there are significant differences in access to the different types of care. There are numerous census tracts in each state in which all visits that should be met by an asthma specialist are instead assigned to a primary care provider because of insufficient specialist capacity. In addition, Medicaid patients requiring specialist care have the greatest driving distances to receive care in almost every state. Because of the lack of seasonality of access to care, seasonal interventions will be insufficient. In order to improve access to care, permanent improvements to the health care network (such as increasing Medicaid acceptance, locating new providers, or increasing asthma training among primary care providers) will be necessary.

To begin our analysis of pediatric depression, we established a baseline for pediatric depression in the Medicaid population for the years 2005 to 2012. Other sources provide prevalence estimates for particular subsets of the pediatric population based on one or two demographic factors; however, they do not provide prevalence information for children specifically in the Medicaid population. By using diagnosis codes, treatment procedure codes, and national drug codes to select records from the MAX files, we identify the population of children age 12-17 with Medicaid insurance that have depression and compute their utilization of depression treatment. One of the most important findings is that the treated prevalence of depression in the Medicaid population is lower than 4% across the entire period for every state except Arkansas and North Carolina, while the CDCs prevalence estimates for depression rates in the total adolescent population have a lower bound of 4%. This under-diagnosis of depression in the Medicaid population is of particular concern because these adolescents have higher risk factors for depression. The utilization of depression treatment services is highly variable between the states, indicating that children in different states do not receive the same types of depression care. In addition, the overall use of psychological service is insufficient to meet the minimally adequate treatment guidelines, while prescription use increases in every state over the entire study period. The low prevalence and psychological service rates suggest that diagnosis and treatment of pediatric depression among the Medicaid population should be improved.

In the final study of the thesis, we build on the depression baseline and analyze the differences in non-depression health care utilization and cost between the depression and non-depression populations in the MAX files. By scaling each patient's visits/prescription units and charge amounts by months of enrollment, we are able to compare the utilization and expenditures of children over a two-year period even when they are enrolled in the system for variable amounts of time. From the Wilcoxon test to compare the median utilization and charge amounts between the two groups in each state, we find that children with depression have both higher utilization and higher charge amounts than children without depression for some service types (IP, RX, OT-Hospitalizations) but not for other service types (OT-ED, OT-Other).

APPENDIX A. ADDITIONAL INFORMATION FOR CHAPTER 2

The results of the logistic regressions for estimating severe asthma outcomes are shown below in Table 33 for Georgia and Table 34 for North Carolina, with the R square values in Table 35.

Table 33. GA Regression Results. For the categorical age variable, age 15 to 17 is omitted as the reference variable. The reference value for numeric variables is 0. Highlighted rows indicate access variables.

	ED Visits		Hospitalizations	
	Estimate (Std. Error)	P-Value	Estimate (Std. Error)	P-Value
(Intercept)	-3.068(0.033)	< 0.001	-6.214(0.108)	< 0.001
Age 5-9	0.554(0.036)	< 0.001	1.606(0.106)	< 0.001
Age 10-14	0.974(0.039)	< 0.001	1.633(0.111)	< 0.001
MedianIncome	-0.375(0.023)	< 0.001	-0.479(0.038)	< 0.001
AdultEducation	-0.187(0.019)	< 0.001	-0.120(0.051)	0.02
Nonhospital	0.127(0.005)	< 0.001	0.087(0.015)	< 0.001
SpecialistDistance	0.029(0.017)	0.102	-0.057(0.047)	0.226
PrimaryDistance	0.013(0.027)	0.648	-0.198(0.047)	< 0.001
VarSpecialistDistance	-0.005(0.021)	0.808	0.050(0.052)	0.337
PrimaryDistance: AdultEducation	0.061(0.023)	0.009	0.125(0.041)	0.003
VarSpecialistDistance: AdultEducation	-0.165(0.029)	< 0.001	-0.200(0.051)	< 0.001
PrimaryDistance:Age 5-9	-0.157(0.027)	< 0.001		
PrimaryDistance:Age 10-14	-0.145(0.029)	< 0.001		
SpecialistDistance: PrimaryDistance	-0.070(0.017)	< 0.001	-0.134(0.047)	0.005
VarSpecialistDistance: Age 10-14	0.108(0.032)	0.001		
PrimaryDistance: MedianIncome	-0.104(0.020)	< 0.001		
SpecialistDistance: MedianIncome	0.115(0.020)	< 0.001		
SpecialistDistance: AdultEducation	0.083(0.017)	< 0.001		
VarSpecialistDistance: MedianIncome	-0.119(0.028)	< 0.001		

Table 34. NC Regression Results. For the categorical age variable, age 15 to 17 is omitted as the reference variable. The reference value for numeric variables is 0. Highlighted rows indicate access variables.

	NC ED Visits		NC Hospitalizations	
	Estimate (Std. Error)	P-Value	Estimate (Std. Error)	P-Value
(Intercept)	-1.727(0.018)	< 0.001	-4.726(0.063)	< 0.001
Age 5-8	0.584(0.023)	< 0.001	1.974(0.063)	< 0.001
Age 9-14	0.165(0.021)	< 0.001	0.485(0.065)	< 0.001
MedianIncome	-0.088(0.013)	< 0.001	-0.278(0.036)	< 0.001
AdultEducation	0.071(0.012)	< 0.001	0.043(0.033)	0.2
NumHospitals	0.120(0.007)	< 0.001	0.053(0.037)	0.1524
SpecialistDistance	0.050(0.016)	0.002	0.072(0.036)	0.045
VarSpecialistDistance	-0.184(0.023)	< 0.001	0.218(0.046)	< 0.001
PrimaryDistance	0.066(0.018)	< 0.001	-0.094(0.042)	0.029
PrimaryDistance:Age5-8	0.061(0.021)	0.005	0.098(0.039)	0.013
PrimaryDist:Age 9-14	-0.052(0.019)	0.009		
PrimaryDist: AdultEducation	-0.030(0.014)	0.033	-0.089(0.042)	0.035
SpecialistDistance: MedianIncome	-0.061(0.012)	< 0.001		
VarSpecialistDist: MedianIncome	-0.120(0.018)	< 0.001		
PrimaryDistance: MedianIncome	0.101(0.014)	< 0.001	-0.086(0.048)	0.073
SpecialistDistance: Age5-8	-0.060(0.025)	0.017		
VarSpecialistDistance: Age5-8	0.156(0.037)	< 0.001		
VarSpecialistDistance: AdultEducation	-0.156(0.015)	< 0.001		
PrimaryDist: SpecialistDist			0.299(0.046)	< 0.001
SpecialistDistance: AdultEducation			-0.154(0.039)	< 0.001
SpecialistDistance: VarSpecialistDistance			-0.095(0.031)	0.002
PrimaryDistance:NumHospitals			0.064(0.023)	0.0074
VarSpecialistDistance: PrimaryDistance			-0.318(0.056)	< 0.001
MedianIncome: AdultEducation			-0.079(0.029)	0.007
MedianIncome: NumHospitals			0.241(0.032)	< 0.001
AdultEducation: NumHospitals			0.302(0.048)	< 0.001
Age9-14: AdultEducation			0.075(0.035)	0.034

Table 35 : Pseudo-R square for logistic regression with replications as provided by the selected fitted models for all four cases

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

APPENDIX B. ADDITIONAL INFORMATION FOR CHAPTER 3

B.1 Season Identification

Because the geographic scope of the project is limited to the Southeast United States, it is assumed that the seasons start at the same time in each state. We identify the start and end dates of each season using the public-school calendars in each state[162]. The start and end dates of each academic semester, fall and spring, are collected for each state for 2010 and the most common date for each season is selected. Table 36 below shows the week number (where week 1 starts on the first Monday of January) for the academic year seasons.

Table 36: Week numbers corresponding to the start and end of the academic year seasons

	AL	AR	FL	GA	LA	NC	MS	SC	TN	TX	Model Selection
Spring Start	1	1	1	1	1	1	1	1	1	1	1
Spring End/Summer Start	25	21	24	22	23	22	22	23	22	23	22
Summer End/Fall Start	36	34	35	33	33	35	34	34	34	34	34
Fall End	52	52	52	52	52	52	52	52	52	52	52

The fall season has 18 weeks, the spring season has 22 weeks, and the summer season has 12 weeks. These seasons will be used in both the provider capacity and the patient demand estimation sections.

