EVALUATING POLICY DECISIONS IN HEALTH SYSTEMS

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Ben Johnson

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EVALUATING POLICY DECISIONS IN HEALTH SYSTEMS

Approved by:

Dr. Nicoleta Serban, Advisor
H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology

Dr. Joel Sokel
H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology

Dr. Julie Swann
H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology

Dr. Susan Griffin
National Center for Chronic Disease Prevention and Health Promotion
Centers for Disease Control and Prevention

Dr. Paul Griffin
H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology

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To my Lord and Savior, Jesus Christ

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LIST OF SYMBOLS AND ABBREVIATIONS

AAPD	American Academy of Pediatric Dentistry
CDC	Centers for Disease Control and Prevention
CDT	Current Dental Terminology
CF	Cystic Fibrosis
CPT	Current Procedural Terminology
CI	Confidence Interval
ED	Emergency Department
FPL	Federal Poverty Line
FFS	Fee for Service
GDA	Georgia Dental Association
GDP	Gross Domestic Product
GDPH	Georgia Department of Public Health
LPI	Logistics performance index
MARA	Mapping Malaria Risk in Africa
NPI	National Provider Index
PMI	Presidents Malaria Initiative
RO	Requisition Order (Date when a customer submits an order)
SBSP	School-Based Sealant Program
SDF	Silver Diamine Fluoride
UN	United Nations
USAID	United States Agency for International Development

SUMMARY

This thesis focuses on four policy decisions relevant in health systems today: (i) the impact of geographic distance to care on patients with cystic fibrosis, (ii) the impact of global health supply chain design on the health outcomes where they operate, (iii) the evaluation of the current state of access to pediatric preventive dental care and the impact of three interventions to improve access to care, and (iv) the impact and cost effectiveness of using silver diamine for treating caries (cavities) in young children.

The first portion of the thesis examines the impact of geographic distance from cystic fibrosis centers on lung function in patients with cystic fibrosis. Clinical patient-level data on 20,351 patients for years 1986-2011 were evaluated from the Cystic Fibrosis Foundation National Patient Registry. Distance was measured using a patient's zip code centroid to the center where they received care. A heteroscedastic mixed effects model was used to capture the association of distance with longitudinal variation in patients' lung function. Children, young adults, and adults in lower socioeconomic categories were found to have lung function measured by $\%FEV_1$ between 3 and 10 percentage-points lower than those living in higher income areas and those privately insured. For patients who changed distance categories, high distance was associated with lower lung function in young adults (p-value<0.001). For older patients we observe the reverse, suggesting that the choice to move farther away is associated with better health (p-value<0.001). For patients who do not change distance categories, only medium distance on children is significant (p-value=0.01) Known confounding factors including age and CFTR mutation class are statistically significantly associated with health outcomes (p-value<0.001). This study

shows distance was not found to be associated with health outcomes among patients whose distance category remained unchanged during the course of the analysis. For patients who move, the association of health with distance depend on the age group of the patient; adult patients further from their care center are healthier. Overall, we find that socioeconomic and genetic factors appear to impact health outcomes to a greater extent than distance.

The second portion of the thesis evaluates the USAID malaria supply chain design in the context of the health outcomes in each of the counties it operates. Malaria is a life-threatening mosquito-borne infectious disease that causes fevers, chills, and vomiting. Sub-Saharan Africa is both resource-constrained and has 90 percent of malaria related deaths. To combat the disease, global health agencies including USAID provide commodities necessary to prevent and treat malaria. The supply chain systems at these organizations are integral to the success of programs aimed to combat malaria. The supply chain factors that are most associated with reduced malaria mortality were determined to inform effective global health supply chain design. Using publicly available data, the impact of funding levels, supply chain performance, GDP per capita and other global development indicators, and known malaria health predictors on malaria mortality were determined. Linear regression was used to determine if there is a significant association between supply chain factors and malaria health. Percent of malaria product shipped by air, population, USAID funding levels, percentage of any antimalarial coverage, life expectancy, physician density, and the malarial season duration in each country were all found to be significantly associated with malaria-based mortality. Population, physician density, and season duration are positively associated. Life expectancy, USAID funding, percent antimalarial coverage, and percent air shipments are negatively associated. Other supply chain and transportation infrastructure variables such as cycle time, total malaria funding, and LPI score were not found to significantly explain any of malaria mortality variability. Supply chain design was found to be an important factor in reducing malaria mortality. While it is important to deliver more product to needed areas and ensure thorough coverage of malaria preventive measures, it is also important to have an adaptable supply chain design capable of responding to shifts in the demand and flexible enough to react to changing developing world conditions.

The third portion of the thesis evaluated how to improve access of pediatric preventive care in Georgia. We used an optimization model to represent the current patient and provider network in Georgia along with network and policy constraints needed to represent the current state of the dental system in Georgia. Network constraints included distance to care and capacity constraints. Policy constraints were insurance acceptance and hygienist supervision requirements. The network was then modified to show the impact of a variety of potential changes. A selection of network interventions were evaluated to determine their impact. Medicaid children were found to have significantly limited access to oral health providers while kids at the top of the income spectrum had good access to preventive care. The results of this section naturally motivate the forth section of methods to improve access.

The fourth portion continues the analysis of improving access to oral healthcare by determining the impact of loan repayment programs, revising Medicaid fee-for-service rates, and changing dental hygienist supervision requirements on access to preventive dental care for children in Georgia. Cost savings were estimated from the three interventions on preventive care for young children. Federal loan repayments to dentists and school-based sealant programs were found to have lower intervention costs (with higher potential cost savings) than raising the Medicaid reimbursement rate. A regression model was used to evaluate the impact of changing the Medicaid reimbursement rates. The impact of supervision was evaluated by comparing general and direct supervision in school-based dental sealant programs. General supervision had costs 56% lower than direct supervision of dental hygienists for implementing a school-based sealant program. Raising the Medicaid reimbursement rate by 10 percentage points would improve utilization by less than 1% and cost over $38 million. Given one parameter set, school-based sealant programs could serve over 27,000 children with an intervention cost between $500,000 and $1.3 million with a potential cost saving of $1.1 million. Loan repayment could serve almost 13,000 children for a cost of $400,000 and a potential cost saving of $176,000. The three interventions all improved met need for preventive dental care. Raising the reimbursement rate alone would marginally affect utilization of Medicaid services but would not substantially increase acceptance of Medicaid by providers. Both loan repayment programs and amending supervision requirements are potentially cost saving interventions. Loan repayment programs provide complete care to targeted areas, while amending supervision requirements of dental hygienists could improve preventive care across the state.

The fourth portion of the thesis evaluates the cost saving potential and cost effectiveness of using silver diamine fluoride (SDF) to treat caries in young children aged 0-5. SDF is a cheaper alternative to traditional restorative care. While it does not have the ability to restore the tooth completely, it provides a treatment option for young children by potentially arresting the caries in affected primary teeth until they are replaced with permanent teeth. Alternatively, for very young children who will need restorative care before their permanent teeth will arrive, SDF has the potential to delay the restorative care until the child is old enough for standard restorative dental treatments. In addition, SDF does not require expensive anesthesia for treatment. This study evaluates the potential of this treatment option using a simulation approach with costs based on the realized costs of treatments found in the Medicaid data. The simulation was conducted by varying the percentage of children who receive treatment with SDF as well as the effectiveness of SDF. We found states could avert significant costs from more expensive restorative care procedures by using SDF in all scenarios. Using the effectiveness published in the literature with 25% of the children receiving SDF, the potential cost savings per state range between $1M and $24M. SDF can also provide a simpler and easier treatment option for children, particularly in low-resource settings.

CHAPTER 1. INTRODUCTION

In recent years, health policies have become ever more important. With the increasing political bias and political foundation for addressing policy decisions, it is more crucial to provide effective data driven evaluations concerning the impact policy decisions will have on the health systems they govern. This thesis focuses on the impact of four policy questions and assessing the alternatives to guide policymakers to make informed policy decisions.

1.1 Chapter 2: Impact of Geographic Distance on patients with Cystic

In the first section of the thesis, patients with cystic fibrosis (CF) were studied to evaluate the potential impact geographic distance has on their health outcomes. Cystic Fibrosis is a genetic disease affecting a patient’s lung function. There are thousands of possible mutations of the gene known to cause CF. The mutations can be classified into severity levels based on whether they are pancreatic sufficient or pancreatic insufficient [1]. The majority of patients with CF have one of the severe pancreatic insufficient mutations. Further, since CF is a rare condition, access to care is limited to specific geographies. The goal of this research was to understand the impact this limited access has on patients. To evaluate this, patient level health records including clinical information and geographic location data were obtained to allow a robust statistical analysis. In prior literature, many demographic factors influencing a CF patient’s health outcome were studied, but the impact of distance to care on patients with a chronic condition like CF had not been addressed. The section looks at this question while controlling for the factors known to influence health outcomes in Cystic Fibrosis to predict a patient's lung function, evaluated through the outcome variable percent predicted FEV_1.

1.1 Chapter 3: Global Health Supply Chain Design

The second section of the thesis looks at the relationship between global health supply chains and the health outcomes in the countries where they operate. This section was motivated during time spent at the United States Agency for International Development (USAID). While there, it became clear the rationale and impact of the majority of the divisions were well known and clearly evaluated. That was not true of the supply chain divisions. The supply chain divisions were there to support the missions of the other USAID implemented programs, but the specific impact of the supply chain divisions was not well known. Additionally, the impact of the supply chain design on health outcomes was not known, meaning the specific design of the supply chain could not be tailored to match the goals of the implemented programs. This study sought to address these questions, providing USAID supply chain divisions with clarity in understanding their impact on USAID health programming. Further, we sought to understand the aspects of supply design that most positively affect health outcomes.

1.2 Chapter 4: Evaluating and Improving Access for Pediatric Preventive Dental Care in Georgia

The third portion of the thesis aims to outline an optimization model for the current structure of the dental network in Georgia. The optimization model is used to match children with dental providers given a number of constraints including distance to care, provider insurance acceptance, capacity, etc. The model is used to evaluate both the current state of access as well as the impact of specific network interventions such as adding dentists and dental hygienists to the network. The model can also be used to target very specific locations for optimal provider placements to maximize the number of children receiving care. The results of the model were motivation for the subsequent chapter on improving access to preventive dental care.

1.3 Chapter 5: Interventions to Improve Access for Pediatric Preventive Dental Care in Georgia

The fourth section of the thesis looks to address a growing need for access to preventive dental care for children as shown in the third section. We know oral disease is one of the greatest unmet health needs among children in the United States [2]. There are also significant disparities in access to dental care [3]. In Georgia, there are a large number of Medicaid children, the vast majority of which do not have access to preventive dental care. This study aims to address this need through the evaluation of three potential interventions that could be used to improve access to preventive dental services for this population. Interventions considered include raising the Medicaid reimbursement rate, providing dental loan repayment programs, and changing the supervision requirements for dental hygienists. This research has been particularly timely as the Georgia Dental Hygienist Association sought to enable hygienists to provide additional preventive services in Georgia. It is also one of the first pieces providing a framework to compare vastly different policies ranging from system level changes to the payment structure to community level targeted interventions. Outcomes evaluated include met need and the cost of implementation.

1.4 Chapter 6: Cost Effectiveness of Silver Diamine Fluoride

Silver Diamine Fluoride (SDF) is an up and coming treatment used to arrest caries. Currently, it is used mostly in Japan. It has been approved for use in the United States to treat tooth sensitivity, but research suggests it can be particularly effective at arresting caries. This study looks to evaluate the potential impact in terms of averted cost and caries arrested in three populations of children under six years old: realized Medicaid claim data, all Medicaid patients, and all children. The study is aimed to show the potential impact and cost savings states can achieve by allowing dentists to perform SDF treatments on young children. This study looks at the realized Medicaid claims payments in place in 3 states in the Southeast and four comparison states in the Northeast using a simulation approach on each population to determine the potential impact given a range in the percentage of children who receive SDF and in the effectiveness of SDF to arrest caries. The results of this study can be used by policymakers to make informed decisions about the impact of using SDF to treat caries in young children.

1.5 Chapter 7: Conclusion

The last portion of the dissertation outlines the main results and implications of each study. The results are reiterated and potential future work is suggested. Additionally, the main impact of each paper is discussed to provide more context of each study in relation to other literature or to current events.

CHAPTER 2. DOES DISTANCE TO A CYSTIC FIBROSIS CENTER AFFECT HEALTH OUTCOMES?

2.1 Introduction

The study of healthcare access is fundamental to understanding variations in health outcomes in the United States [4]. One dimension of healthcare access is geographic access or distance to healthcare providers, particularly important for chronic disease management. With the reduction in distance and ease of access to providers, patients have regular health maintenance visits and monitoring that could prevent medical crises, reduce the use of the emergency room, and preempt severe adverse outcomes.

Cystic Fibrosis (CF) is a chronic, life-shortening disease, with great variation in patient outcomes [5]. Recent research has shown that a significant proportion of the variation in CF-related outcomes can be attributed to socio-economic factors, but unexplained disparities remain [6]. Since CF is a rare condition, geographic proximity to care is limited, with only 121 accredited care centers in the continental United States [7].

While there has been significant interest in the relationship between CF disease management and outcomes [6, 8], there is little research that addresses the association with geographic distance to care and how the relationship varies across different age groups. In this study, we evaluate the link between geographic access (measured by travel distance to CF centers) and one common outcome measure for CF, lung function as measured by percent predicted Forced expiratory volume in 1 second (% FEV_1) while controlling for known confounding factors such as the CFTR mutation class, socioeconomic environment, insurance, gender, and age. The study is longitudinal, using patient-level data over multiple years acquired from the CF Foundation Patient Registry (CFFPR). Specific aims the study addresses include the following.

> Aim 1: To identify factors associated with longitudinal health outcomes
>
> Aim 2: Contrast the differences in factors identified for children vs adults
>
> Aim 3: Focus on the impact of geographic access on health outcomes.

Aim 1 was fulfilled using mixed-effect modeling to assess the significance of factors thought to be associated with a patient's health outcome. Aim 2 was fulfilled by splitting the patient data into three age categories: children, young adults, and adults. Models were run on each group to determine differences in how factors affect each age group. Aim 3 was accomplished by including geographic distance to care as a potential factor influencing health outcomes. We initially hypothesized patients closer to care centers would have better health outcomes.

2.2 Methods

We used mixed-effect modeling as described in this section, which also provides an explanation of assumptions and choices made regarding study design and methodology.

2.2.1 Study Population

The population in this study consists of patients with CF who received care at CF Foundation (CFF)-accredited centers and who were listed in the CFFPR during the years 1986-2011 (IRB and CF Foundation approvals were obtained for this research.) The CFF estimated that it currently captures data on 81-84% of all persons with CF in the U.S. [7].

We removed visits for patients with missing $\%FEV_1$ values, and further excluded patients who reported a foreign address or unidentifiable zip code, those with missing or unknown provider zip codes, and those without valid insurance and genetic information. We then excluded any patient with four or fewer valid visits in the dataset. This was done in order to ensure we had sufficient longitudinal data and to ensure sufficient data for each random effect in the model. Much of the missing data comes from the structure of the CFFPR, which did not require quarterly $\%FEV_1$ measurements until 1995 and underwent another significant change in 2003.

2.2.2 Outcome Measure

We used forced expiratory volume in 1 second as a percentage of predicted ($\%FEV_1$) using the equations of Wang [9] and Hankinson [10], calculated directly by the CFF from data submitted by the centers, as our health outcome measure [8, 11-13]. We classified patients with a $\%FEV_1$ lower than 60 as low $\%FEV_1$ and patients that have a $\%FEV_1$ above 60 as high $\%FEV_1$.

2.2.3 Geographic Distance or Access Measure

We measured geographic access or distance using the travel distance between the zip codes of each patient's home location and the location of the center where the patient received care. Each patient's geographic access was determined as the road distance in miles computed through Bing Maps using the R package taRifx.geo [14]. Since patient zip codes were only recorded on some visits, we assumed that a patient lived at the same location until the patient's zip code changed in the dataset. This measure is a form of healthcare accessibility [15, 16]; we assumed that once a patient reaches a CF facility, care services will be made available for the patient's care regardless of the medical insurance provisions.