B.2 Provider Type

The National Uniform Claims Committee [47] maintains the list of standard Taxonomy Codes that identify the different provider types. From the complete list of Taxonomy Codes, we extract the subset that identify primary care physicians and asthma specialists. The codes for primary care providers are based on the work of Gentilli et al. [163] and include those for Pediatricians, Pediatric Nurse Practitioners, Family Medicine and Internal Medicine. The set of codes for asthma specialists includes those for Pulmonologists, Pediatric Pulmonologists, Allergists, and Pediatric Allergists. The full list of included taxonomy codes is listed in Table 37 below.

Table 37: NUCC Taxonomy Codes for Primary Care Providers and Asthma Specialists

Taxonomy Code	Type	Classification	Specialization
208000000X	Allopathic & Osteopathic Physicians	Pediatrics	Allopathic & Osteopathic Physicians
2080A0000X	Allopathic & Osteopathic Physicians	Pediatrics	Adolescent Medicine
208D00000X	Allopathic & Osteopathic Physicians	General Practice	Allopathic & Osteopathic Physicians
207R00000X	Allopathic & Osteopathic Physicians	Internal Medicine	Allopathic & Osteopathic Physicians
207RA0000X	Allopathic & Osteopathic Physicians	Internal Medicine	Adolescent Medicine
207Q00000X	Allopathic & Osteopathic Physicians	Family Medicine	Allopathic & Osteopathic Physicians
207QA0000X	Allopathic & Osteopathic Physicians	Family Medicine	Adolescent Medicine
363LP0200X	Physician Assistants & Advanced Practice Nursing Providers	Nurse Practitioner	Pediatrics
208D00000X	Allopathic & Osteopathic Physicians	General Practice	Allopathic & Osteopathic Physicians
207Q00000X	Allopathic & Osteopathic Physicians	Family Medicine	Allopathic & Osteopathic Physicians
207R00000X	Allopathic & Osteopathic Physicians	Internal Medicine	Allopathic & Osteopathic Physicians
363A00000X	Physician Assistants & Advanced Practice Nursing Providers	Physician Assistant	Physician Assistants & Advanced Practice Nursing Providers
363L00000X	Physician Assistants & Advanced Practice Nursing Providers	Nurse Practitioner	Physician Assistants & Advanced Practice Nursing Providers
207K00000X	Allopathic & Osteopathic Physicians	Allergy & Immunology	
207KA0200X	Allopathic & Osteopathic Physicians	Allergy & Immunology	Allergy
207KI0005X	Allopathic & Osteopathic Physicians	Allergy & Immunology	Clinical & Laboratory Immunology
207RA0201X	Allopathic & Osteopathic Physicians	Internal Medicine	Allergy & Immunology
207RP1001X	Allopathic & Osteopathic Physicians	Internal Medicine	Pulmonary Disease
2080P0201X	Allopathic & Osteopathic Physicians	Pediatrics	Pediatric Allergy/Immunology
2080P0214X	Allopathic & Osteopathic Physicians	Pediatrics	Pediatric Pulmonology

B.3 Distance Computations

We used version 10.5 of the ArcMap software to compute all of the distances that are needed for the model. Locations are loaded into the software using latitude and longitude coordinates. The software computes distances between specified locations using the US Highway Network rather than a distance estimate such as the Euclidean or Manhattan distance. This is an important distinction because using the highway network to compute distances provides the distance that an individual would have to drive to get from one location to another using the actual roads available, which is a much more accurate representation of the real distances traveled.

B.3.1 Provider to Tract Distances

Our access models assume the travel distance to be the cost of matching a patient visit to a provider. These distances are computed using ArcMap10 and the US Highway Network. It is assumed that all patients in a particular census tract are located at the centroid of that tract. We use the ArcMap software rather than a distance estimate (Euclidean, Manhattan etc.) so that the optimization model's output will be driving distances to receive care.

ArcMap uses latitude and longitude coordinates to locate the origins and destinations. These values are readily available for census tract centroids from the Tiger Files [164]. The NPI database lists the street address of each provider, and the corresponding latitude and longitude are obtained by using the Texas A&M Geocoding Service [94].

For each state, the origin set consists of all census tracts in the state and the destination set contains the complete list of providers (primary and specialist care) that see asthma patients. We compute the distance between each origin and destination pair, and the distance between census tract i and provider j is used as the cost to assign 1 visit from census tract i to provider j in the optimization model.

B.3.2 Neighboring Census Tracts

For each state, both the origin and the destination set is the list of census tract centroids. The output from the ArcMap software is the distance between each pair of census tract centroids. Two tracts are considered to be neighbors if the distance between their centroids is less than 10 miles, so we create a binary matrix indicating which pairs of tracts are neighbors, and a data matrix with the distances between only those tracts that are neighbors to use as inputs for the optimization model.

B.3.3 Driving Distance Guidelines for Identification of Unmet Need

The United States Department of Health and Human Services has published access guidelines for primary and specialist care for the Medicaid population in some states[100]. There are not guidelines for all of the states considered in this work, and there are large differences in the guidelines for different states even when they do exist. Table 38 below shows the access guidelines as presented in Appendix A of the Department of Health and Human Services Report.

Table 38: US Government Medicaid access standards for Urban and Rural Primary and Specialist care

State	Primary Care	Specialist Care
GA	Urban: Two providers within 8 miles Rural: Two providers within 15 miles	Urban: One provider within 30 miles Rural: One provider within 45 miles
MS	Urban: Two providers within 30 miles Rural: Two providers within 60 miles	No Standard
TN	Urban: 1 provider within 20 miles Rural: 1 provider within 30 miles	1 provider within 60 miles for 75% of enrollees and 1 provider within 90 miles for all enrollees

B.4 Providers Other than Primary and Asthma Specialists

In each of the seven states, there are over 100 providers in the Medicaid MAX files that have at least 11 different claims per year reported with diagnosis codes that are not in the categories for either primary or asthma specialist providers. There are 79 different physician classifications (from the NUCC Taxonomy Codes) with physicians that have asthma claims. Many of these providers will not realistically treat asthma patients, and only 11 of the classifications have at least 15 providers with asthma records in one or more states.

Table 39 below lists the number of physicians and the percent of ‘other Medicaid’ physicians in that category by type and classification for the classifications with more than 15 providers or 10% of the total ‘other Medicaid’ providers for at least one state.

The number of the other Medicaid providers in each state may also provide another measure of the quality of the data in each state and/or the types of providers that may be actually treating asthma patients. For example, it is unlikely that a medical supplier is providing asthma treatment, and there are between 9 and 152 of these providers with asthma claims in each state. Nurse Practitioners (without a pediatric specialty), however, are likely to treat children with asthma and there are 286 of these providers in MS. In addition, the number of ‘other’ providers is not directly related to the size of the population in the state- MS has 1,050 and TX only has 159.

Table 39: Other Medicaid providers that have asthma visits

		AL		AR		GA		LA		MS		NC		TN	
Total 'Other' Medicaid Providers		256		114		478		690		1059		555		426	
Type	**Classification**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**
Suppliers	Durable Medical Equipment & Medical Supplies	61	24%	9	8%	49	10%	66	10%	152	14%	109	20%	43	10%
Allopathic & Osteopathic Physicians	Emergency Medicine	54	21%	25	22%	60	13%	71	10%	92	9%	77	14%	50	12%
Other Service Providers	Specialist	34	13%	9	8%	33	7%	38	6%	26	2%	20	4%	53	12%
Allopathic & Osteopathic Physicians	Radiology	17	7%	11	10%	36	8%	45	7%	54	5%	25	5%	20	5%
Physician Assistants & Advanced Practice Nursing Providers	Nurse Practitioner	12	5%	5	4%	24	5%	60	9%	286	27%	3	1%	48	11%
Ambulatory Health Care Facilities	Clinic/Center	11	4%	16	14%	31	6%	36	5%	58	5%	31	6%	5	1%
Allopathic & Osteopathic Physicians	Pediatrics	10	4%	4	4%	48	10%	17	2%	8	1%	12	2%	13	3%
Suppliers	Pharmacy	10	4%	0	0%	3	1%	0	0%	7	1%	82	15%	3	1%
Hospitals	General Acute Care Hospital	3	1%	1	1%	67	14%	200	29%	224	21%	93	17%	95	22%
Physician Assistants & Advanced Practice Nursing Providers	Physician Assistant	1	0%	0	0%	30	6%	10	1%	9	1%	2	0%	13	3%
Student, Health Care	Student in an Organized Health Care Education/Training Program	1	0%	13	11%	0	0%	3	0%	4	0%	1	0%	6	1%
Allopathic & Osteopathic Physicians	Pathology	1	0%	0	0%	0	0%	3	0%	0	0%	1	0%	0	0%

B.5 Additional Statistical Test Results for Unmet Need

The results of the statistical tests to determine for which pairs of states the difference in unmet need is significantly different for each provider type in a rural and urban setting are shown in the tables below. Significant differences have p-values that are highlighted in green.