Because we hypothesized that the association between health outcomes and geographic distance is nonlinear, we transformed travel distances into a discrete variable with three categories – high distance for distances greater than 75 miles; medium distance for distances between 25 and 75 miles; and low distance for distances less than 25 miles. The 25 mile limit for low distance was suggested by the U.S. Department of Health and Human Services defining underserved areas for primary care, thus setting the limits of the expected travel for routine care. Because willingness to travel higher distances for specialty care of rare conditions may be different from primary care, we set the 'medium' distance category with distances up to 75 miles, where this threshold was suggested by the shape of the distribution of travel distances. Patients were also filtered to remove any patient who traveled excessive distances (1000 miles) to care, as this extraordinary distance was clearly chosen by patients with the means to electively bypass care centers at a closer distance. Patients in Montana, Idaho, Wyoming, Alaska, and Hawaii were not filtered for excessive distance since the lack of CF care centers in those states during the analysis period forced these patients to travel further distances. To determine the effect of moving closer or farther away from CF centers on patient outcomes, the final dataset was split based on whether or not a patient changed distance categories during the course of the study. In the paper, these groups are referred to as patients who moved and patients who did not move. A STROBE diagram outlining the process to obtain the final dataset is provided in Figure 1.

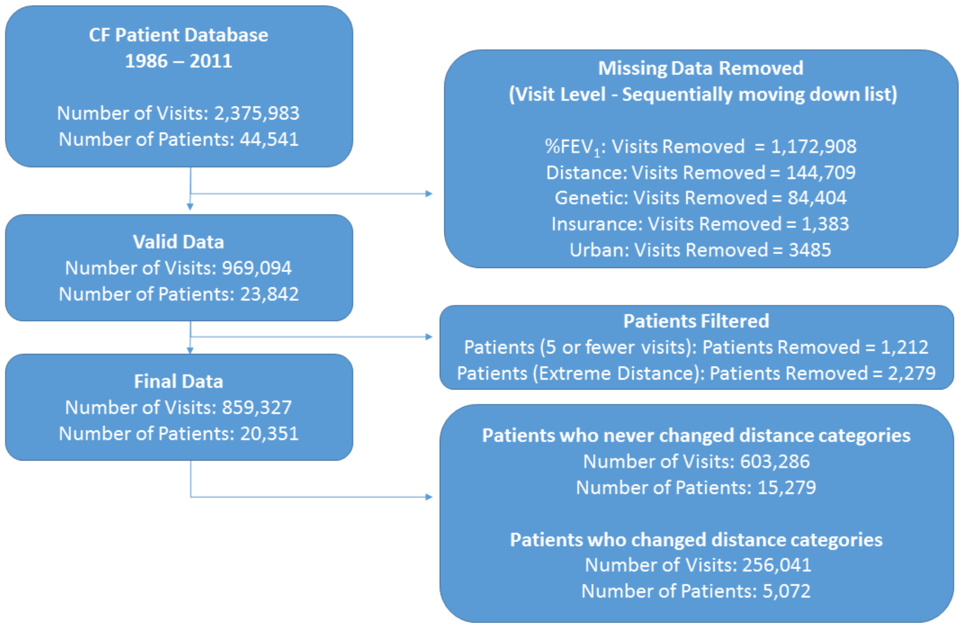

Figure 1. STROBE diagram of final data selected. This figure shows the progression of data removal used to obtain the final data sets used for analysis.

2.2.4 Model Covariates

Patient-level model covariates include the patient's gender, age at the time of FEV measurement, insurance status, and CFTR mutation class, all of which have been shown in the literature to be predictors of %FEV$_1$ in patients with CF [8]. The year of the visit was included an as additional covariate to account for changing trends in treatment over time. Years were grouped into buckets of roughly 5 years throughout the duration of the study. Year groups include 1986-1990, 1991-1995, 1996-2000, 2001-2005, and 2005-2011. The most recent year group (2005-2011) was used as the baseline in the analysis.

Insurance status of a patient was encoded as a binary variable defined by the participation in the Medicaid program. Patients who had ever been on Medicaid during the period of analysis were placed in the Medicaid category and compared with patients who never reported to have received Medicaid.

A patient's genotype was encoded into two categorical groups based on the class of the patient's genetic mutation. We used the system of Green et al. [1] to categorize CF mutations into five functional classes with further grouping into two severity groups: one representing genotype mutations in classes I, II and III (classic or pancreatic insufficient) and the other representing genotype mutations in classes IV and V (mild or pancreatic sufficient).

In section 2.2.5, we provide supporting visual displays for the inclusion of age (Figure 2) along with exploratory analysis motivating the inclusion of the other suggested covariates (Figure 3 through Figure 6).

2.2.5 Exploratory Analysis of Model Covariates

To capture the economic and geographic environment of each patient, we included the median household income of each zip code [17] and the Rural Urban Continuum Codes (RUCC) urban/rural classification for each county [18]. The median income was normalized by the maximum median income in the dataset, resulting in a final number between 0 and 1 so that its coefficients can be accurately compared to those of other binary variables. Normalized incomes provides the added benefit of an accurate comparison with the coefficients of other variables to assess which variables have the strongest impact on patient outcomes. Counties with RUCC codes 5 or less were classified as urban. The average urban value was used for zip codes crossing multiple counties.

We consider a set of variables that can affect the long-term outcome of patients as described in the main paper and in this supplemental material. The plots below show the possible variables considered and their relationships to %FEV_1. The variables considered below have been identified in previous research work as being important determinants of outcomes for patients with cystic fibrosis.

In Figure 2, we show the plot of the %FEV_1 of 200 randomly selected patients in each age group against their age at each visit. We see that generally %FEV_1 decreases as Age increases. To account for this effect, we included the variable age in our models. We allow the intercept and the slope of Age to vary randomly across patients because we model longitudinal data that are unbalanced (number of visits per patients vary from one patient to the other) and because we want to account for the within-patient variations.

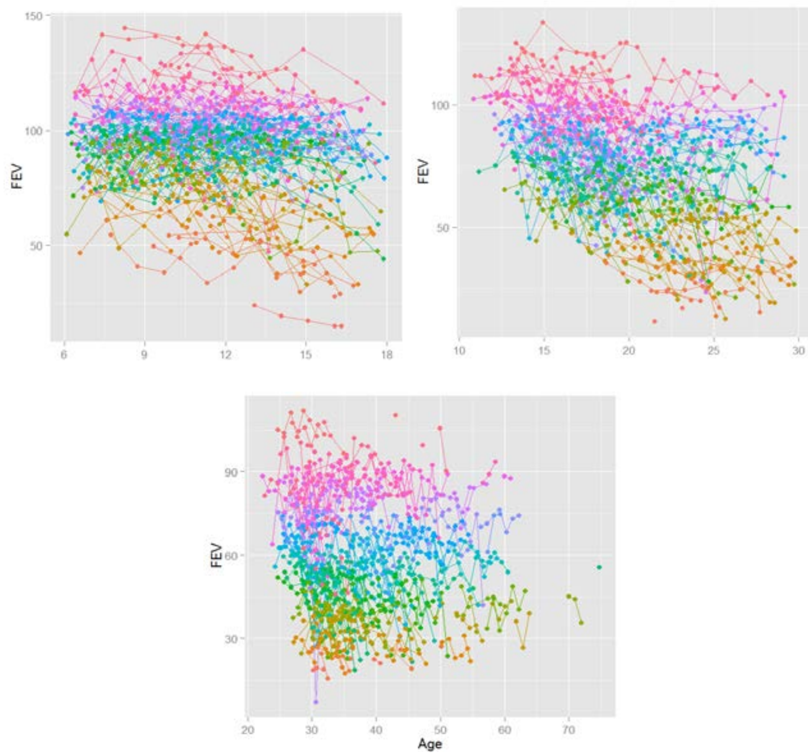

Figure 2. Plot of the %FEV$_1$ of 200 randomly selected patients in each age group vs. Age (children in top left, young adults in top right, and adults in the bottom).

In Figure 3 through Figure 6, we show the boxplots of other variables that are known to affect %FEV$_1$. The first variable of interest is gender; in Figure 3 we see that the presence of significant differences between the %FEV$_1$ of male and female patients. Thus, we added a categorical variable to account for gender. Figure 4 shows the boxplot of the %FEV$_1$ divided by age groups and by a proxy for socio economic status (Medicaid status).

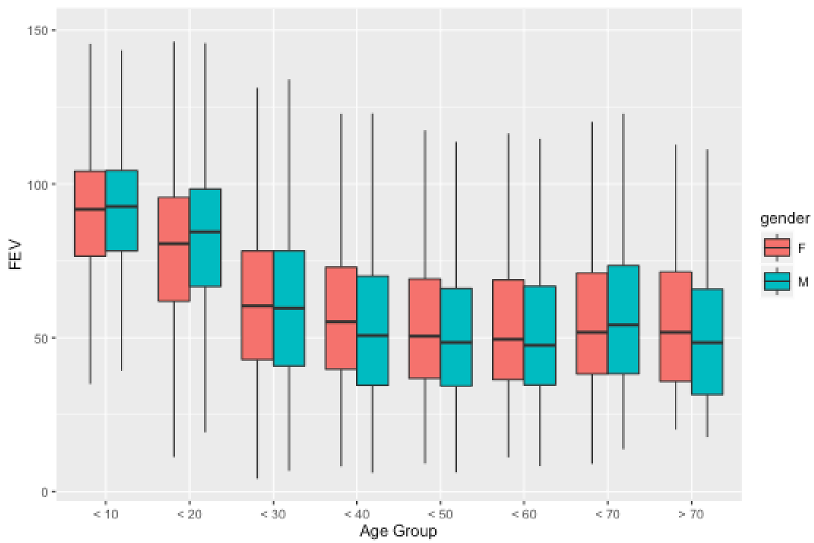

Figure 3. %FEV$_1$ by Age and Gender.

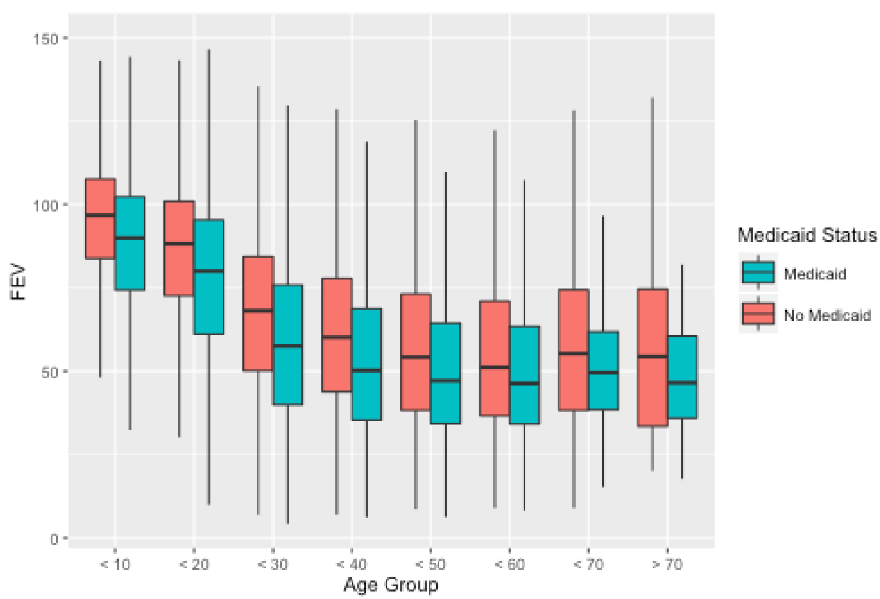

Figure 4. %FEV$_1$ by Age and Medicaid.

In Figure 5, we illustrate the importance of adding a variable that captures the genetic severity of the disease. Patients with less severe mutations have better outcome than patients with more severe mutations.

We last show the boxplot of %FEV_1 across distance groups. As explained earlier we proposed to group the patients in three categories. The patients who lived within 25 miles of their care provider are in the group small, the patients living between 25 and 75 (more than 75) miles away from their care provider belong to the medium (large). The boxplot in Figure 6 reveals very little about the potential influence of distance on outcome.

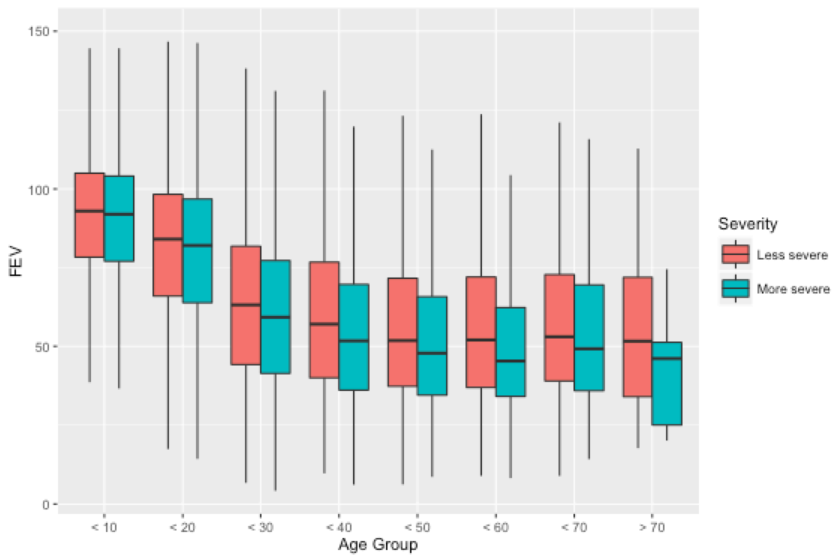

Figure 5. %FEV_1 by Age and genetic mutation severity.

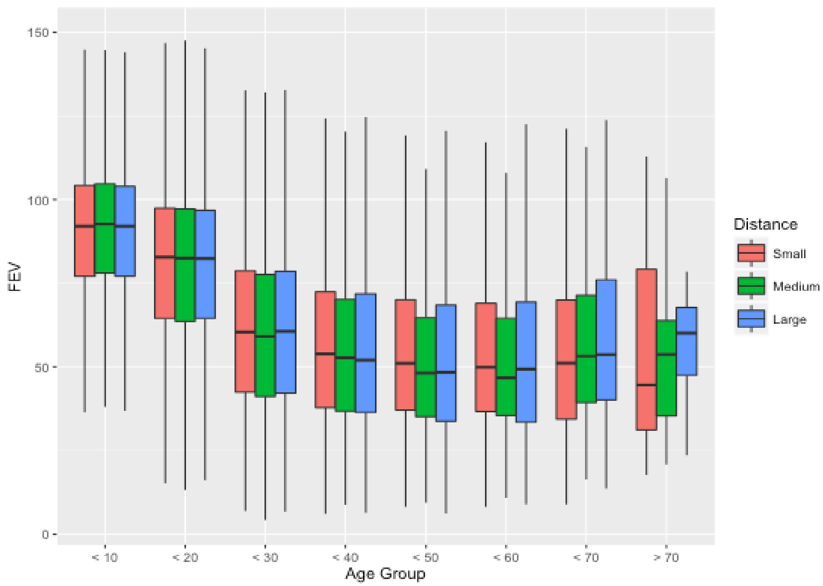

Figure 6. %FEV_1 split Age and distance group.

2.2.6 Statistical Method

We employed mixed-effects modeling as in [12] to assess the statistical significance of the association of geographic distance to %FEV_1. In addition to the fixed effects for the covariates described above, the model also included random effects for the intercept and the age-at-visit factor to capture the within-individual and age-specific variability, respectively. We fit separate mixed effects models for children (patients 18 years old or younger), young adults (patients between 19 and 30) and adults (older than 30 years). The statistical model considered the non-constant nature of the variance of the errors in the mixed-effects model. We modeled the variance of the residuals as a power function of age.