Table 40: Tukey Test results for unmet need (percent of visits that cannot be assigned to a provider within an acceptable distance) in rural areas in each state

	MD Rural		MDM Rural		S Rural		SM Rural	
	diff	p-value	diff	p-value	diff	p-value	diff	p-value
AR-AL	-0.0027	1.0000	0.0237	0.5171	-0.0135	0.9879	-0.1070	0.0172
GA-AL	-0.0418	0.3784	0.0052	0.9998	-0.0770	0.0007	-0.1274	0.0039
LA-AL	-0.0170	0.9959	0.0366	0.3977	-0.0593	0.1983	-0.1694	0.0040
MS-AL	-0.0369	0.7448	0.0163	0.9553	-0.0581	0.1304	-0.1629	0.0017
NC-AL	0.0016	1.0000	0.0342	0.1223	-0.0245	0.8172	-0.0608	0.5165
TN-AL	-0.0332	0.7912	0.0206	0.8432	-0.0619	0.0583	-0.0729	0.5134
GA-AR	-0.0390	0.2015	-0.0185	0.6148	-0.0636	0.0004	-0.0204	0.9899
LA-AR	-0.0143	0.9971	0.0129	0.9851	-0.0458	0.3670	-0.0624	0.7239
MS-AR	-0.0341	0.6853	-0.0074	0.9986	-0.0446	0.2521	-0.0559	0.7122
NC-AR	0.0044	1.0000	0.0104	0.9497	-0.0110	0.9864	0.0462	0.5565
TN-AR	-0.0305	0.7315	-0.0031	1.0000	-0.0485	0.1118	0.0341	0.9512
LA-GA	0.0248	0.9560	0.0314	0.4943	0.0177	0.9870	-0.0421	0.9542
MS-GA	0.0049	1.0000	0.0111	0.9897	0.0189	0.9678	-0.0356	0.9649
NC-GA	0.0434	0.1258	0.0290	0.1264	0.0526	0.0103	0.0666	0.2112
TN-GA	0.0086	0.9996	0.0154	0.9292	0.0151	0.9863	0.0545	0.7214
MS-LA	-0.0199	0.9929	-0.0203	0.9387	0.0012	1.0000	0.0065	1.0000
NC-LA	0.0186	0.9882	-0.0024	1.0000	0.0348	0.7060	0.1086	0.1148
TN-LA	-0.0162	0.9972	-0.0160	0.9770	-0.0027	1.0000	0.0965	0.3664
NC-MS	0.0385	0.5646	0.0179	0.8808	0.0336	0.6160	0.1021	0.0770
TN-MS	0.0037	1.0000	0.0043	1.0000	-0.0039	1.0000	0.0900	0.3398
TN-NC	-0.0348	0.6066	-0.0136	0.9539	-0.0375	0.4018	-0.0121	0.9998

Table 41: Tukey Test Results for unmet need (percent of visits that cannot be assigned to a provider within an acceptable distance) in urban areas in each state

	MD Urban		MDM Urban		S Urban		SM Urban	
	diff	p-value	diff	p-value	diff	p-value	diff	p-value
AR-AL	0.0294	0.0001	0.0488	0.0000	0.0155	0.1714	0.0284	0.0052
GA-AL	-0.0115	0.1526	0.0003	1.0000	-0.0244	0.0000	-0.0703	0.0000
LA-AL	0.0705	0.0000	0.0773	0.0000	0.0306	0.0000	-0.0164	0.1131
MS-AL	-0.0056	0.9693	-0.0076	0.9409	0.0088	0.7558	-0.0514	0.0000
NC-AL	-0.0026	0.9975	0.0058	0.9279	-0.0078	0.5663	-0.0412	0.0000
TN-AL	-0.0067	0.8049	0.0036	0.9959	-0.0074	0.7030	-0.0604	0.0000
GA-AR	-0.0409	0.0000	-0.0485	0.0000	-0.0398	0.0000	-0.0987	0.0000
LA-AR	0.0410	0.0000	0.0285	0.0032	0.0152	0.1891	-0.0448	0.0000
MS-AR	-0.0350	0.0000	-0.0563	0.0000	-0.0067	0.9642	-0.0798	0.0000
NC-AR	-0.0320	0.0000	-0.0429	0.0000	-0.0232	0.0012	-0.0696	0.0000
TN-AR	-0.0361	0.0000	-0.0452	0.0000	-0.0228	0.0030	-0.0888	0.0000
LA-GA	0.0820	0.0000	0.0770	0.0000	0.0550	0.0000	0.0538	0.0000
MS-GA	0.0059	0.9411	-0.0079	0.8991	0.0332	0.0000	0.0189	0.0843
NC-GA	0.0089	0.2385	0.0055	0.8910	0.0166	0.0002	0.0290	0.0000
TN-GA	0.0048	0.9179	0.0033	0.9951	0.0170	0.0008	0.0098	0.4730
MS-LA	-0.0761	0.0000	-0.0849	0.0000	-0.0219	0.0042	-0.0350	0.0000
NC-LA	-0.0731	0.0000	-0.0715	0.0000	-0.0384	0.0000	-0.0248	0.0001
TN-LA	-0.0772	0.0000	-0.0737	0.0000	-0.0380	0.0000	-0.0440	0.0000
NC-MS	0.0030	0.9982	0.0134	0.3877	-0.0165	0.0369	0.0102	0.7413
TN-MS	-0.0011	1.0000	0.0111	0.6690	-0.0161	0.0675	-0.0090	0.8637
TN-NC	-0.0041	0.9551	-0.0023	0.9993	0.0004	1.0000	-0.0192	0.0027

APPENDIX C. ADDITIONAL INFORMATION FOR CHAPTER 4

C.1 3M Clinical Risk Group (CRG) Classification

A Clinical Risk Group (CRG) is assigned to each Medicaid patient for each year using the 3M Clinical Risk Grouping Software. CRGs relate an individual's utilization history to the amount and type of healthcare resources they will use in the future. To assess how expenditure changes over time, only one year of history was processed at a time.

The software assigns one of 1,080 possible CRGs to each patient primarily using the diagnosis codes, procedure codes, and national drug codes (NDCs) found in their claims. These codes are used to determine Episode Diagnostic Categories (EDCs) and Episode Procedure Categories (EPCs). EPCs are not heavily used by the software in order to prevent organizations from being incentivized to avoid enrolling people with a history of major procedures and because poor-quality care may result in procedures that are otherwise avoidable. EDCs, on the other hand, are used to determine a patient's Primary Chronic Disease, which is the most significant chronic disease actively being treated, and its severity for each organ system. This is done in a hierarchical fashion so that more severe chronic conditions and more recent or recurrent conditions are given priority. A severity level, which describes the disease's progression and the need for future medical services, is also determined for each Primary Chronic Disease based on the sites of service and other EDCs and EPCs. Finally, a patient is assigned to the CRG with the most serious status for which they qualify based on their Primary Chronic Diseases, EDCs, and EPCs. The first digit of this CRG represents a patient's status, and the last digit represents their severity within that status.

The 3M Software also further combines CRGs into three levels of Aggregated Clinical Risk Groups (ACRGs). ACRG 1 is the least aggregated and ACRG 3 is the most. In these aggregations, the first digit is maintained, but the digit representing severity may be adjusted.

In our analysis, we consider only the first digit of a patient's ACRG 1 code unless that digit is '5'. CRG Status 5 is divided into two groups based on whether the patient's condition, as described by their assigned ACRG 1, is episodic or lifelong.

C.1 Stratified Depression Visits

Figure 23 through Figure 34 below show the breakdown of depression visits in each state by stratification. The values represent the percent of total depression visits each strata subcategory utilized in a single year, where visits are classified as any depression related behavioral therapy treatments, emergency room uses, or medication fills.