We estimated the model parameters by using maximum likelihood estimation. The p-values and the confidence intervals associated with the model parameters relied on large sample approximations; the sample sizes for all population groups were sufficiently large.

We implemented the model using the package *nlme* in the R statistical software (version 3.2.1).

The model goodness-of-fit was assessed by visually evaluating the distributional assumptions of the marginal and conditional residuals [19, 20] as shown later.

2.2.7 Model

In this study, we applied a mixed effects model to longitudinal data consisting of repeated measurements of %FEV$_1$ of patients present in the registry between 2002 and 2011. The premise of this model is that each patient in the population has his own subject-specific mean response trajectory over time, and some of the parameters used in our regression model are random, i.e. they vary across different groupings of the population.

Let y_{ij} be the %FEV$_1$ measured at the j^{th} visit for the i^{th} patient. In this model n_i denotes the number of recorded measurement for the i^{th} patient and m represents the total number of patients used in the study. The Linear Mixed-Effects Model (LMM) presented below follows the formula

$$\boldsymbol{y_i} = \boldsymbol{X_i\beta} + \boldsymbol{Z_i b_i} + \boldsymbol{\varepsilon_i}$$

where $\boldsymbol{y_i}$ is the vector of continuous responses, in this study, corresponding to all the %FEV$_1$ measurements associated with one patient;

$\boldsymbol{X_i} = \begin{bmatrix} X_{11}^{[i]} & \cdots & X_{1p}^{[i]} \\ \vdots & \ddots & \vdots \\ X_{n_{i1}}^{[i]} & \cdots & X_{n_iq}^{[i]} \end{bmatrix}$ is the design matrix consisting of the fixed effects in the model;

$\boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_p \end{bmatrix}$ is the vector of the fixed effects;

n_i is the recorded measurements for the i^{th} patients and p is the number of fixed effects; and

$\boldsymbol{Z_i} = \begin{bmatrix} Z_{11}^{[i]} & \cdots & Z_{1q}^{[i]} \\ \vdots & \ddots & \vdots \\ Z_{n_{i1}}^{[i]} & \cdots & Z_{n_i q}^{[i]} \end{bmatrix}$ contains known values of q covariates corresponding the random effects associated with random effects coefficients $\boldsymbol{b_i} = \begin{bmatrix} b_{i1} \\ \vdots \\ b_{iq} \end{bmatrix}$.

Moreover, $\boldsymbol{b_i} \sim N_q(\mathbf{0}, \sigma^2 \boldsymbol{D})$ and $\boldsymbol{\varepsilon_i} \sim N(\mathbf{0},\ \sigma^2 \mathbf{R}_{\boldsymbol{i}})$, the residuals associated with the ith patient, are independent. We assume that σ^2 is an unknown scale parameter whereas $\boldsymbol{D}$ and $\mathbf{R}_{\boldsymbol{i}}$ are unknown covariance matrices.

In our study the matrix of fixed effects covariates $\boldsymbol{X_i}$ is composed of 7 fixed effects, 2 quantitative variables (Age , median income) and 5 qualitative variables (Gender, Genetic Severity, Medium Distance indicator, Large Distance indicator, and a Medicaid insurance indicator. The covariates $\boldsymbol{Z_i}$ associated with the random effects are for the intercept and age.

The parameters in the vector $\boldsymbol{\beta}$ capture the population characteristics that are shared by all the patients, while $\boldsymbol{b_i}$ captures subject-specific variations. For instance in the model specified above, by including age as a random effect in the model, we can not only measure how the mean response changes in the population as Age increases, it is also possible to determines how individual %FEV_1 trajectories change as Age increases.

To take into account the fact that the variance of the residuals $\boldsymbol{\varepsilon_i}$ associated with i^{th} patient has a non-constant variance with age we proposed to model the variance of the error as a power function of age. So the variance for each patient is given by $\boldsymbol{\sigma_{ij} = \sigma\left(Age_j\right)^{\delta}}$ where Age_j is the age at which the j^{th} %FEV_1 measurement was taken. We thus assume that the variance of the residuals of %FEV_1 is a power function of age and we can capture the heteroscedasticity of observations within the i^{th} group.

2.3 Results

2.3.1 Study Population

After removing missing data and filtering, the population was reduced from 44,541 to 20,400 patients (Figure 1). Missing outcome (%FEV_1) and distance information, which is vital for the question considered, account for 87% of the missing data. A comparison analysis of removed data to data used in the study is included in the online appendix section IV. We then split our analysis into three population groups, patients 18 years old and younger (7,909 patients), patients between 19 and 30 (7,726 patients), and patients older than 30 years (4,765 patients) to allow for differences in lifestyle between the age groups. Figure 7 displays the distribution of the %FEV_1 obtained from patients considered in this study.

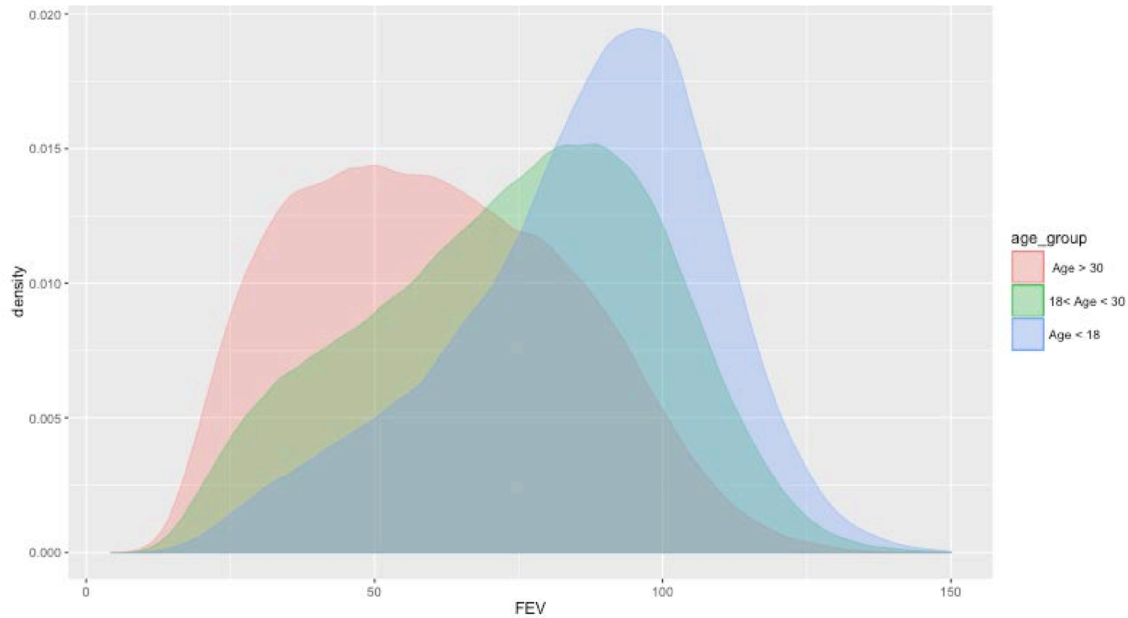

Figure 7: Density of %FEV$_1$ across age categories.

2.3.2 Geographic Distance or Access Measure

Table 1 presents the number and percentage of patients within each population group and across model covariates along with information about patients' change of geographic distance categories. We note that 36.3% of older adult patients moved between geographic distance categories during the time covered by the analysis, compared with 30.3% of young adults and only 12.7% of children and adolescents.

Table 1: Patient demographics by maximum age groups including number of patients who are women, have Medicaid, have severe mutation, and who live within a certain distance to care.

	Maximum Age in Years							
Patient Characteristic	<=18		>18 and <=30		>30		All Ages	
N (%)	7875	(38.7%)	7717	(37.9%)	4759	(23.4%)	20351	(100.0%)
Women	3967	(50.4%)	3621	(46.9%)	2234	(46.9%)	9822	(48.3%)
Severe Mutation	5830	(74.0%)	5713	(74.0%)	2979	(62.6%)	14522	(71.4%)
Medicaid	4915	(62.4%)	5483	(71.1%)	3008	(63.2%)	13406	(65.9%)
Distance								
Patient did not change categories								
Low (<=25 miles)	2510	(31.9%)	1967	(25.5%)	1159	(24.4%)	5636	(27.7%)
Medium (>25 and <= 75 miles)	2534	(32.2%)	1788	(23.2%)	1004	(21.1%)	5326	(26.2%)
High (>75 miles)	1828	(23.2%)	1621	(21.0%)	868	(18.2%)	4317	(21.2%)
Subtotal	6872	(87.3%)	5376	(69.7%)	3031	(63.7%)	15279	(75.1%)
Patient changed categories								
Low ↔ Medium	282	(3.6%)	566	(7.3%)	400	(8.4%)	1248	(6.1%)
Low ↔ High	257	(3.3%)	698	(9.0%)	559	(11.7%)	1514	(7.4%)
Medium ↔ High	374	(4.7%)	809	(10.5%)	519	(10.9%)	1702	(8.4%)
Low↔Medium↔High	83	(1.1%)	262	(3.4%)	247	(5.2%)	592	(2.9%)
Subtotal	996	(12.6%)	2335	(30.3%)	1725	(36.2%)	5056	(24.8%)

For patients who did move and those who did not move, a box plot showing the difference in %FEV_1 with distance is shown for each age group in Figure 8. For children, the median distance from a care center is higher than that for adults with the exception of the heathiest adults. As patients age, the heathiest patients tend to be the farthest away from their CF care centers. For adults who change geographic distance categories, the mean value of distance to a care center is 92.8 for patients who have a low %FEV_1 and 107.3 for patients that have a high %FEV_1 ($p<0.001$). For children and adolescents who change distance categories in the study, the difference in means between these two groups is not significant (p-value of 0.12).

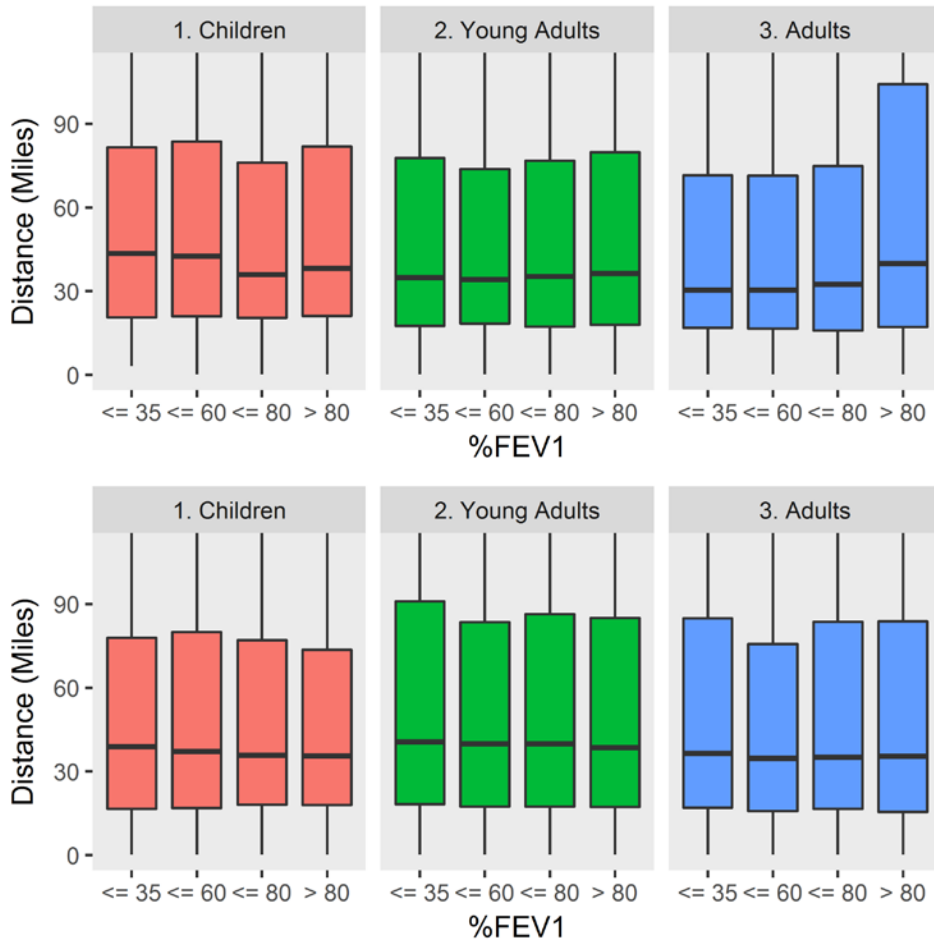

Figure 8: Boxplot of distribution of distance in miles by age group and outcome severity for patients who moved (top) and patients who did not move (bottom).

For children who did not change distance categories, patients in the high %FEV$_1$ group have a mean 1.43 miles farther from a care center (p-value <0.001) while adults who did not change distance categories and were in the high %FEV$_1$ category have a mean 2.94 miles farther (p-value <0.001). For young adults, the difference is not significant.

2.3.3 Model Fit

All the models were estimated using maximum likelihood estimation and implemented using the library **nlme** available in the R statistical software. To test whether the variables incorporated in the model are significant we perform hypothesis testing using the Wald test.

In Figure 9, we report the fitted values of $\%FEV_1$ for all the patients in each age group. Each vertical set of points in black correspond to the entire $\%FEV_1$ curve of a patient and the red points on the x-axis correspond to the fitted values of $\%FEV_1$. We see that the fitted model captures a large proportion of the variability present in the data, since the fitted values follow closely the true $\%FEV_1$ values with the exception of some outliers for lower values of observed $\%FEV_1$.

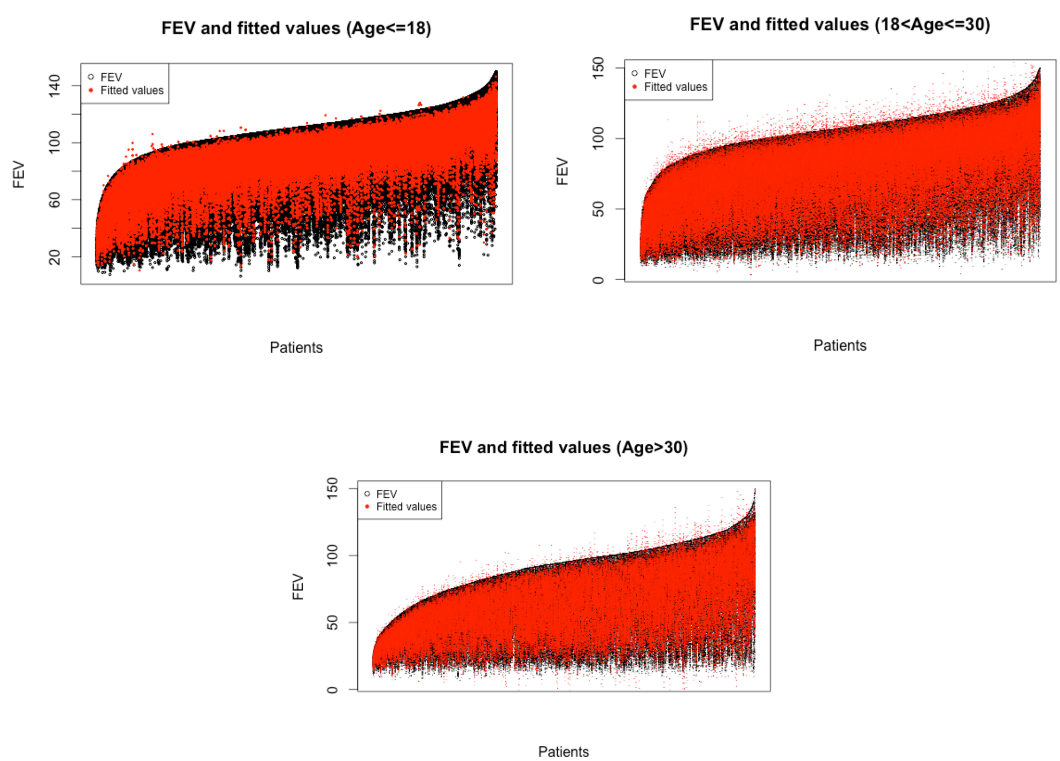

Figure 9: Plot of the fitted values and the $\%FEV_1$ measurements for models across age groups, each vertical line corresponds to measurements associated with one patient.

In Figure 10, we plot the Pearson marginal residuals $\frac{\hat{\boldsymbol{\varepsilon}}_{(\boldsymbol{m})\boldsymbol{i}}}{\sqrt{\widehat{\boldsymbol{var}}}(\hat{\boldsymbol{y}}_{(\boldsymbol{m})\boldsymbol{i}})}$ against the marginal fitted values $\hat{\boldsymbol{y}}_{\boldsymbol{i}} = \boldsymbol{X}_{\boldsymbol{i}}\widehat{\boldsymbol{\beta}}$. Based on these residuals plots, we can conclude that the mean structure of our model is appropriate since there is no discernable nonlinear pattern.

In mixed effect models, it is also important to inspect the conditional residuals defined as

$$\hat{\boldsymbol{\varepsilon}}_{(c)i} = \boldsymbol{y}_{\boldsymbol{i}} - \boldsymbol{X}_{\boldsymbol{i}}\,\widehat{\boldsymbol{\beta}} - \boldsymbol{Z}_{\boldsymbol{i}}\widehat{\boldsymbol{b}}_{\boldsymbol{i}}$$

where $\widehat{\boldsymbol{b}}_{\boldsymbol{i}}$ is the conditional expectation of $\boldsymbol{b}_{\boldsymbol{i}}$. And the marginal residuals are defined as

$$\hat{\boldsymbol{\varepsilon}}_{(m)i} = \boldsymbol{y}_{\boldsymbol{i}} - \boldsymbol{X}_{\boldsymbol{i}}\,\widehat{\boldsymbol{\beta}}.$$

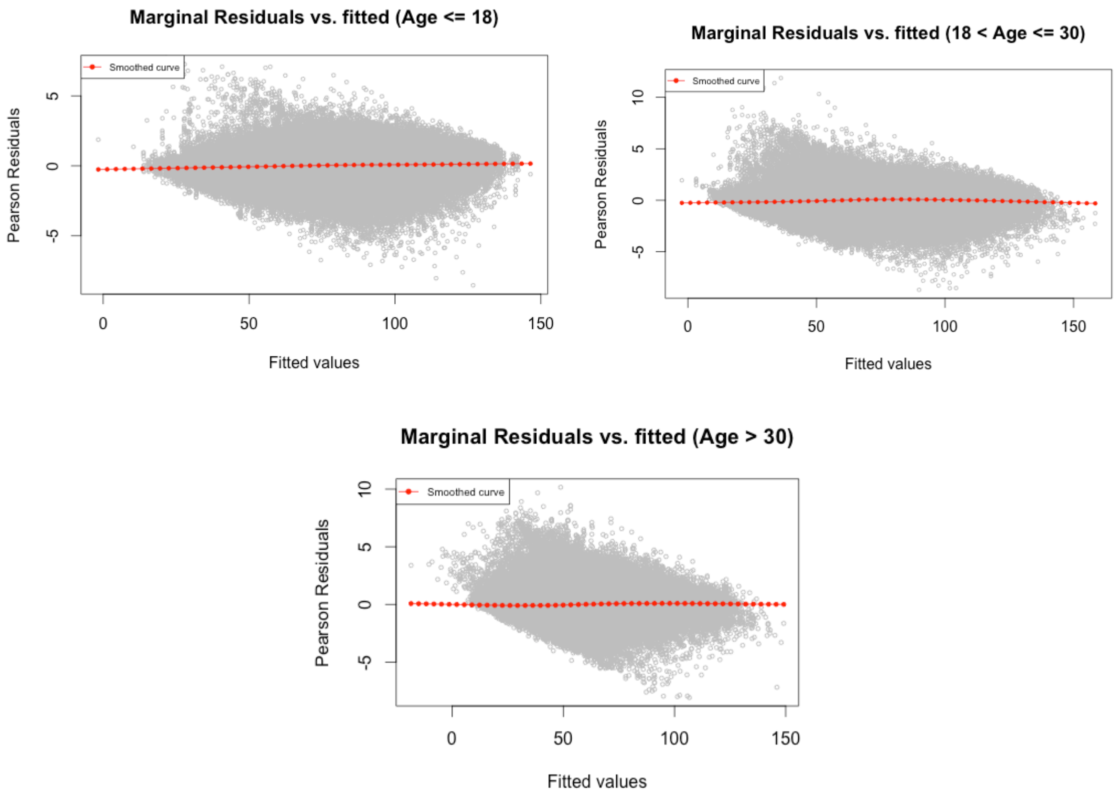

Figure 10: Scatterplot of the standardized marginal residuals versus the fitted values and smoothed trend lines shown in red.

To verify that the residuals errors are homoscedastic, we follow the recommendations of Santos Nobre and da Motta Singer (2007) [21] and plot the conditional Pearson residuals $\frac{\hat{\varepsilon}_{(c)i}}{\sqrt{\widehat{var}(\hat{y}_{(c)i})}}$ against the conditional fitted values $\hat{\boldsymbol{y}}_{(c)i} = \boldsymbol{X}_i\hat{\boldsymbol{\beta}} + \boldsymbol{Z}_i\,\hat{\boldsymbol{b}}_i$. Based on Figure 11, we conclude that the residual errors for the model used for children may not be heteroscedastic, since there is not an increase or decrease in their range as the conditional fitted values increase.

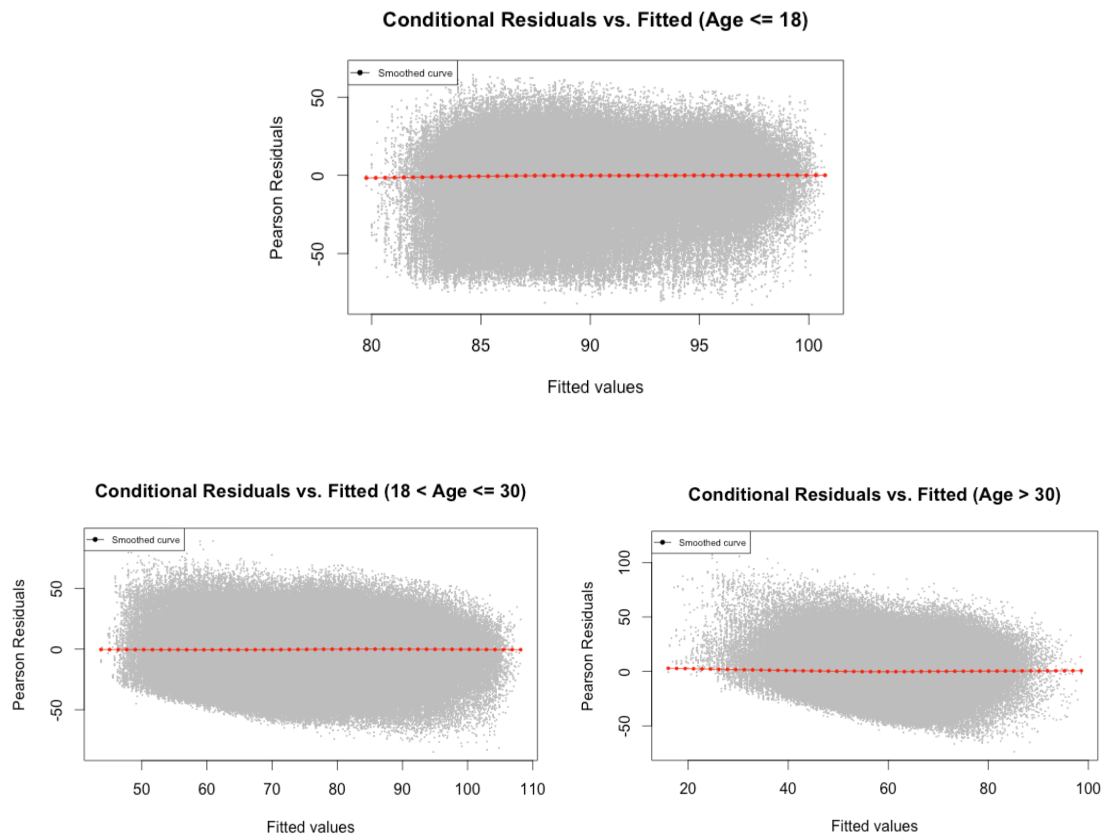

Figure 11: Plot of the conditional residuals vs. fitted values and smoothed trend line in red.

We also assess the validity of the normality assumption when we use the conditional Pearson residuals. The Q-Q plots in Figure 12 show that the sample quantiles of the residuals are aligned with the theoretical quantiles of the normal distribution. It is important to add that these graphs do not necessarily allow us to conclude that the residuals are following the assumed distribution, but they allow us to assess if there is a substantial deviation from the normality assumption.

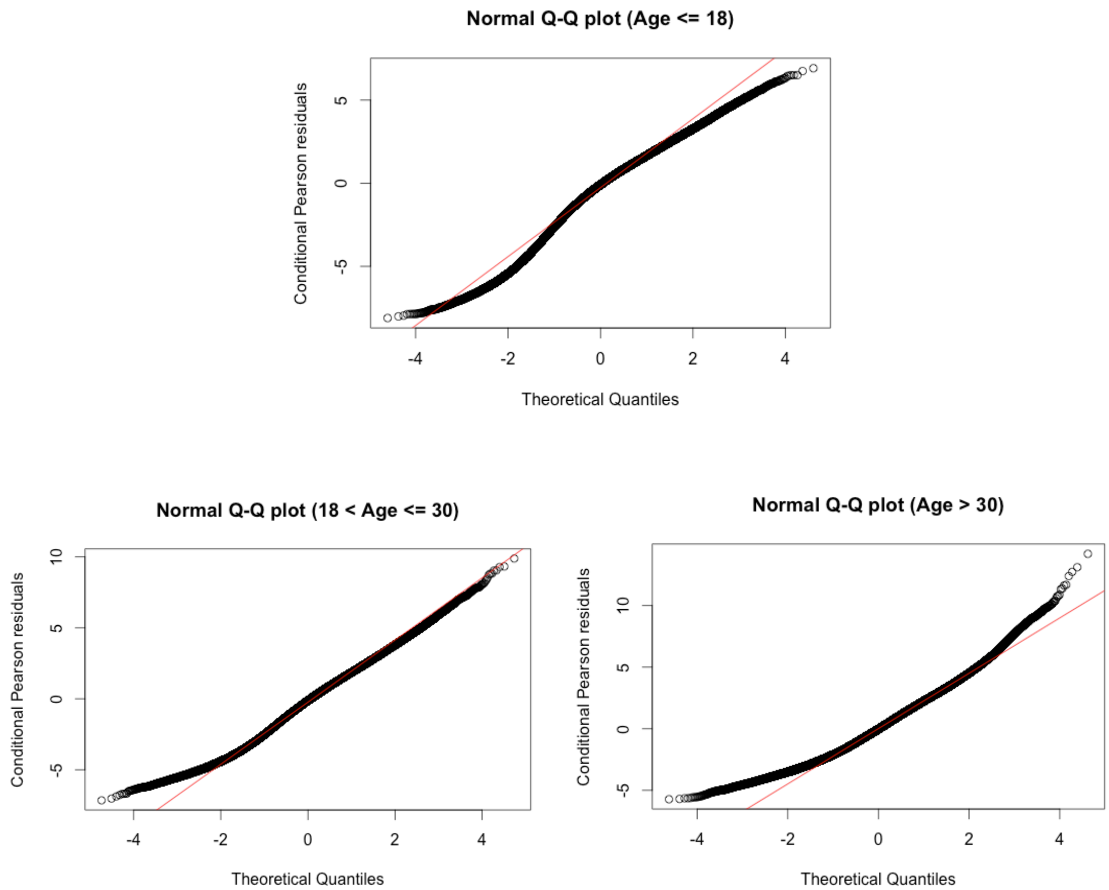

Figure 12: Normality plot of the residuals across age groups models.

Figure 13 shows the relationship between the marginal Pearson residuals and the predictor Age. By fitting a model per age group, we were able to remove an upward trend in the plot of the residuals against the predictor age. The red curve is a locally weighted smoothed line that shows that there is no apparent pattern between the marginal residuals and the predictor age and the marginal residuals are centered at mean 0. Thus, we can conclude that no transformation of the predictor age was needed.

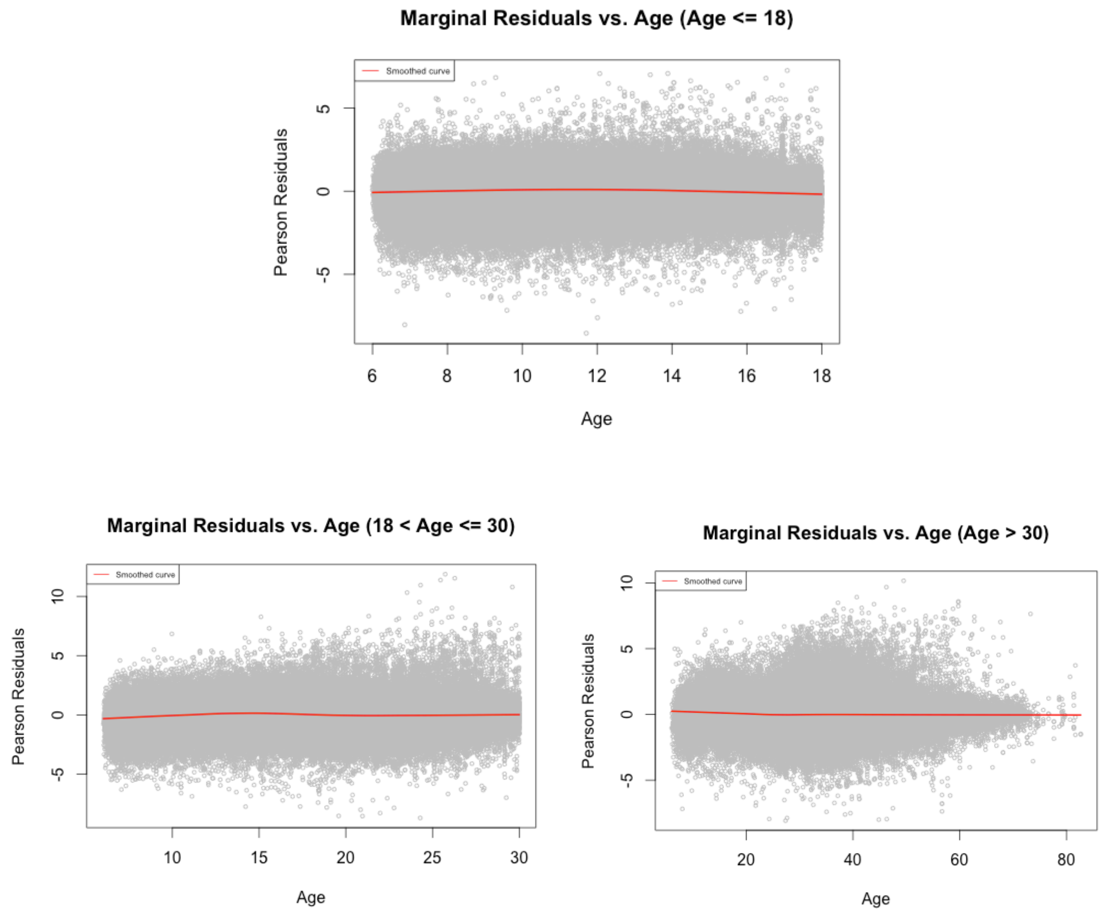

Figure 13: Marginal Pearson Residuals against the covariate Age.

To justify further the validity of the model and the choices considered for the variance covariance structure of these models, we conduct an Analysis of Variance test on a series of models with simpler assumptions. The alternative models considered are

1- **The Basic Model** contains fixed effects (age, gender, disease severity, Medicaid status, median income, medium distance and large distance indicators) and the random effects intercept and age. Additionally, we assume that the residuals are homoscedastic and that they are uncorrelated.