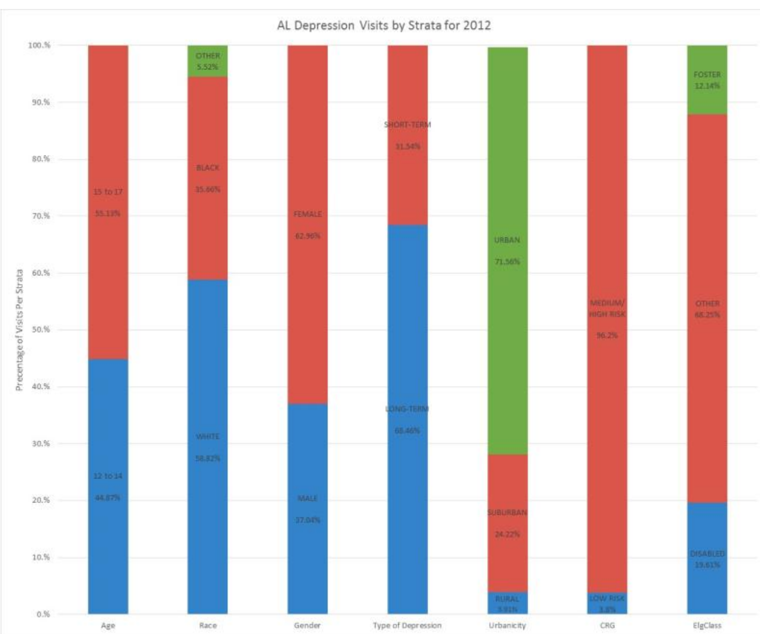

Figure 23: Depression visits by strata in Alabama for 2012

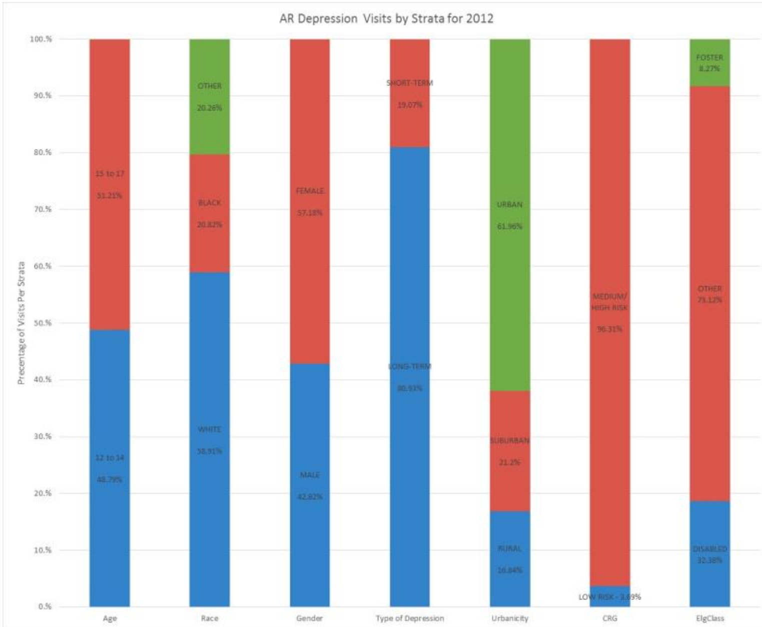

Figure 24: Depression visits by strata in Arkansas for 2012

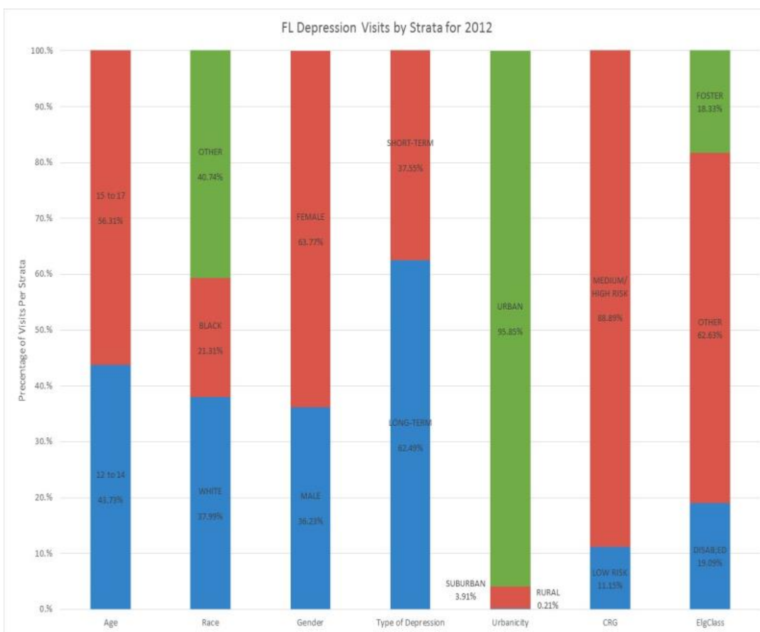

Figure 25: Depression visits by strata in Florida for 2012

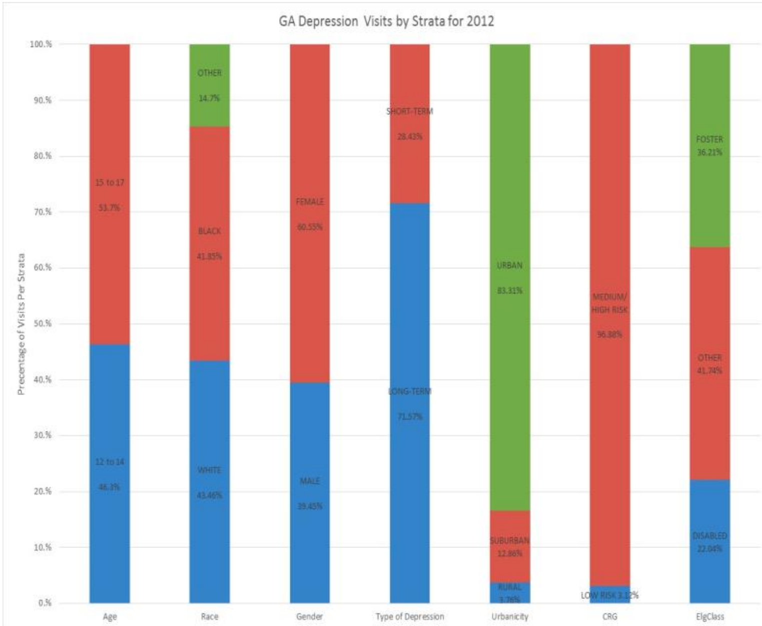

Figure 26: Depression visits by strata in Georgia for 2012

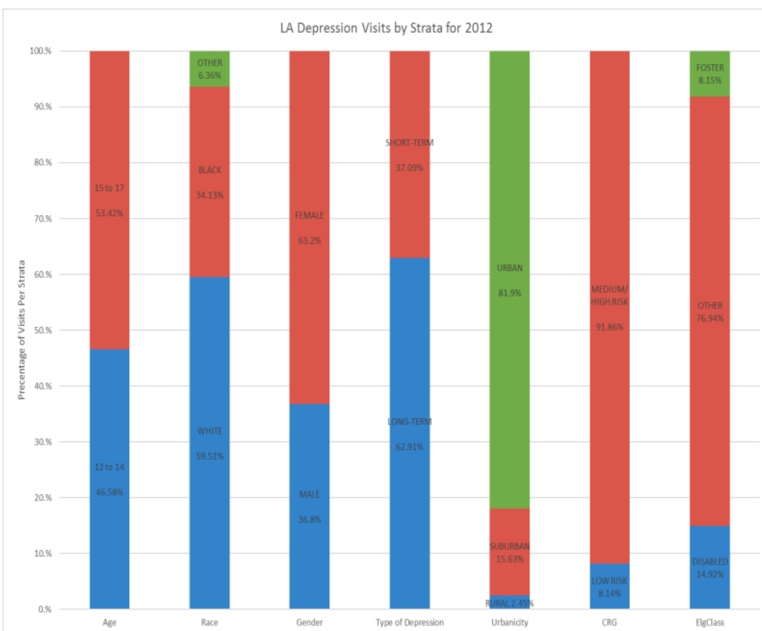

Figure 27: Depression visits by strata in Louisiana for 2012

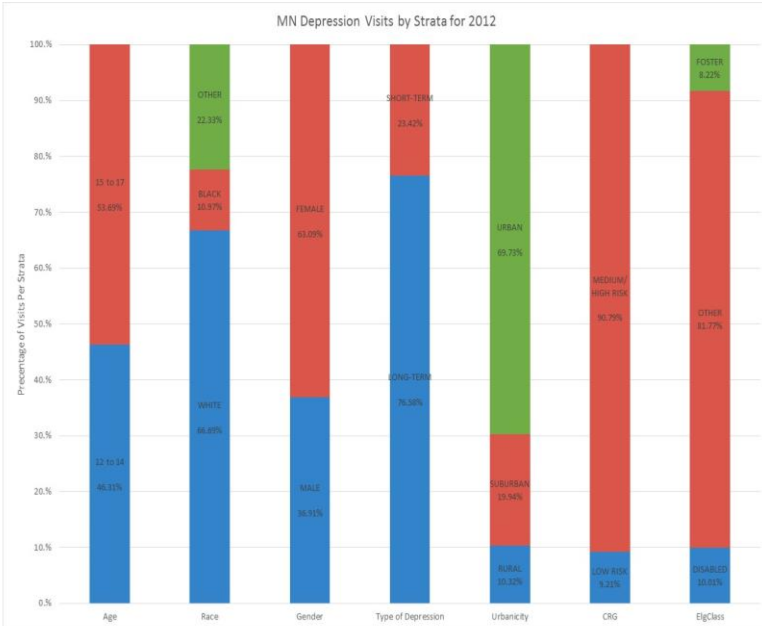

Figure 28: Depression visits by strata in Minnesota for 2012

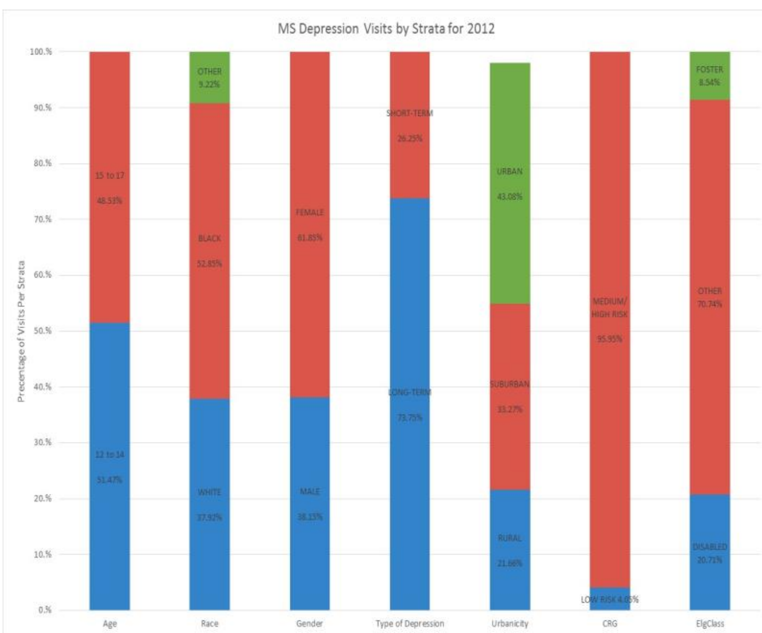

Figure 29: Depression visits by strata in Mississippi for 2012

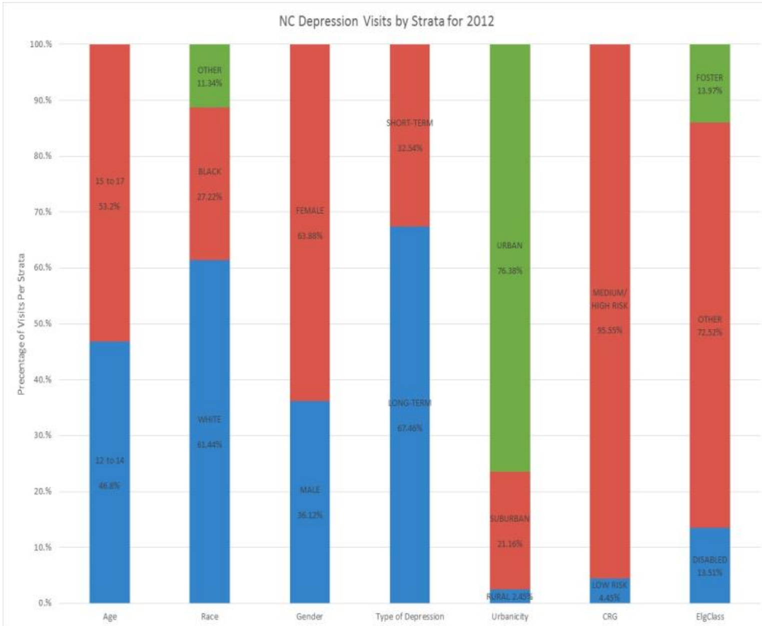

Figure 30: Depression visits by strata in North Carolina for 2012

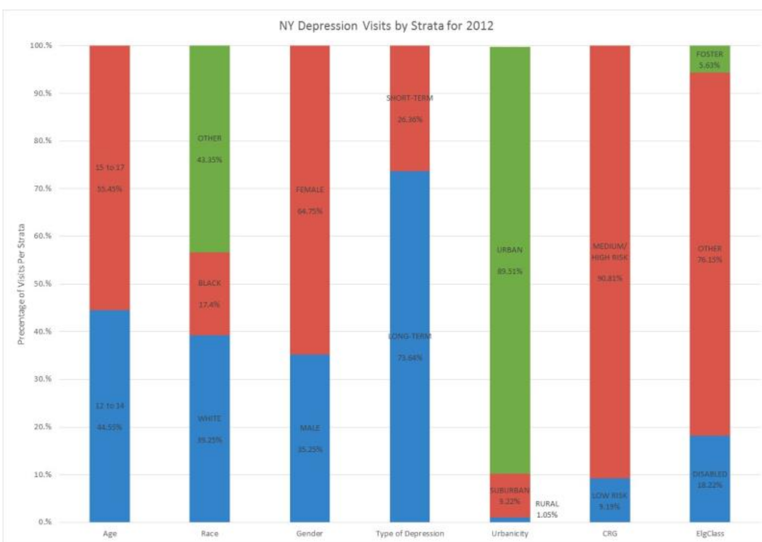

Figure 31: Depression visits by strata in New York for 2012

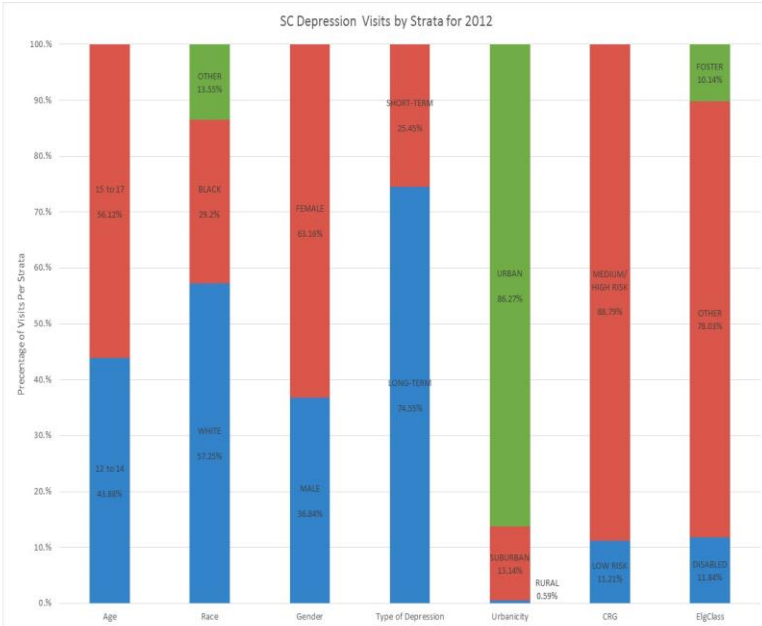

Figure 32: Depression visits by strata in South Carolina for 2012

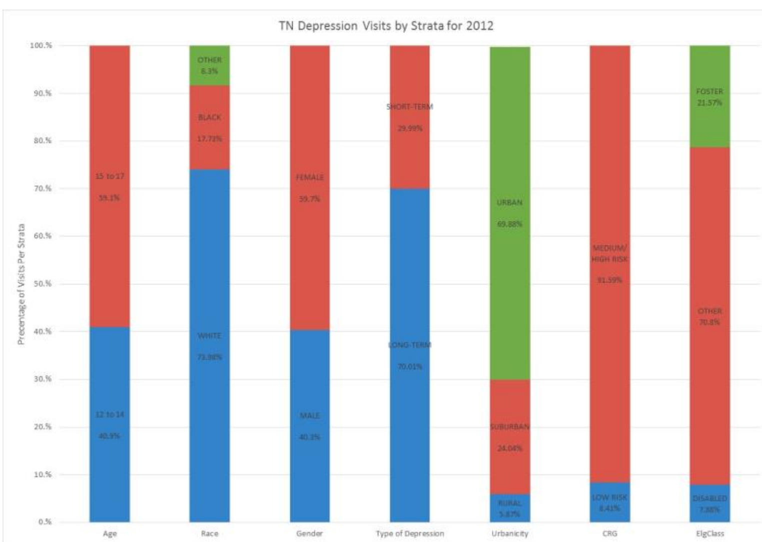

Figure 33: Depression visits by strata in Tennessee for 2012

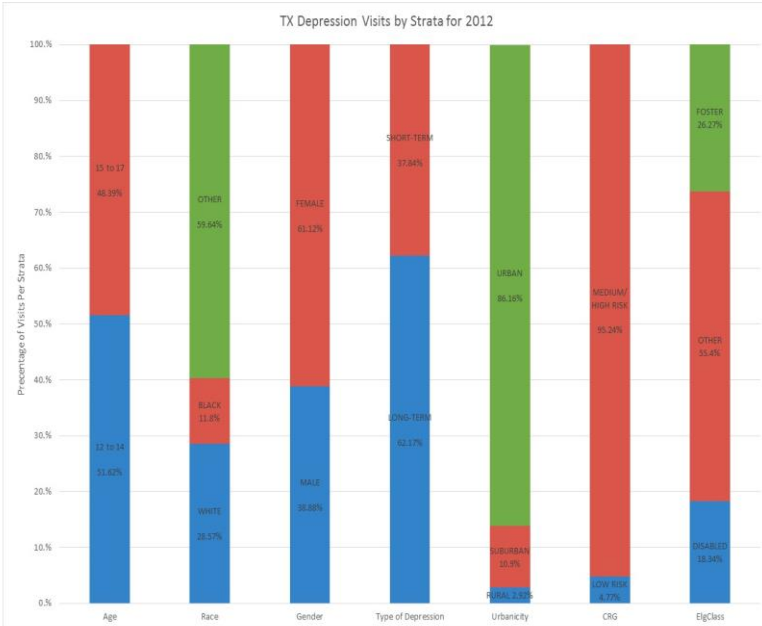

Figure 34: Depression visits by strata in Texas for 2012

APPENDIX D. ADDITIONAL INFORMATION FOR CHAPTER 5

D.1 Unmatched Children with Depression

There are many children with depression in each state that we are not able to match to a similar child that does not have depression. The number of such children in each state with each set of characteristics (for those combinations with at least 11 children) are shown in Table 42 below.

Table 42: Count of unmatched children with depression by state broken down by stratification

Age	Race	Gender	Urbanicity	AL	AR	CA	FL	GA	LA	MN	MS	NC	NY	PA	SC	TN	TX
15 to 17	White	F	Urban	816	2049	6438	1116	1954	2188	3229	316	5185	2383	1234	1371	5158	3623
15 to 17	Other	F	Urban	45	278	7805	978	352	160	938	61	854	2618	191	203	405	9094
15 to 17	Black	F	Urban	742	837	3112	1263	2153	1833	846	307	4065	1274	432	836	1788	2749
15 to 17	White	M	Urban	327	814	4146	374	880	652	1972	109	2546	840	523	391	2855	1956
15 to 17	Other	M	Urban	38	221	4904	778	392	116	465	65	568	1320	88	146	337	4846
15 to 17	Black	M	Urban	357	334	2187	552	1133	800	441	179	2278	505	236	278	1109	1601