2- The Basic Model + Heterogeneous variance have the same fixed effects and the same random effects contained in the basic model. We also add a variance power function that depends on the age during the visit.

The tables below show the Analysis of Variance for the alternative models and the model we selected and each table corresponds to an age group. We can see that the model with heterogeneous variance always has the minimum AIC, BIC and negative log-likelihood and thus they always provide the best fit. Additionally when we test the null hypothesis of homogeneous variance $H_0: \delta = 0\ vs. H_a: \delta \neq 0$ we reject the null hypothesis for all models, since the p-value associated with the test 1 vs. 2 is less than 0.0001 for all the age groups. This implies all age groups we used the model with heterogeneous variance.

Table 2: Likelihood ratio test for the model fitted with patients 18 and younger for patients who did not change proximity categories.

	Model	df	AIC	BIC	logLik	Test	L.Ratio	p-value
Basic Model	1	16	1475711	1475874	-737839.6			
Basic Model + Heterogeneous Variance	2	17	1474264	1474437	-737115.2	1 vs. 2	1448.752	<.0001

Table 3: Likelihood ratio test for the model fitted with patients between 19 and 30 for patients who did not change proximity categories.

	Model	df	AIC	BIC	logLik	Test	L.Ratio	p-value
Basic Model	1	17	2138204	2138383	-1069085			
Basic Model + Heterogeneous Variance	2	18	2134326	2134516	-1067145	1 vs. 2	3879.644	<.0001

Table 4: Likelihood ratio test for the model fitted with patients older than 30 for patients who did not change proximity categories.

	Model	df	AIC	BIC	logLik	Test	L.Ratio	p-value
Basic Model	1	17	1036442	1036609	-518204			
Basic Model + Heterogeneous Variance	2	18	1034137	1034313	-517050.3	1 vs. 2	2307.303	<.0001

Table 5: Likelihood ratio test for the model fitted with patients 18 and younger for patients who changed proximity categories.

	Model	df	AIC	BIC	logLik	Test	L.Ratio	p-value
Basic Model	1	16	279614.7	279750.4	-139791.3			
Basic Model + Heterogeneous Variance	2	17	279474.9	279619	-139720.4	1 vs. 2	141.7977	<.0001

Table 6: Likelihood ratio test for the model fitted with patients between 19 and 30 for patients who changed proximity categories.

	Model	df	AIC	BIC	logLik	Test	L.Ratio	p-value
Basic Model	1	17	1025835	1026002	-512900.5			
Basic Model + Heterogeneous Variance	2	18	1023801	1023977	-511882.3	1 vs. 2	2036.431	<.0001

Table 7: Likelihood ratio test for the model fitted with patients older than 30 for patients who changed proximity categories.

	Model	df	AIC	BIC	logLik	Test	L.Ratio	p-value
Basic Model	1	17	691729.2	691888.9	-345847.6			
Basic Model + Heterogeneous Variance	2	18	690643.9	690812.9	-345303.9	1 vs. 2	1087.33	<.0001

For each age group, we modeled the variance of the residuals as a power function of age. We observed that the variance of these residuals decreased as the age of the patients increased. For patients who did not change proximity categories, the power coefficients are -0.25, -0.27, and -0.26 for children, young adults and adults respectively. For patients who change proximity categories, the coefficients are -0.19, -0.28, and -0.23 for each age group respectively. For all groups we see the variance of the residuals decrease as patients age, meaning our model produces a tighter fit.

For the patients younger than 18 who changed proximity categories the variance covariance matrix of the random effects is given by

$\sigma_{intercept} = 29.88$, $\sigma_{age} = 2.68$ and $corr(intercept, age) = -0.80$.

For the young adults between 19 and 30 who changed proximity categories the variance covariance matrix of the random effects is given by

$\sigma_{intercept} = 27.44$, $\sigma_{age} = 1.65$ and $corr(intercept, age) = -0.77$.

For older patients with an age over 30 at the time of the final visit who changed proximity categories, we have

$\sigma_{intercept} = 44.87$ $\sigma_{age} = 1.36$ and $corr(intercept,\ age) = -0.89$

For the patients younger than 18 who did not change proximity categories the variance covariance matrix of the random effects is given by

$\sigma_{intercept} = 27.57$, $\sigma_{age} = 2.53$ and $corr(intercept, age) = -0.79$.

For the young adults between 19 and 30 who did not change proximity categories the variance covariance matrix of the random effects is given by

$$\sigma_{intercept} = 27.85, \sigma_{age} = 1.74 \text{ and } corr(intercept, age) = -0.79.$$

For older patients with an age over 30 at the time of the final visit who did not change proximity categories, we have

$$\sigma_{intercept} = 54.29, \sigma_{age} = 1.48 \text{ and } corr(intercept,\ age) = -0.90$$

The negative correlation between the random effects intercept and age validates that %FEV_1 decreases as patients get older.

2.3.4 Mixed Effect Model Results

Table 8 presents the parameter estimates for the mixed effects model, the 95% confidence intervals and the associated p-values for each of the three models for patients who did not change geographic distance categories throughout the study. Table 9 presents the same results for patients who did change categories.

Table 8: The parameter estimates for the mixed effects model, the 95% confidence intervals and the associated p-values for patients who did not change geographic distance categories.

	Point Estimate	Lower 95% CI	Upper 95% CI	P Value
Intercept				
Children and Adolescents (Age <= 18)	107.60	105.85	109.34	< 0.001
Young Adults (18 < Age <= 30)	123.42	121.63	125.21	< 0.001
Adults (Age > 30)	102.63	99.23	106.04	< 0.001
Age				
Children and Adolescents	-0.85	-0.92	-0.78	< 0.001
Young Adults	-2.26	-2.31	-2.20	< 0.001
Adults	-0.80	-0.87	-0.74	< 0.001
Male (ref. female)				
Children and Adolescents	0.52	-0.30	1.34	0.22
Young Adults	2.72	1.78	3.67	< 0.001
Adults	-2.92	-4.64	-1.20	< 0.001
Severe Mutation				
Children and Adolescents	-2.32	-3.26	-1.37	< 0.001
Young Adults	-1.63	-2.70	-0.56	0.00
Adults	-9.27	-11.05	-7.48	< 0.001
Medium Distance (ref. Low Distance)				
Children and Adolescents	1.33	0.34	2.31	0.01
Young Adults	-0.42	-1.56	0.73	0.47
Adults	-1.13	-3.16	0.90	0.28
High Distance (ref. Low Distance)				
Children and Adolescents	0.12	-1.03	1.27	0.84
Young Adults	-0.45	-1.67	0.78	0.48
Adults	-1.02	-3.20	1.16	0.36
Urban				
Children and Adolescents	0.63	-0.21	1.47	0.14
Young Adults	-0.56	-1.22	0.11	0.10
Adults	-0.74	-1.75	0.26	0.15
Medicaid Insurance				
Children and Adolescents	-6.82	-7.68	-5.96	< 0.001
Young Adults	-6.80	-7.86	-5.74	< 0.001
Adults	-10.20	-12.01	-8.38	< 0.001

Table 8 (continued)

Median Income				
Children and Adolescents	-7.76	-9.72	-5.80	< 0.001
Young Adults	-3.86	-5.07	-2.66	< 0.001
Adults	-5.63	-7.26	-3.99	< 0.001
Year 2001 - 2005				
Children and Adolescents	-2.68	-2.89	-2.47	< 0.001
Young Adults	-0.22	-0.39	-0.06	0.01
Adults	-1.94	-2.17	-1.70	< 0.001
Year 1996 - 2000				
Children and Adolescents	-7.55	-8.26	-6.84	< 0.001
Young Adults	-2.14	-2.43	-1.86	< 0.001
Adults	0.36	-0.05	0.77	0.08
Year 1991 - 1995				
Children and Adolescents	-16.88	-19.80	-13.97	< 0.001
Young Adults	-6.37	-6.81	-5.93	< 0.001
Adults	3.04	2.46	3.62	< 0.001
Year 1986 - 1990				
Children and Adolescents	N/A	N/A	N/A	N/A
Young Adults	-12.89	-13.79	-11.99	< 0.001
Adults	4.94	4.14	5.74	< 0.001

Table 9: The parameter estimates for the mixed effects model, the 95% confidence intervals and the associated p-values for patients who changed geographic distance categories.

	Point Estimate	Lower 95% CI	Upper 95% CI	P Value
Intercept				
Children and Adolescents (Age <= 18)	107.63	103.82	111.44	< 0.001
Young Adults (18 < Age <= 30)	121.34	118.88	123.80	< 0.001
Adults (Age > 30)	98.11	94.45	101.77	< 0.001
Age				
Children and Adolescents	-1.28	-1.47	-1.09	< 0.001
Young Adults	-2.19	-2.26	-2.11	< 0.001
Adults	-0.89	-0.97	-0.81	< 0.001
Male (ref. female)				
Children and Adolescents	1.49	-0.76	3.75	0.20
Young Adults	2.42	0.99	3.85	0.00
Adults	-2.00	-3.97	-0.03	0.05
Severe Mutation				
Children and Adolescents	-0.69	-3.32	1.95	0.61
Young Adults	-1.90	-3.62	-0.17	0.03
Adults	-5.04	-7.21	-2.86	< 0.001
Medium Distance (ref. Low Distance)				
Children and Adolescents	-0.40	-0.97	0.17	0.17
Young Adults	-0.48	-0.77	-0.20	< 0.001
Adults	0.07	-0.27	0.40	0.69
High Distance (ref. Low Distance)				
Children and Adolescents	0.40	-0.19	0.98	0.18
Young Adults	-0.55	-0.83	-0.27	< 0.001
Adults	1.53	1.21	1.85	< 0.001
Urban				
Children and Adolescents	-0.21	-1.25	0.83	0.69
Young Adults	-1.15	-1.64	-0.65	< 0.001
Adults	0.66	-0.02	1.34	0.06
Medicaid Insurance				
Children and Adolescents	-7.45	-9.91	-5.00	< 0.001
Young Adults	-7.03	-8.62	-5.44	< 0.001
Adults	-6.41	-8.52	-4.30	< 0.001

Table 9 (continued)

Median Income				
Children and Adolescents	-2.77	-5.09	-0.44	0.02
Young Adults	-6.62	-7.64	-5.61	< 0.001
Adults	-4.03	-5.19	-2.87	< 0.001
Year 2001 - 2005				
Children and Adolescents	-2.41	-2.90	-1.91	< 0.001
Young Adults	0.27	0.03	0.52	0.03
Adults	-0.97	-1.27	-0.67	< 0.001
Year 1996 - 2000				
Children and Adolescents	-6.76	-8.26	-5.25	< 0.001
Young Adults	-0.02	-0.45	0.42	0.94
Adults	0.34	-0.18	0.86	0.20
Year 1991 - 1995				
Children and Adolescents	-19.20	-23.50	-14.91	< 0.001
Young Adults	-2.43	-3.08	-1.78	< 0.001
Adults	2.26	1.52	2.99	< 0.001
Year 1986 - 1990				
Children and Adolescents	N/A	N/A	N/A	N/A
Young Adults	-5.84	-7.10	-4.59	< 0.001
Adults	4.60	3.60	5.61	< 0.001

Among children and adolescents who did not move, those residing at medium distance had a slightly higher $\%FEV_1$ than those in the low distance category, but no other age groups showed any associations of distance with $\%FEV_1$ in our multivariable models. For patients who moved during the course of the study, we found statistically significant but clinically trivial differences in $\%FEV_1$ by distance in young adults. On the other hand, there appeared to be a trend whereby older adults who lived furthest from the CF center had higher $\%FEV_1$, with a coefficient of 1.53 for high distance.

As shown in the tables, Medicaid insurance, age, and severe CFTR mutation class are generally found to be associated with lower $\%FEV_1$, as reported in previous studies [1, 6, 8]. We also find median family income by zip code is associated with lower $\%FEV_1$. We found an advantage to male sex in young adults, a disadvantage in older adults, and no difference for children and adolescents.

Urban classification is negatively associated with $\%FEV_1$ for young adults and adults who do not change distance categories. For those that do change categories, it is negatively associated for young adults and positively associated for adults. Interactions between income and distance as well as urban and distance were also studied, but none yielded statistically significant results.

2.3.5 Comparison of Removed Data

A comparison of removed data was conducted to show the potential effect missing data has on the results. Below are plots showing the number of visits per year prior to filtering, the number of visits per year used in the final dataset, the number of visits per year removed, and the percent of data removed in each year. Finally, since 87% of the missing data is from missing $\%FEV_1$ and missing distance information, we have also included plots showing which years are missing $\%FEV_1$ and distance information. As you can tell from Figure 14 and Figure 15, the majority of the included data is from the more recent years. This is due to a significantly higher percentage of missing $\%FEV_1$ and distance data in the earlier years. Additional plots of the distributions over time of the data are shown in 0.

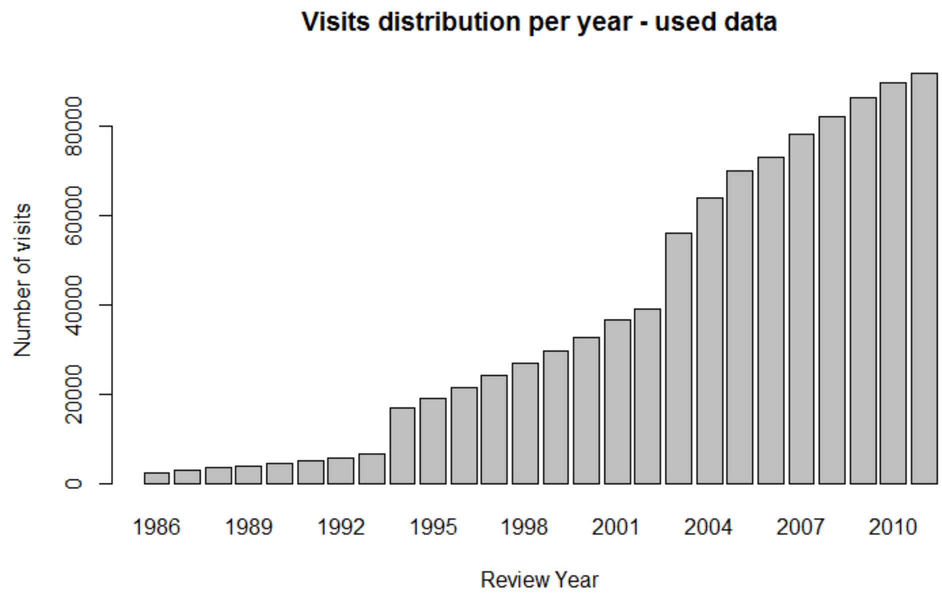

Figure 14: Visits distribution per year for all data used in the analysis.

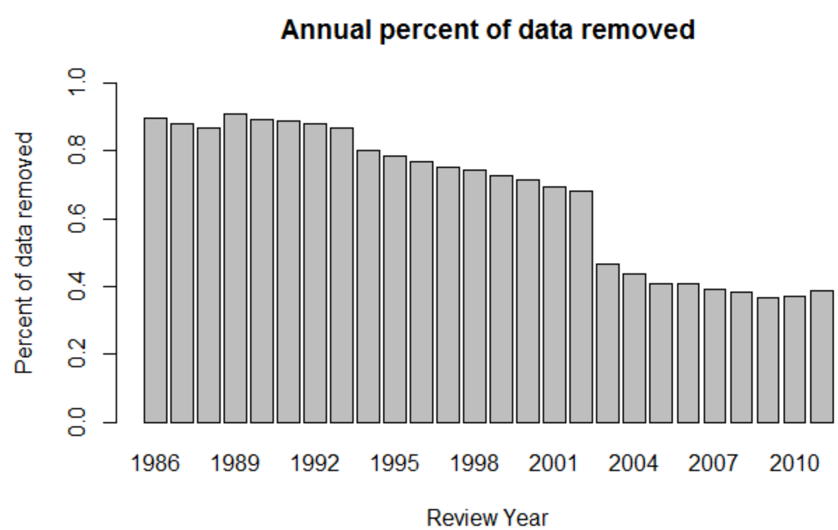

Figure 15: Percent of data removed in each year.

Table 10 shows a comparion of the outcome and main predictor variables in both the data used for analysis as well as the data removed. Note for the data removed, the values shown are the means of the data available that is not missing.

Table 10: The mean values of data used in the analysis and data removed from the analysis.

Variable	Mean: Data used	Mean: Data removed
Age	19.7	15.0
Male	0.499	0.512
Severe Genetics	0.759	0.595
Small Distance	0.372	0.379
Medium Distance	0.345	0.331
Large Distance	0.283	0.290
Medicaid	0.712	0.753
Median Income	0.298	0.308
Review Year	2004.6	1999.6
FEV	73.2	58.4

Overall, the data used has a higher mean age, higher percent of severe genetics patients, higher Review year, and higher $\%FEV_1$. As expected based on the plots above, the data removed is on average older than the data used, which could account for some of the differences as treatments have evolved over time. This is also shown in the regression analysis as the data in older years has lower $\%FEV_1$ than data in newer years.

2.4 Discussion

In this study, we evaluated the impact of geographic distance that patients must travel between their zip code of residence and the location of their CF care center. This study found no strong evidence of an effect of geographic distance from care center on $\%FEV_1$

in patients who did not change distance categories during the study period. On the other hand, we found that for patients who did change geographic distance categories, the average %FEV$_1$ was slightly higher for older adults who moved further from their CF center and marginally worse for young adults who moved farther from a CF care. Further, as distance increased, the outcomes became better for older adults and worse for young adults. We found no significant interactions between the geographic distance and socioeconomic status or urban/rural characteristics. Because most CF centers are located in urban areas, which typically have higher incomes, there is a correlation between median income and a patient's geographic distance to care. To check the impact of this, the model was run without income and similar results were observed to the models presented.

This study found associations between median income, geographic distance to a CF center, and urban/rural designations. It appears CF centers are located in urban areas, many of which are also in zip codes with a higher median income. Thus, patients with the smallest distances to care are also more likely to be associated with high median incomes and urban environments. The associations between geographic distance to care, urban environments, and median family income by zip code make it difficult to differentiate the true impact of each variable independently.

An important challenge in characterizing the association between outcomes and distance to care was the high level of mobility in adults. In our study, less than 13% of children changed distance categories. In contrast, more than 36% of the adult population moved between geographic distance categories. This could partially explain the inconclusive results obtained in attempting to determine the impact of distance on health outcomes in the older patients. With patient mobility, it is difficult to determine the impact of mobility versus the impact of distance, given this population is inherently different. As changes in lung function generally occur gradually over time, it is difficult to assign a temporal relationship between moves and worsening lung disease. As a result, this study did not attempt to evaluate the temporal relationship between patient movement and a change in %FEV_1. This makes speculation on causation even more difficult. We suspect that older patients who are healthier are more comfortable moving further from the CF center, whereas those who are sicker are more likely to move closer. On the other hand, it is plausible to speculate that younger adults who move further away from the CF center (due to jobs or school) may suffer consequences of this move.

While our study uncovers new results, the model and the data collected have inherent limitations. First, the CF registry does not include the entire population of cystic fibrosis patients in the United States, and in fact, patients who are farthest away may be those who are likely to seek care from non-CFF accredited providers and therefore be excluded from the analysis. This bias is probably even more likely in those with milder disease since they are likely to seek care less often, so the true relationship of better health with higher distance may be greater than we report here. Second, we excluded patients with incomplete information regarding health outcomes and/or predictors, which may also have biased our results because these characteristics may be associated with both our predictor and our outcome variables. Third, the discretization of the continuous variable distance only allows us to partially capture the nonlinear effect of geographic distance on health outcome. A nonparametric model could better capture the relationship between geographic access and %FEV_1; however, its interpretation could be more challenging. Fourth, this study focused only on travel distance. Travel time to a care center would also play a significant role.

In conclusion, contrary to our original hypothesis, it appears that geographic distance to CF centers has no significant association with lung health in patients who maintained the same distance category during the course of our analysis. Among those who changed distance categories, we believe that the association that we found between better lung function and geographic distance in older adults is more likely from relocation following lung function rather than distance affecting lung function. We believe the association between worse lung function and distance in young adults may be due to the more heterogeneous population among young adults who move. Further investigations into the effect of patient mobility and any self-selecting bias in patient mobility are warranted. One method to address this would be to use more detailed patient mobility and health data to study the relationship between lung function and distance taking into account each time a patient moves closer to a care center or farther from a center.

CHAPTER 3. ESTIMATING THE IMPACT OF SUPPLY CHAIN PERFORMANCE ON MALARIA MORTALITY IN AFRICA

3.1 Background

Global health supply chains support several traditional functions including procurement, transportation, and warehousing in addition to the specific functions of preparedness and associated planning [22, 23]. Some of the key challenges for effective management of global supply chains include understanding the dynamics that arise such as high variation in demand and long lead times [24-26], coordinating activities between various parties [22, 27, 28], and satisfying several different types of objectives such as efficiency, equity, and quality [29, 30]. In addition, many of the locations that global health supply chains need to support have poor transportation infrastructure [31]. This greatly complicates the "last mile" problem of delivering products to the end customer [32-34].

Malaria is a life-threatening mosquito-borne infectious disease, which causes fevers, chills, and vomiting approximately 10 to 15 days after infection. A disproportionately high number of cases are in the Sub-Saharan Africa region; 88% of global malaria cases and 90% of malaria deaths [35]. In 2015, the World Health Organization (WHO) estimated that there were over 210 million cases and 438,000 deaths [35]. Although this burden is high, global and national efforts in Africa led to a decline in mortality; malaria deaths in Africa decreased from 1.61 million in 2004 to 1.13 million in 2010 [36]. As a result, the average annual percent change in malaria age-standardized death rate is projected to decrease by roughly 1.4% through the year 2030 [37].

One of the roles of the United States Agency for International Development (USAID) is to work with national governments to build supply chain capacity to prevent and treat malaria. One of the programs under USAID is the President's Malaria Initiative (PMI) in partnership with the Centers for Disease Control and Prevention (CDC). Focusing primarily in Africa, USAID's malaria supply chain targets nineteen focus countries to deliver materials and drugs necessary for prevention and treatment, insecticide-treated mosquito nets, and insecticides for indoor residual spraying around homes. The global malaria supply chain analyzed in this article moves product from the manufacturers to the first point of entry in a country. Generally, the point of entry will be a central medical store for the country, but sometimes the transfer could occur at the border.

Due to the complexity of running global health supply chains, it is important to identify the factors that are most important for their effectiveness; namely, the reduction of the morbidity and mortality associated with malaria. We use publicly available data on malaria mortality [38-40], the USAID malaria supply chain [41-43], and other factors known to impact malaria disease severity, in-country supply chains, or country specific demographics and development levels [17, 44, 45]. The supply chain data covers topics such as procurement, transportation, and some performance measures in the supply chain across the network of international suppliers, international warehouse locations, and an international distribution system to the target countries. Our overall goal is to determine which (if any) supply chain factors are significantly associated with mortality, and to make recommendations for supply chain improvement based on these factors.

3.2 Methods

The full set of data elements and their summary statistics are provided in Table 11. The independent data variables are described below.

Table 11. Data Elements, Sources, and Summary Statistics.

Data Element	Source	Average	St. Dev.
Estimated Malaria Deaths	WHO World Malaria Report [40]	21397.4	40664.1
Supply Chain Cycle Time	USAID public supply chain data [41]	109.5	47.7
Supply Chain Percentage of Air Shipments	USAID public supply chain data [41]	0.7	0.3
Average Annual Temperature	World Bank [17]	24.1	2.8
Average Annual Precipitation	World Bank [17]	1089.2	480.5
Latitude	CIA [45]	0.4	12.1
UN Population	WHO World Malaria Report [40]	31023494	35609926
Average USAID Funding	WHO World Malaria Report [40]	21596086	12595110
Average Total Funding	WHO World Malaria Report [40]	55215281	47968047
Percentage of any Antimalarial Coverage	WHO World Malaria Report [40]	82.0	28.6
GDP per capita	World Bank [17]	1038.2	1012.5
LPI Score	World Bank [17]	2.4	0.3
Life Expectancy	World Bank [17]	57.9	5.1
Physician Density	CIA [45]	0.1	0.1
Malaria Season Duration	MARA [44]	2.4	0.7
Sparsity	World Bank [17], WHO World Malaria Report [40]	97.6	110.7

Malaria supply chain metrics were obtained from the global health commodity procurement contract under section J-9 of the solicitation for the new commodity procurement contract recently awarded [41]. This data includes information on 343 unique Malaria shipments delivered over the course of two years. Products shipped included drugs, insecticide treated bed nets, rapid diagnostic testing kits, and other malaria commodities.

Countries analyzed include all countries to which USAID shipped Malaria commodities during the time span of the data. These include Angola, Benin, Burkina Faso, Burundi, Cambodia, Democratic Republic of the Congo, Ethiopia, Ghana, Guinea, Kenya, Laos, Liberia, Madagascar, Malawi, Mali, Mozambique, Nigeria, Rwanda, Senegal, Sudan, South Sudan, Tanzania, Uganda, Zambia, and Zimbabwe. In the final model, Cambodia, Laos, Sudan, and South Sudan were omitted due to significant amounts of missing data. The data was separated into two groups in order to approximately match the mortality data: i) shipment arrival dates on or before September 30, 2011, and ii) shipment arrival dates on October 1, 2011, or later. Cycle time was computed as the time between the requisition order (RO) date (i.e., the date when a customer submits an order) and the date the product arrives in country at its final destination. Percentage of air shipments is computed as the percentage of total shipments distributed via air.

Other controlling factors include health specific factors and infrastructure or country specific factors. Health specific controlling factors include factors related to Malaria itself as well as factors affecting a country more broadly. Funding for malaria and anti-malaria coverage for each country in the study was obtained from the World Malaria Report [38-40]. We expect mortality will decrease higher levels of anti-malarial coverage. The length of the malaria season by country was determined from the MARA (Mapping Malaria Risk in Africa) project [44]. Infrastructure and overall development levels in each country were obtained from the World Bank Database, including GDP per capita, land area, the Logistics Performance Index (LPI), climate data (monthly and annual temperature and precipitation levels), and life expectancy [17]. Physician density and latitude data were collected from the CIA's database on countries around the world [45]. Physician density and life expectancy were used to control for the health infrastructure levels in each country, while life expectancy and GDP per capita were used to control for overall levels of development in each country. Temperature and precipitation have been previously shown to impact malaria mortality [46-48]. Population was used to control for the different sized populations found in each country. As population increases in a Malaria area, we expect malaria mortality to increase due to the added exposure.

Since the goal is to determine which supply chain variables had a significant impact in the malaria health in each country, it is important to control for overall logistics differences between countries in the study. The LPI (Logistics Performance Index) was used to control for the logistics infrastructure in each country. Sparsity (geographic area divided by population) was used as a proxy for population density to determine the potential impact of a spread out population.

In the case of missing elements in the data (roughly 1.5% of the total data used), imputation was done by using the average of the surrounding years (or the prior year if the missing element was in the most recent year available) for around 1% of the data. There were 0.5% of the total data elements that were not estimated by imputation, and those observations were dropped.

Estimated malaria mortality, defined as the total number of deaths attributed to malaria during a specified year, for each country in the study was obtained from the World Health Organization's World Malaria Report [39, 40, 49]. In order to test the impact of supply chain variables on malaria health, linear regression was used to determine the impact of the independent variables on malaria mortality, measured as total malaria deaths in a year in each country. Final variable selection was done using best subsets as well as forward and backward stepwise regression. The data was standardized in order to allow direct comparison of the regression coefficients.

3.3 Results

Summary statistics on the dependent and independent variables are provided in Table 11. Average cycle time is 109.5 days with a standard deviation of 47.7 days. The average percentage of air shipments was 69% with a standard deviation of 26%. Overall, average antimalarial coverage is 82% with a standard deviation of 29%. Between the two periods considered, cycle time decreased by 18 days on average while the percentage of air shipments increased by 12%. Mortality decreased year 1 to year 2 by around 11,500 deaths overall, while population grew by approximately 32 million people between all the countries considered. Also, the percentage of antimalarial coverage increased by 5% and the average life expectancy increased by one year from year 1 to year 2.

Table 12. Regression Results.

Coefficient	Standardized Estimates	Std. Error	t	Sig.	
Intercept	0.661	0.117	5.63	2.86E-06	***
Percent Air Shipments	-0.094	0.034	-2.77	0.009183	**
Population	0.61	0.051	11.97	1.49E-13	***
USAID Funding	-0.12	0.04	-3.03	0.00471	**
Percent Antimalarial Coverage	-0.112	0.028	-3.99	0.000346	***
Life Expectancy	-0.757	0.123	-6.18	5.74E-07	***
Physician Density	0.223	0.051	4.33	0.00013	***
Season Duration	0.126	0.035	3.62	0.000965	***

N	41
Adj. R2	0.9491
Resid Std. Error	0.04586

The final model selected includes malaria mortality regressed on the percent of air shipments, population, USAID funding levels, percentage of any antimalarial coverage, life expectancy, physician density, and the malarial season duration in each country and is given in Table 12.

Population, physician density, and season duration were found to be positively associated with malaria mortality. Physician density is also positively correlated directly with malaria deaths, so the positive association in the model is consistent with the data. For countries with higher populations, higher physician densities, and longer malaria seasons, we find increased mortality.

Life expectancy, USAID funding, percent antimalarial coverage, and percent air shipments were found to be negatively associated with malaria mortality. For counties with larger USAID funding, higher percentages of antimalarial coverage, higher life expectancy, and higher percentage of air shipments, we find malaria mortality was lower. The variables total malaria funding, cycle time, and LPI score were not included in the final model selection.

Many of the independent variables are not under the direct control of USAID. On the other hand, two variables included are the USAID funding level and the percentage of air shipments. Based on the regression, we can estimate the impact of a change in USAID funding levels or percentage of air shipments on mortality, holding all other factors constant. For example, increasing the percentage of air shipments (representing the agility of the supply chain) or the funding levels by a half standard deviation, or 13% and $6.3M, can reduce mortality in an average country by 11% and 14% respectively as shown in Table 13.

Table 13. Prediction results for new supply chain parameters.

	Average	Medium Air Perc.	High Air Perc.	Medium Fund	High Fund
Percentage Air Shipments	0.69	0.82	0.95	0.69	0.69
USAID Funding	21596086	21596086	21596086	27893641	34191196
Predicted Deaths (fit)	22398	19842	17285	19232	16065
Lower Prediction Interval	2760	147	-2644	-461	-3908
Upper Prediction Interval	42037	39537	37214	38924	36039
Difference (fit) from Average	N/A	-2557	-5113	-3166	-6333
Perc. Difference	N/A	-0.11	-0.23	-0.14	-0.28

3.4 Discussion

As expected, in countries where the population has longer on-average lifespans, there is significantly less malaria mortality. This suggests it is important to focus on the overall system to promote life expectancy; this could include investments in water, sanitation, livelihood programs, and health infrastructure.

The supply chain factors that reduce malaria mortality are USAID funding and percent antimalarial coverage, which are proxies for supply chain throughput, or the total amount of malaria commodities shipped through the supply chain. While USAID funding is significant, interestingly, total funding was not. This suggests that the throughput of the USAID supply chain has a greater impact than the throughput of the donors in total. It also suggests that USAID is serving as a type of safety net, sending emergency shipments as needed to help cover specific needs. Further analysis outside the scope of this study on supply chain data from other donors would be beneficial to understand this issue.