15 to 17	White	F	Suburban	369	1185	362	108	651	796	692	251	1030	396	525	100	2354	779
15 to 17	White	M	Suburban	162	321	214	32	277	155	382	105	548	144	185	11	1064	379
15 to 17	White	F	Rural	59	924	62		298	108	317	145	95		161		492	76
15 to 17	Black	F	Suburban	122	260	15	42	343	299		435	570			81	187	84
12 to 14	Black	F	Urban					20			12	682				526	490
12 to 14	White	F	Urban					11			12	809				421	416
15 to 17	Other	F	Suburban	22	103	91	56	81	26	109	79	208			21	97	602
12 to 14	Black	M	Urban									591				398	418
15 to 17	Black	M	Suburban	78	76		23	126	92		224	343			29	140	74
15 to 17	White	M	Rural	38	313	44		113	21	128	58	12		63		142	41
15 to 17	Other	M	Suburban		84	53	46	105	20	52	70	114			11	100	277
12 to 14	White	M	Urban									382				124	407
12 to 14	Other	F	Urban									95				83	562
15 to 17	Black	F	Rural	67	187			95	70		242	21				27	
15 to 17	Other	F	Rural		50	24		38		283	49					12	21
12 to 14	Other	M	Urban									21				30	407
15 to 17	Black	M	Rural	22	74			91	28		100					19	
15 to 17	Other	M	Rural		75	15		43		92	43					19	14
15 to 17	White	F	Unknown	17				17			39		18				

Age	Race	Gender	Urbanicity	AL	AR	CA	FL	GA	LA	MN	MS	NC	NY	PA	SC	TN	TX
12 to 14	White	F	Suburban													23	29
15 to 17	White	M	Unknown	13							20		14				
15 to 17	Black	F	Unknown	13							22						
15 to 17	Black	M	Unknown								22						
15 to 17	Other	F	Unknown								12						

D.2 Pairs Where One Child Has No Utilization or Expenditures

Tables 43 through 46 show the number of pairs for each visits type in which one of the children has visits and charges and the other does not. This is important when considering the difference in charges especially because we have many children with a charge amount of 0 for a particular visit type because they do not have visits of that type, not because the charge was 0 for visits that occurred. The results comparing the median charges may be different for a comparison that excludes these zero values and conducts the comparison using only the pairs in which both children have non-zero charges. However, removing all of the pairs in which one child has no visits would introduce unnecessary bias into the analysis.