As expected, as the population grows in a country with malaria, the number of people exposed grow, which results in a greater number of deaths due to malaria. Similarly, the longer the malarial season in a given country, the more time residents of that country are susceptible to the disease, also resulting in higher mortality. Physician density has an unexpected positive sign, meaning an increase in the physician density is associated with an increase in mortality. One possible reason we could see malaria mortality increase with physician density is the lack of diagnosed malaria cases in areas without physicians. Without a physician present to diagnose a death due to malaria, the death may be missed in the data entirely biasing the morality results toward areas with the most physicians.

The majority of countries have high antimalarial coverage. It is important to note, however, that this is based on any type of antimalarial coverage including indoor residual spraying, insecticide treated nets, and ACT treatment courses. This suggests, therefore, that the majority of countries considered in the study have received sufficient initial quantities of some antimalarial preventive measure. Hence, the majority of the startup operations have been completed. In responding to a need such as malaria, there is a startup period when countries build up their preventive and treatment infrastructure. After this period is complete, there is a steady stage period where it is important to resupply to maintain stock so no country runs out of preventive measures or treatment drugs.

There are several differences between the initialization phase of a supply chain and ongoing operations. In the first stage, it is important to ship commodities to a country as quickly as possible. Until effective preventive and treatment measures are in place, there will be a constant need for prevention and treatment for the population that is susceptible to malaria. Supply chain cycle time is important in order to place commodities in a timely way. In the second stage, cycle time may become less important, as long as a county's stock of product is maintained. This is consistent with classic supply chain operations [50]. The key challenge when there are long cycle times in stage two is that in order to keep commodities delivered consistently, they have to be planned for in advance and those plans may not be very flexible. This becomes problematic in countries where demand is uncertain and hence hard to predict in advance. In these situations, emergency orders may be used to deal with the uncertainty in demand or supply, to effectively reduce the cycle time.

There is in addition the complexity of working with multiple donors. With a single donor, they are able to control the entire supply chain and take responsibility for what occurs. With multiple donors, the responsibilities become decentralized and based on agreements between donors [27]. If one donor is not performing reliably, it can put pressure on other donors to make up the gap. In this environment, while cycle time may not be as important, it is important to be adaptable. While reducing cycle time is one method of making a supply chain more flexible, an alternative approach to adapting to change is through the shipment method, which can decrease both cycle time and increase adaptability. By switching from sea shipments to air shipments, quick changes can be made as soon as a commodity is available at a manufacturer or at a warehouse. This decrease in cycle time and increase in adaptability gives USAID the ability to respond appropriately to changes or shocks in the supply chain.

From Table 12, it can be seen that the percent of air shipments is one of the variables predicting a reduction in malaria mortality. This indicates that this adaptability in the supply chain is important in reducing malaria mortality and should be utilized as part of a key strategy in developing a global health supply chain.

In the supply chain, another choice that can be made is how far to distribute supplies into a country. When treating a widespread disease, it is clear that coverage of preventive measures would be important, and this was shown in the results. The supply chain needs to be capable of distributing the necessary commodities for prevention and treatment throughout the country. The distribution network in many of these countries can be extremely difficult. Thus, it is imperative that this last mile problem of delivering commodities to the final service delivery points is paramount to solving the full problem.

As expected, we found an increase in coverage of antimalarial treatments yields a lower mortality rate for a country.

Lastly, it is interesting to consider the impact of various changes to the supply chain structure. Table 13 shows the estimated change in the dependent variable for several levels of USAID funding and percentage of air shipments, where each is varied by both one half and one standard deviation. Even a one-half standard deviation increase in either value is associated with an estimate change in mortality of over 10%. The estimated change in health outcomes is bigger for funding than for the variable associated with agility (air shipments). However, for a given budget, using a more agile supply chain design for malaria commodities in Africa could prevent deaths due to malaria.

It is important to point out that this study has several limitations. First, linear regression is quantifying associations and does not directly imply cause and effect. Second, there could be errors in data, such as in current coverage of antimalarial products. Third, the supply chain data that was utilized for the study is a subset of the complete data of the USAID program. Finally, the approach used is an ecological one with predictors at the country level; an analysis at a higher level of geographic granularity could be useful.

3.5 Conclusions

We found that several supply chain factors affect malaria mortality in Africa. Many of the other factors considered are natural to the areas in which these countries are located and cannot be changed. However, given malaria is endemic in these countries, there is an opportunity to battle malaria with the prevention and treatments procedures that have been developed through the years. While conventional public health knowledge provides a vast array of information about what procedures to use, which drugs to take, and how to apply prevention methods most effective, it is paramount to include the supply chain design and global health supply chain practitioners as part of the solution. The model presented in this paper demonstrates the relationship between supply chains and malaria mortality. Without a functioning supply chain, countries would not be able to maintain global health best practices. The global health supply chain not only plays an integral role in operating a global health mission, but supply chain design plays a key role in the effective implementation of those programs. As seen in the results here, having an adaptable malaria supply chain capable of responding to shifts in the demand and flexible enough to react to changing developing world conditions could save lives.

CHAPTER 4. EVALUATING AND IMPROVING ACCESS FOR PEDIATRIC PREVENTIVE DENTAL CARE IN GEOGRIA

4.1 Background

Among US children, poor oral health is the most prevalent unmet healthcare need and tooth decay the most common chronic condition [51]. In Georgia, this problem is further exacerbated by a large number of Medicaid enrolled children combined with few providers accepting Medicaid. This results in scarce capacity at Medicaid providers and children too distant from providers to receive the necessary care. Policies regulating supervision of dental hygienists have been recently considered in Georgia. If enacted, these policies could lead to additional capacity for Medicaid-enrolled children.

Currently in Georgia, there is a dichotomy in dental care. Depending on perspective, different organizations say there is both an excess and a shortage of dental supply. The Georgia Dental Association has said explicitly, "There is no shortage of dentists or dental hygienists in Georgia" [52]. They mention they have dentists with additional capacity that needs to be filled. However, the opposite is quoted by the State Office of Rural Health. They list a number of counties around Georgia as Dental Health Professional Shortage Areas as shown in Figure 16 [53].

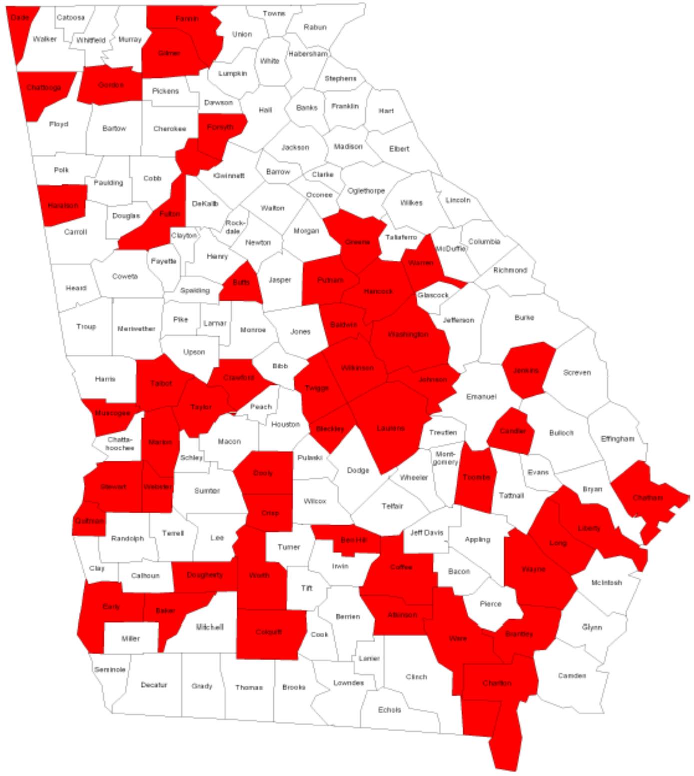

Figure 16. Georgia Dental Health Professional Shortage Areas.

The goal of this research is two part. First, we determine the current state of pediatric preventive dental care in Georgia due to the current provider network and policy structure. Second, we evaluate the impact of potential solutions including policy changes and targeted interventions on the provider network.

Specific questions the research will address include the localized impact on unmet need of policy decisions regarding supervision levels, budget limits for expansion, and where additional providers should be targeted for maximum impact.

4.2 Method

We developed an optimization model to evaluate policies for improving access to preventive dental care for children. The model matches need for pediatric preventive care with the supply available for pediatric preventive care by taking in census tract level demographic data, existing public and private dental networks, and local dental regulations and insurance acceptance. We evaluate the impact from adding dental providers or adding dental hygienists in "safety net" settings such as Federally Qualified Health Centers (FQHCs).

One novel feature to this model is the use of capacity for dental care determined in the time available for these services. Other papers looking at capacity for dental care consider the supply only in terms of the number of providers and not in terms of the time available for these services [54-56]. This allows us to split apart dental care into the time spent on pediatric vs. adult care as well as on preventive care vs. treatment as shown in Cao et. al. [57].

4.2.1 Network and Policy Levers Considered

We consider two network and policy levers in the analysis: (i) relaxing hygienist supervision requirements, and (ii) dentist and hygienist network expansion levels. Relaxing supervision requirements would allow hygienists to operate more independently to provide preventive care. Changing the dentist or dental hygienist network expansion levels would add providers to the current dental network by locating dentists or hygienists respectively at FQHC's around the state.

To understand the impact of changing dental hygienist supervision requirements, we evaluate the model under the assumptions of both direct supervision and general supervision. Under direct supervision, a dentist is required to be physically present with a hygienist for the hygienist to perform procedures. In this model, direct supervision means we can only locate dentists and hygienist together, meaning that, under this policy, we only consider the addition of dental offices. General supervision allows hygienists to operate independently when authorized to do so by a dentist. Under general supervision, we allow hygienists to locate and operate independent of dentists, using the assumption they are authorized to do so under the general supervision of a dentist.

We changed the dentist or hygienist expansion levels by adding dentists or hygienists at FQHCs across Georgia. Any FQHC was available to locate new providers. In this case, we assumed all new providers added to the system would provide preventive services to Medicaid children. We varied the dental expansion levels by increasing the number of Medicaid dentists by five percent (16 dentists assisted by 32 hygienists) as well as adding 25, 50, 75, 100, 150, and 200 hygienists to the provider network. These cases are chosen based the budget available for the Georgia Department of Public Health (GDPH) and the GDPH estimate of the supply of providers available in Georgia. The GDPH estimated they could potentially increase the number of dentists taking Medicaid by 5% but estimated even that number may be a stretch.

4.2.2 Baseline

The current state of pediatric preventive dental care was determined with respect to the current policy structure and provider network. This established a baseline with which we can compare network and policy inventions to evaluate their effectiveness. Baseline parameters represented the existing state of the dental and provider network at the beginning of the study. These included direct supervision (no hygienists operating independently), no additional dental providers beyond those already practicing, and the current Medicaid acceptance of each of those providers.

4.2.3 Outcome Measure

We compute the difference in *unmet need* for each census tract in Georgia before and after each policy implementation. Unmet need is defined as the percentage of children who do not have access to preventive dental care. The estimates are used to identify subpopulations and communities with the greatest need for interventions, allowing decision makers to improve access to preventive dental care for children under limited resources, such as a limited budget that can be used for additional facilities or providers.

4.2.4 Input Data and Model Specifications

The model and data descriptions used to evaluate the effectiveness of the proposed network and policy interventions are given in APPENDIX B. Note the model does not compute provider types explicitly. Each provider type is chosen by altering relevant input data in the model to allow for additional providers with the capacity of a dentist or a hygienist.

To run the model, input data consisted of the population by age, risk status, and Medicaid eligibility for each census tract in Georgia. The time needed for preventive dental care is then taken from the dental guidelines for each age and risk class to determine the average time needed to serve a person in each risk class in each census tract. Since the guidelines for care differ by age, the average is weighted by the number of people in each age class. The patient population is broken down into three groups according to their income: Medicaid children at the lowest incomes, children with no financial access in the middle, and children with financial access at the upper income levels. Children with no financial access are above Medicaid limits but do not have access to care and children with financial access either have private insurance or the ability to pay out of pocket as described in Cao et. al. [57].

This need is then matched to the supply available at each dental provider site, which is also determined according to the time available for pediatric primary care. Cao et. al. [57] describes the methods used to compute the input supply and need parameters used in the model, including the need at each census tract by risk class and Medicaid status, provider capacity, and both Medicaid and total supply available at each provider. Some provider locations may have more than one provider, so it is possible to have different amounts of Medicaid supply and total supply at one location.

Salary information was determined from the average annual wages from the US Bureau of Labor Statistics for dentists and dental hygienists. Budget information was built into the model but in the end was not used in the final analysis. Based on discussion with the GDPH, the budget information was translated into the dental or hygienist network expansion levels discussed earlier. We limited the number of additional providers to mimic the impact of both state budgets for providing care as well as the supply of providers available in the state.

The total existing and potential provider network was determined by the National Provider Index (NPI) list of dental providers and the list of FQHCs determined from the Health Resources and Service Administration Health Care Service Delivery Sites Data Mart. We determined distance using the Texas A&M geocoding service as the distance between the center of each census tract (children locations) to each provider's actual geocoded address.

4.2.5 Solution Method

We used CPLEX running on Georgia Tech servers to solve the dental access optimization model for each of the parameters discussed. We programmed the model, including the objective function and each constraint, using the ILOG CPLEX C++ API to call the CPLEX optimization solver. We submitted each job using CONDOR to run each parameter set independently. We evaluated and mapped output results using R.

4.2.6 Model Description

The objective of the model is to maximize the number of children receiving care. Decision variables available in the model include the percentage of need met for children with financial access and for Medicaid children, a binary variable deciding where to open new facilities and the number of additional providers to locate at each open facility. Constraints represent the problem structure, provider network, and current policy. Examples of constraints include distance to care limited to 45 miles, capacity limits for all patients, capacity limits for Medicaid patients, budget constraints, and constraints on the number of additional providers allowed. Detailed constraints are shown in APPENDIX B.

4.3 Results

4.3.1 Baseline Results

Overall, we found that out of 159 counties in Georgia, there are currently 81 with no Medicaid provider and 16 with no dental provider at all. When reviewing provider acceptance of Medicaid, we find only 293 of the provider locations in our model accept Medicaid out of the 2513 provider locations included.

We found that under the current dental situation in Georgia, there are around 1.5 million children lacking access to preventive dental care. As shown in Figure 17, the current provider network is able to meet all the demand for children with financial access. However, a significant number of Medicaid children are left without care.

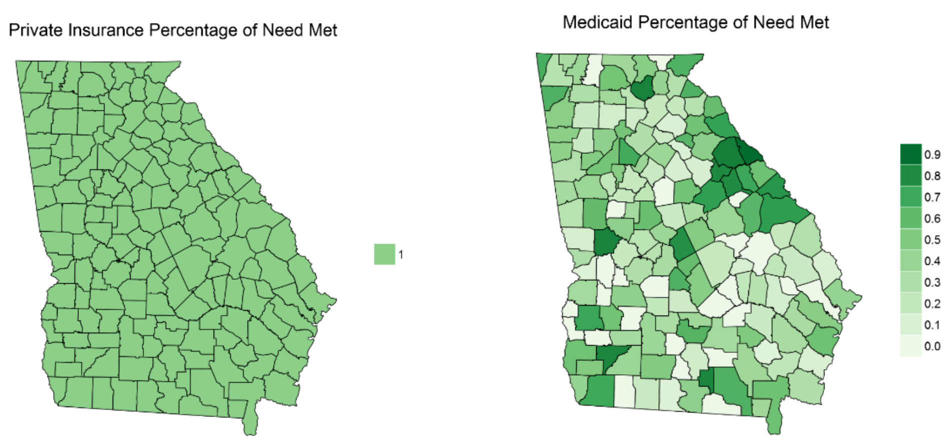

Figure 17. Percentage of Need Met for private vs. Medicaid insurance.

Despite this lack of capacity for Medicaid children, most counties in Georgia still have excess capacity that is currently unused. Figure 18 shows the counties with excess capacity in green compared to the counties without capacity in white.