Table 43: Number of pairs of children in which one child has visits or charges in the IP table and the other does not have any visits or charges. The utilization and charges for children without visits (or charge amounts) of a particular type are 0s. Ex: # Depression 0s is the number of pairs in which the child with depression has no utilization or charges but the child without depression does have visits or charges.

	IP				
		Visits		Charges	
State	Pairs of Children	# Depression 0s	# Non-Depression 0s	# Depression 0s	# Non-Depression 0s
AL	10863	9044	9832	9044	9832
AR	14212	12745	13621	12745	13621
CA	111308	100563	108925	101991	109161
FL	26389	22607	24748	22607	24748
GA	20896	18268	19537	18268	19539
LA	15170	13504	14354	13504	14354
MN	17411	15965	16923	16719	17141
MS	8671	7108	7870	7113	7879
NC	16049	14584	15264	14584	15264
NY	44020	39085	41792	40157	42135
PA	11930	11103	11728	11103	11728
SC	11376	10171	10809	10172	10809
TN	8940	8183	8590	8234	8621
TX	42546	37159	39154	37176	39197

Table 44: Number of pairs of children in which one child has units or charges in the RX table and the other does not have any units or charges.

	RX				
		Units		Charges	
State	Pairs of Children	# Depression 0s	# Non-Depression 0s	# Depression 0s	# Non-Depression 0s
AL	10863	1311	3542	1311	3542
AR	14212	2151	5031	2151	5031
CA	111308	30058	81160	30066	81161
FL	26389	5838	14151	5841	14152
GA	20896	2946	6524	2946	6525
LA	15170	2397	6854	2397	6854
MN	17411	2962	7658	2983	7685
MS	8671	1001	2903	1002	2903
NC	16049	2379	4070	2379	4070
NY	44020	8404	21193	8420	21237
PA	11930	4399	7820	4399	7820
SC	11376	3076	5346	3076	5346
TN	8940	804	1807	804	1807
TX	42546	5199	10665	5457	11062

Table 45: Number of pairs of children in which one child has visits or charges in the OT table and the other does not have any visits or charges.

	OT				
		Visits		Charges	
State	Pairs of Children	# Depression 0s	# Non-Depression 0s	# Depression 0s	# Non-Depression 0s
AL	10863	165	373	428	1356
AR	14212	237	638	782	1501
CA	111308	6300	56520	17166	68384
FL	26389	1277	3436	2818	8687
GA	20896	139	462	1126	2710
LA	15170	170	1739	172	1751
MN	17411	436	1385	441	1404
MS	8671	466	1209	466	1215
NC	16049	130	193	130	193
NY	44020	1360	5450	1384	5613
PA	11930	153	664	3109	5654
SC	11376	163	267	163	267
TN	8940	12	89	359	861
TX	42546	655	1256	1792	3754

Table 46: Number of pairs of children in which one child has charges of any kind and the other does not.

	Total		
		Charges	
State	Pairs of Children	# Depression 0s	# Non - Depression 0s
AL	10863	374	1282
AR	14212	695	1402
CA	111308	13398	66696
FL	26389	2473	8257
GA	20896	982	2479
LA	15170	144	1669
MN	17411	391	1327
MS	8671	415	1137
NC	16049	123	190
NY	44020	1227	5292
PA	11930	2926	5233
SC	11376	150	262
TN	8940	301	741
TX	42546	1588	3389

D.3 Median Utilization and Expenditures

Tables 47 and 48 show the median utilization and expenditures for IP, OT, and RX claims in each state, as well as the median total charge per patient per month enrolled.

Table 47: Median number of visits (or units for RX) and charge amounts per patient per month enrolled for the depression population

State	OT Visits	OT Charges	IP Visits	IP Charges	RX Units	RX Charges	Total Charges
AL	3.3	$220.00	0.012	$0.00	22.7	$39.26	$344.80
AR	3.9	$252.50	0.008	$0.00	15.9	$25.04	$335.50
CA	2.8	$59.46	0.008	$0.00	8.3	$3.80	$77.60
FL	3.2	$211.20	0.000	$0.00	12.1	$14.52	$292.40
GA	3.8	$165.00	0.011	$0.00	17.7	$18.45	$228.60
LA	5.6	$483.50	0.015	$0.00	20.9	$44.33	$617.10
MN	3.0	$134.40	0.006	$0.00	17.8	$6.00	$167.50
MS	2.5	$338.70	0.013	$0.00	20.0	$32.30	$443.30
NC	5.4	$349.20	0.007	$0.00	17.2	$32.45	$456.60
NY	2.6	$194.10	0.015	$0.00	15.5	$22.10	$307.80
PA	3.0	$103.20	0.005	$0.00	6.8	$12.86	$166.90
SC	3.0	$259.50	0.008	$0.00	6.7	$9.55	$308.20
TN	3.5	$133.20	0.007	$0.00	23.3	$39.63	$211.30
TX	3.6	$255.00	0.011	$0.00	1093.0	$64.90	$498.30

Table 48: Median number of visits (or units for RX) and charge amounts per patient per month enrolled for the non-depression population

State	OT Visits	OT Charges	IP Visits	IP Charges	RX Units	RX Charges	Total Charges
AL	5.5	$382.30	0.00879	$0.00	6.6	$8.71	$440.70
AR	7.3	$467.00	0.00358	$0.00	4.0	$4.69	$492.00
CA	0.0	$0.00	0.00214	$0.00	0.0	$0.00	$0.00
FL	3.1	$111.40	0.00973	$0.00	0.0	$0.00	$131.90
GA	6.0	$218.60	0.01327	$0.00	6.4	$4.72	$255.40
LA	6.4	$404.00	0.01032	$0.00	2.3	$3.39	$454.00
MN	6.0	$169.10	0.00224	$0.00	1.6	$0.40	$181.20
MS	4.0	$436.40	0.00871	$0.00	5.8	$7.14	$475.30
NC	8.0	$420.40	0.00649	$0.00	8.3	$11.25	$472.60
NY	4.3	$242.30	0.00961	$0.00	0.8	$0.70	$280.10
PA	3.4	$15.89	0.00206	$0.00	0.0	$0.00	$30.52
SC	5.3	$392.60	0.00568	$0.00	0.9	$0.85	$415.60
TN	7.1	$232.60	0.00357	$0.00	9.5	$12.78	$278.70
TX	10.1	$616.50	0.00000	$0.00	473.3	$21.20	$850.40

D.4 Statistical Test Results

Table 49 shows the p values for the Wilcoxon tests for IP and RX utilization and charges, and Table 50 and Table 51 contain the results for utilization and charges in the four OT subsets. These tests were conducted on the subset of pairs in which at least one child in the pair had a claim for the particular type (IP, OT-ED etc).

Table 49: Number of pairs of children with visits by type, and p-values for the one-sided Wilcoxon test comparing monthly visits/prescription units and charges per person for IP and RX services between the depression population and the non-depression population. Significant p-values (p<0.0071) are highlighted in green

	IP			RX		
State	Pairs	P-Value (Visits)	P-Value (Charges)	Pairs	P-Value (Units)	P-Value (Charges)
AL	2633	1.58E-23	1.42E-31	10245	6.5E-228	9E-181
AR	1977	2.13E-65	7.24E-61	13113	0	2.5E-260
CA	12697	0	0	87517	0	0
FL	5067	7.1E-120	3.7E-99	22655	0	0
GA	3727	1.12E-48	1.58E-40	19479	4.6E-214	5E-258
LA	2357	3.6E-37	5.04E-32	13913	0	0
MN	1868	1.53E-84	3.64E-29	15646	0	0
MS	2137	8.28E-37	7.98E-46	8165	9.1E-166	2.3E-162
NC	2142	1.88E-25	1.22E-25	15107	5.6E-142	6.1E-135
NY	6775	7.9E-128	3.68E-71	38895	0	0
PA	1004	1.49E-51	2.62E-44	8681	2.4E-232	1.5E-247
SC	1697	2.76E-33	6.42E-33	9569	1.1E-195	5.3E-142
TN	1055	4.01E-27	1.48E-26	8631	2.5E-138	4.72E-77
TX	8171	1.36E-51	3.57E-52	40186	2.5E-134	4.3E-174

Table 50: Number of pairs of children with visits by type and p-value for the one-sided Wilcoxon test comparing monthly visits and charges per person for OT hospital and office visits between the depression population and the non-depression population. Significant p-values (p<0.0071) are highlighted in green

	Hospital- Urgent Care - Ambulance			Office		
State	Pairs	P-Value (Visits)	P-Value (Charges)	Pairs	P-Value (Visits)	P-Value (Charges)
AL	9842	6.06E-45	1.04E-09	10692	1.24E-05	0.019367
AR	13352	1.38E-58	8.7E-65	13938	0.953808	0.018498
CA	77604	0	0	97801	0	0
FL	22024	0	0	24267	1.8E-110	1.9E-190
GA	17367	1.7E-120	1.4E-99	20251	0.002799	1.4E-55
LA	13881	2.8E-262	1.2E-289	14967	2.2E-170	1.4E-182
MN	15529	1.9E-165	1.3E-127	17066	0.999995	0.48697
MS	6492	7.23E-48	2.27E-34	8450	0.117307	2.82E-05
NC	10816	1.7E-13	1.12E-09	15672	6.88E-25	1.56E-56
NY	40906	0	0	41748	0.999996	1.92E-35
PA	8947	3.2E-293	0	10423	0.000373	1.9E-31
SC	9123	1.06E-43	1.21E-52	10800	1	1
TN	8273	2.32E-21	3.5E-171	8819	1	0.000333
TX	37986	1.5E-87	6E-151	41976	1	1

Table 51: Number of pairs of children with visits by type and p-value for the one-sided Wilcoxon test comparing monthly visits and charges per person for OT ED and Other visits between the depression population and the non-depression population. Significant p-values (p<0.0071) are highlighted in green

	ED			Other		
State	Pairs	P-Value (Visits)	P-Value (Charges)	Pairs	P-Value (Visits)	P-Value (Charges)
AL	10758	1	1	10854	1	1
AR	14042	1	1	14198	1	1
CA	102737	1	1	108063	1.79E-77	2.2E-128
FL	25368	1	1	26190	1	1
GA	20570	1	1	20889	1	1
LA	15063	1	1	15158	1	1
MN	17196	1	1	17352	1	1
MS	8550	1	1	8587	1	1
NC	15850	1	1	16035	1	1
NY	43399	1	1	43844	1	1
PA	10990	1	1	11924	1	1
SC	11002	1	1	11366	1	1
TN	8862	1	1	8938	1	1
TX	42226	1	1	42503	1	1

Table 52: Tukey's Test results for the pairwise comparison of state utilization and expenditures

	IP Visits	IP Charges	RX Units	RX Charges	OT Visits	OT Charges	Total Charges
AR-AL	0.9643	0.9999	1.0000	1.0000	0.0000	0.9630	0.9980
CA-AL	0.0018	0.9600	1.0000	1.0000	0.0000	0.0000	0.0017
FL-AL	0.9787	0.0968	1.0000	1.0000	1.0000	1.0000	0.9863
GA-AL	0.0000	0.7418	1.0000	1.0000	0.9205	0.9950	1.0000
LA-AL	0.9857	0.9981	1.0000	1.0000	0.0000	0.5789	0.9083
MN-AL	0.9997	0.9996	1.0000	1.0000	0.0000	0.0980	0.9897
MS-AL	0.9234	1.0000	1.0000	1.0000	0.9793	0.8915	0.9953
NC-AL	0.2355	0.9999	1.0000	1.0000	0.1214	0.3528	0.9839
NY-AL	0.2643	0.9827	0.0000	0.0000	0.4665	0.1314	0.0000
PA-AL	1.0000	1.0000	1.0000	1.0000	0.3641	0.3110	0.9378
SC-AL	1.0000	1.0000	1.0000	1.0000	0.9984	0.9897	1.0000
TN-AL	1.0000	0.9999	1.0000	1.0000	0.0023	0.0143	0.7030
TX-AL	0.0000	0.4123	1.0000	0.9995	0.0000	0.0032	0.1628
CA-AR	0.3333	0.1870	1.0000	1.0000	0.0000	0.0000	0.0000
FL-AR	1.0000	0.4388	1.0000	1.0000	0.0000	0.9772	1.0000
GA-AR	0.0000	0.9916	1.0000	1.0000	0.0000	0.1006	0.9937
LA-AR	1.0000	1.0000	1.0000	1.0000	0.0022	1.0000	1.0000
MN-AR	1.0000	1.0000	1.0000	0.9996	0.0059	0.0000	0.2934
MS-AR	1.0000	0.9971	0.9982	1.0000	0.0000	0.0601	0.5410
NC-AR	0.0002	1.0000	1.0000	1.0000	0.0000	0.0007	0.2676
NY-AR	0.9992	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PA-AR	0.6709	1.0000	1.0000	1.0000	0.0000	0.0009	0.1852
SC-AR	0.6430	1.0000	1.0000	1.0000	0.0000	0.1563	0.8859
TN-AR	0.9999	1.0000	1.0000	1.0000	0.0000	0.0000	0.0654
TX-AR	0.0000	0.9091	1.0000	1.0000	0.0000	0.3774	0.8779
FL-CA	0.0090	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000
GA-CA	0.0000	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000
LA-CA	0.1594	0.0431	1.0000	1.0000	0.0000	0.0000	0.0000
MN-CA	0.0099	0.0507	1.0000	1.0000	0.0000	0.2998	0.0638
MS-CA	0.9316	0.9998	0.9999	1.0000	0.0000	0.1068	0.5758
NC-CA	0.0000	0.1157	1.0000	1.0000	0.0000	0.0586	0.1267
NY-CA	0.4903	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000
PA-CA	0.0000	0.7236	1.0000	1.0000	0.0000	0.3531	0.6338
SC-CA	0.0000	0.5059	1.0000	1.0000	0.0000	0.0014	0.0301
TN-CA	0.0952	0.4407	1.0000	1.0000	0.0000	1.0000	0.9967
TX-CA	0.0000	0.0000	1.0000	0.6084	0.0000	0.0000	0.0000
GA-FL	0.0000	0.9938	1.0000	1.0000	0.8025	0.7409	0.9434
LA-FL	1.0000	0.6762	1.0000	1.0000	0.0000	0.5109	1.0000

	IP Visits	IP Charges	RX Units	RX Charges	OT Visits	OT Charges	Total Charges
MN-FL	1.0000	0.4449	1.0000	1.0000	0.0000	0.0010	0.0716
MS-FL	1.0000	0.0531	0.9993	1.0000	0.8691	0.4685	0.3013
NC-FL	0.0000	0.3884	1.0000	1.0000	0.0231	0.0185	0.0658
NY-FL	0.9306	0.2989	0.0000	0.0000	0.1133	0.0002	0.0000
PA-FL	0.6784	0.2071	1.0000	1.0000	0.1762	0.0232	0.0480
SC-FL	0.6500	0.4157	1.0000	1.0000	0.9712	0.7842	0.6902
TN-FL	1.0000	0.7810	1.0000	1.0000	0.0002	0.0002	0.0147
TX-FL	0.0000	0.9975	1.0000	0.9857	0.0000	0.0000	0.7361
LA-GA	0.0000	0.9996	1.0000	1.0000	0.0000	0.0044	0.7819
MN-GA	0.0000	0.9956	1.0000	1.0000	0.0000	0.5406	0.9403
MS-GA	0.0000	0.5350	1.0000	1.0000	0.0870	0.9999	0.9810
NC-GA	0.0376	0.9902	1.0000	1.0000	0.9144	0.9235	0.9197
NY-GA	0.0000	0.9983	0.0000	0.0000	1.0000	0.6798	0.0000
PA-GA	0.0000	0.9099	1.0000	1.0000	0.9949	0.8768	0.8071
SC-GA	0.0000	0.9817	1.0000	1.0000	0.1491	1.0000	1.0000
TN-GA	0.0000	0.9993	1.0000	1.0000	0.0912	0.1164	0.4692
TX-GA	0.7736	1.0000	1.0000	0.9635	0.0000	0.0000	0.0173
MN-LA	1.0000	1.0000	1.0000	0.9997	1.0000	0.0000	0.0432
MS-LA	1.0000	0.9760	0.9990	1.0000	0.0000	0.0048	0.1751
NC-LA	0.0004	1.0000	1.0000	1.0000	0.0000	0.0000	0.0392
NY-LA	0.9921	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PA-LA	0.7722	1.0000	1.0000	1.0000	0.0000	0.0000	0.0273
SC-LA	0.7463	1.0000	1.0000	1.0000	0.0000	0.0143	0.4720
TN-LA	1.0000	1.0000	1.0000	1.0000	0.0234	0.0000	0.0082
TX-LA	0.0000	0.9861	1.0000	0.9999	0.0000	0.9328	0.9989
MS-MN	0.9995	0.9893	0.9983	1.0000	0.0000	0.9995	1.0000
NC-MN	0.0021	1.0000	1.0000	1.0000	0.0000	1.0000	1.0000
NY-MN	0.7818	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000
PA-MN	0.9526	1.0000	1.0000	1.0000	0.0000	1.0000	1.0000
SC-MN	0.9407	1.0000	1.0000	1.0000	0.0000	0.9145	1.0000
TN-MN	1.0000	1.0000	1.0000	1.0000	0.0049	0.9972	0.9987
TX-MN	0.0000	0.9270	1.0000	0.7769	0.0000	0.0000	0.0000
NC-MS	0.0009	0.9958	1.0000	1.0000	0.0010	1.0000	1.0000
NY-MS	1.0000	0.8992	0.0000	0.0000	0.0060	1.0000	0.0000
PA-MS	0.6095	1.0000	0.9999	1.0000	0.0084	1.0000	1.0000
SC-MS	0.5827	0.9997	0.9999	1.0000	1.0000	1.0000	1.0000
TN-MS	0.9987	0.9976	1.0000	1.0000	0.0000	0.8579	0.9999
TX-MS	0.0000	0.2513	0.9996	0.9992	0.0000	0.0000	0.0026
NY-NC	0.0000	1.0000	0.0000	0.0000	0.9910	1.0000	0.0000

	IP Visits	IP Charges	RX Units	RX Charges	OT Visits	OT Charges	Total Charges
PA-NC	0.5877	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
SC-NC	0.6607	1.0000	1.0000	1.0000	0.0015	0.9965	1.0000
TN-NC	0.0724	1.0000	1.0000	1.0000	0.9291	0.9469	0.9995
TX-NC	0.7124	0.8889	1.0000	0.9980	0.0000	0.0000	0.0000
PA-NY	0.0281	0.9992	0.0000	0.0000	1.0000	1.0000	0.0000
SC-NY	0.0269	1.0000	0.0000	0.0000	0.0087	0.9827	0.0000
TN-NY	0.8700	1.0000	0.0000	0.0000	0.1679	0.8789	0.0000
TX-NY	0.0000	0.8998	0.0000	0.0000	0.0000	0.0000	0.0000
SC-PA	1.0000	1.0000	1.0000	1.0000	0.0149	0.9887	0.9992
TN-PA	0.9982	1.0000	1.0000	1.0000	0.8554	0.9913	1.0000
TX-PA	0.0006	0.6584	1.0000	0.9997	0.0000	0.0000	0.0000
TN-SC	0.9973	1.0000	1.0000	1.0000	0.0000	0.3998	0.9612
TX-SC	0.0012	0.8756	1.0000	0.9988	0.0000	0.0000	0.0120
TX-TN	0.0000	0.9896	1.0000	0.9996	0.0000	0.0000	0.0000

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