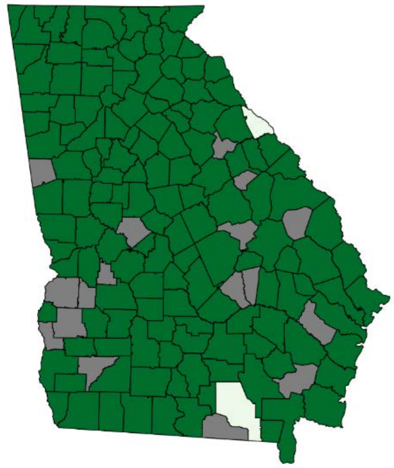

Figure 18. Counties with excess capacity (green) compared to counties without excess capacity (white).

4.3.2 Intervention: Dental Providers

The result of adding five percent of dentists (16 dentists with 32 assisting hygienists) accepting Medicaid is shown in Figure 19. While there is improvement in this model, the improvement was limited and only improved access to preventive care for approximately 1.3% (~20,000) of Medicaid-enrolled children.

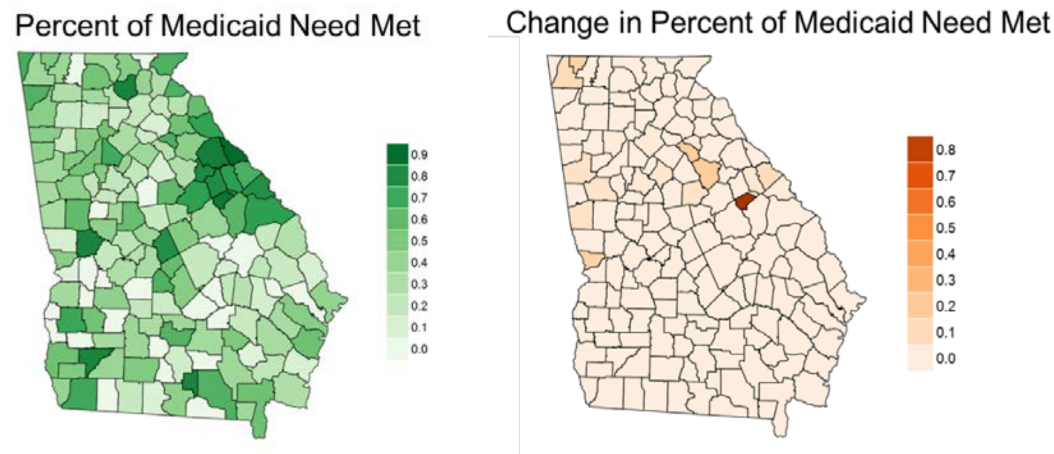

Figure 19. Improvement in Medicaid need met by adding 5% additional Medicaid Dentists.

4.3.3 Intervention: Hygienist Providers

Figure 20 shows the results of adding hygienists at FQHCs to the current provider network.

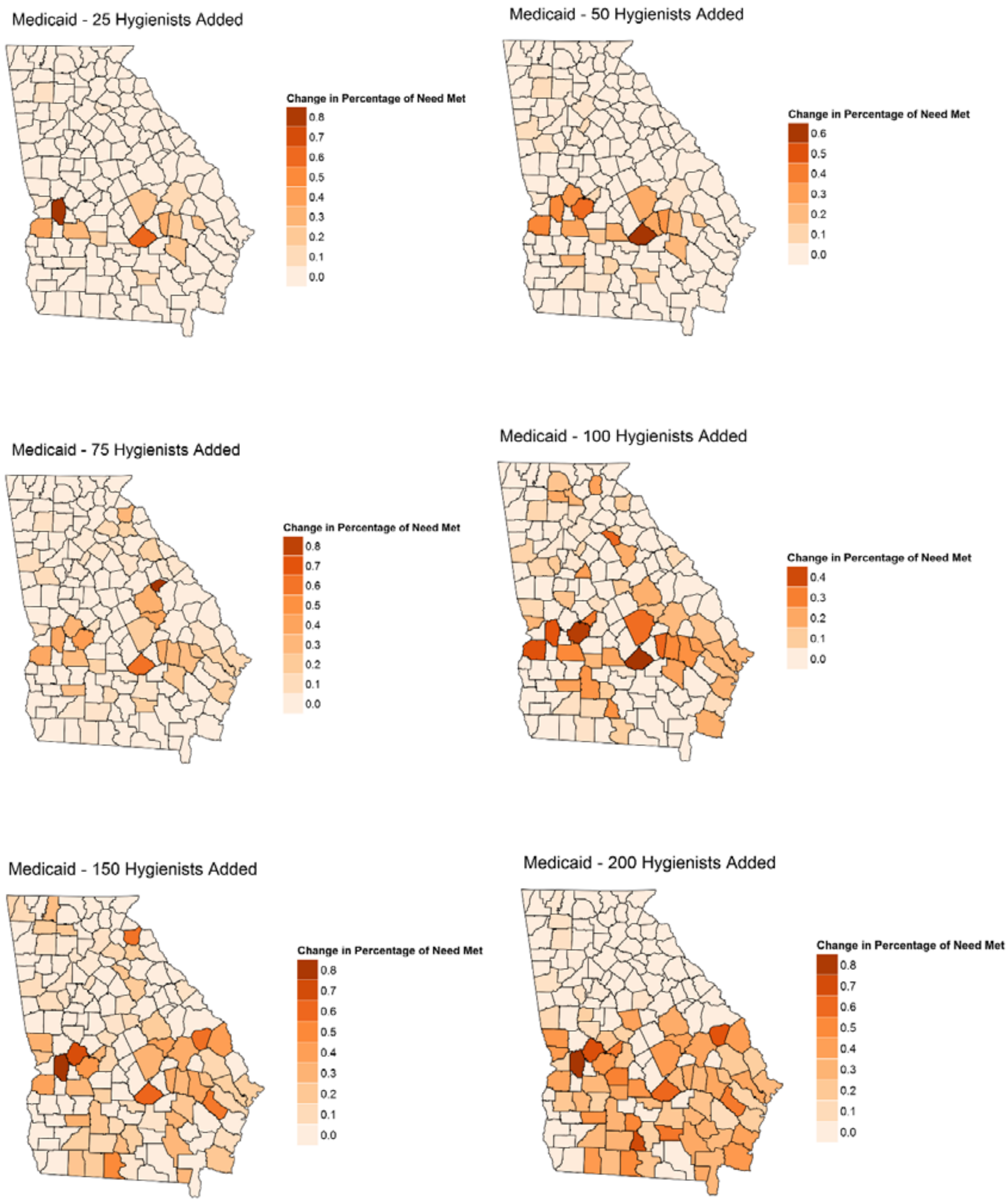

Figure 20. Change in Percentage of Need Met for adding 25, 50, 75, 100, 150, and 200 Hygienists.

Adding 100 dental hygienists to the network under the assumption of relaxed policy on Medicaid reimbursement and supervision improves the percentage of Medicaid children who receive preventive care by 4.5% (~70,000), a substantial improvement compared to that of only adding dentists to the network. Further, when 200 hygienists were added to the system, the total Medicaid children served can be increased from 37.7% in the base case to 46.8% (9% difference). This creates access for an additional 135,000 Medicaid children.

4.4 Discussion

Evaluating the baseline results, we see clearly the root of this dichotomy. As shown in Figure 17, we found we meet all need for children with financial access while leaving significant unmet need in the Medicaid population. Additionally, we found both unmet need in the Medicaid population and unused capacity at providers. It is clear that a large portion of the access problem within the Medicaid population was due to capacity constraints at current Medicaid providers and a lack of providers accepting Medicaid in many geographic areas. The current dental network results in limited access for Medicaid children across Georgia. The stems from the lack of Medicaid acceptance among dentists in Georgia and demonstrates the system is not functioning as it was intended. There is a need to fill both unmet capacity as well as unmet need under the current structure.

Under the initial policy structure of direct supervision, only dentists were allowed to provide unsupervised preventive care. As a result, the provider network interventions were limited to adding additional dentists to the provider network. Since private capacity is already met, we first focused on adding Medicaid providers to the current system and on the impact observed in the Medicaid population.

We found adding dentists is not sufficient to achieve the statewide change that was sought. There are two additional challenges with this approach. First, the GDPH believes adding this many dentists would be a stretch given the limited number of dentists and the even fewer proportion of them who take Medicaid under the Georgia Medicaid system. Second, there is an additional challenge of a predicted shortage of dentists. The U.S. Department of Health and Human Services says the 2012 shortage of 280 dentists in Georgia is only expected to grow. They are expecting a shortage of 386 dentists by 2025 [58]. With the low percentage of dentists willing to accept Medicaid and the predicted dental shortage, alternative methods are needed to improve access for Medicaid children in Georgia. One of those strategies considered is relaxing the supervision of dental hygienists [59, 60].

Relaxing supervision of dental hygienists allows hygienists to operate independently performing preventive dental care procedures such as sealants, cleanings, etc. Since hygienists are not allowed to perform treatment services, all of their time can be spent on prevention. Additionally, they operate at a lower price point, making it more likely they will be able to operate under the lower reimbursements seen in the Medicaid program. Due to the capacity and treatment constraints on dentists, the addition of dental hygienists impacts access more substantially than adding dentists.

While the need is great throughout Georgia, the model identified specific areas believed to have the strongest impact on unmet need, allowing Department of Public Health officials to target specific locations and stage interventions over time, addressing the strongest need first. The model, thus far, identifies southern Georgia as the best place to target interventions when the focus of the intervention is FQHC's. The current results presented focus on interventions targeted at the general Medicaid population, meaning the additional providers are allowed capacity to see both children and adult patients. Interventions focused on children will have a more pronounced effect on the kids in this model.

There are added benefits of using hygienists to help solve the dental access problem in Georgia. Not only are hygienists more likely to be able to operate at the current price point of Georgia's Medicaid program, but there is also a current surplus of dental hygienists that is predicted to grow to 924 hygienists by 2025 [58]. For interventions targeted at preventive care, the use of dental hygienists provide a great tool to help resolve the access issue and the dental dichotomy in Georgia.

Due to the nature of the type of model used, there are some inherent model limitations seen in the results of the model. First, the model only considers preventive care. While preventive care is a great start for looking at dental care, treatment need still exists. Further, it is likely the need for treatment will depend on the coverage of preventive dental services. Second, the model focuses on matching patient need as opposed to demand. The model attempts to maximize the patients served, attempting to meet the need for all children in Georgia. Likely, there will be a significant population of children who will not seek preventive dental care at the recommended level. These patients will cause the corresponding demand for dental care to be less than the need represented here. Third, this model assumes all new providers accept Medicaid. Given the nature of this model and its intended use by the Georgia Department of Public Health for providing additional providers under their budget, this is a reasonable assumption, but it should still be noted. Lastly, solution stability can be problematic with a model of this type. Since there are many optimal solutions, the model will work through the nodes corresponding to single census tracts and providers before moving on to the next node. This can create areas in close proximity with different levels of unmet need. A smoothing algorithm applied on top of the optimization results would allow results that are more representative.

In conclusion, the current shortage of dentists and surplus of hygienists in Georgia further enforces the conclusion observed in the model. The model shows that adopting practice acts for relaxing supervision requirements for dental hygienists can improve access to preventive dental care for children in Georgia.

CHAPTER 5. THE COST-EFFECTIVENESS OF THREE INTERVENTIONS FOR PROVIDING PREVENTIVE SERVICES TO LOW-INCOME CHILDREN

5.1 Introduction

Oral disease is cited as the greatest unmet health need among U.S. children [2], and significant disparities exist [3]. Fewer than 9% of low-income children receive topical fluoride or pit-and-fissure sealants [61], even though these are highly effective at preventing caries [62]. Utilization of preventive care services is hampered by many factors, including access to dental care [63, 64], patient barriers to care such as transportation or education [65-67], affordability, provider availability, provider attitudes towards publicly insured children, and accommodation to children with special needs [15, 68, 69].

To reduce oral health disparities, several policy and network interventions have been proposed and/or implemented. One example is the provision of dental services through federally-qualified health centers (FQHCs), which primarily serve uninsured and publicly insured populations [69]. Additionally, the Oral Health Initiative has encouraged targeted oral health interventions such as school-based sealant programs [70].

Three commonly proposed interventions are dentist loan repayments, increasing the acceptance of Medicaid-enrolled children by dentists [65, 68, 71], and amending supervision requirements for dental hygienists in public health and safety net settings, allowing hygienists to perform specific preventive services without the physical presence of a dentist [72]. Loan repayment is commonly used to encourage providers to choose areas of practice with higher need, such as rural areas [73, 74]. The increase in the acceptance of public insurance affects the availability of providers for children eligible for Medicaid and Children's Health Insurance Program (CHIP). Difficulty in identifying a dentist accepting Medicaid is a frequently reported barrier to children seeking dental services [69]. Many factors affect a dentist's willingness to participate in the Medicaid program, including paperwork associated with filing claims, low service payment fees, and substantial "no-shows" among the Medicaid-eligible population that deter dentists from participating [75, 76]. Loosening supervision requirements for dental hygienists from direct or indirect supervision (where a dentist needs to be present for the service delivery) to general supervision (when the dentists need not be present) has been undertaken in many states. Currently, three states do not allow general supervision, and five states allow general supervision only for some services and under specific settings. General supervision can facilitate improved access to dental care for vulnerable population [72, 77].

We estimated the impact of the three interventions on the availability of dental services for children with unmet preventive care needs. We focused on availability since it is a precursor to many other interventions for increasing utilization of preventive services to infants [78] and children with complex conditions [79]. Availability addresses specific dimensions of care, such as oral health literacy [80]. Without the availability of providers, these interventions would have limited impact.

Our aim was to determine which policy interventions are most effective in terms of met need and cost. It was conducted for the state of Georgia, which has a low Medicaid acceptance rate among dentists [81], restrictive supervision of dental hygienists, and recently reinstated the loan repayment program [82].

5.2 Methods

We modeled three policy interventions to evaluate their impact on provider availability for preventive services. Methods used to model each policy range from multivariate linear regression to mathematically modeling the structure of a school based sealant program.

5.2.1 Data Sources

We used the Medical Panel Expenditure Survey data to evaluate the resulting supply of additional providers from the intervention to obtain the hours available for pediatric preventive services at each provider. The American Academy of Pediatric Dentistry (AAPD) guidelines on dental care were used for each age group and risk class to define need [83]. We obtained information for the regression analysis on Medicaid programs from the Kaiser Family Foundation. We obtained additional data used for the regression on state Medicaid acceptance rates, Medicaid structure, Medicaid fee for service (FFS) as a percentage of private rates, dentists per population ratios, and Medicaid utilization rates from the American Dental Association [81]. Additional details on selected data elements are in APPENDIX C.

We obtained data for school-based sealant programs for each public school in Georgia—including type of school, student enrollment, and percentage of students on free and reduced lunch—from the National Center of Education Statistics for the 2011–2012 school year. The free and reduced lunch is a program offered to children in families with lower incomes. A common federal target for school-based programs is schools with a high percentage (> 50%) of free and reduced lunch students. Three out of 1,818 elementary and middle schools had missing information and were not included in the analysis. Example data is given in APPENDIX C.

5.2.2 Study Population

We considered children aged ≤19 years living in Georgia, differentiated by insurance status. Children were considered to be *publicly insured* if they were eligible for Medicaid or CHIP (that is, had family incomes less than 247% of the Federal Poverty Line (FPL) according the eligibility levels). Other children were considered to be either privately insured or to have limited financial access based on family income [57]. Medicaid programs in the U.S. provide different coverage for dental care as compared to the child population; thus, this study applies to the child population only. For example, in Georgia, only emergency dental care services are provided under Medicaid for the adult population.

5.2.3 Need and Supply

Need (as defined by AAPD guidelines) was estimated at the census tract level and measured as the total hours required to provide preventive dental procedures at their recommended annual frequency annually [83]; these differ by age group (0-3, 4-5, 6-7 and 8-18 years) and caries risk. We estimated supply at the provider level and measured as the number of hours of allocated pediatric preventive dental care using the national estimated percentages for general and pediatric dentists multiplied by the average annual work hours per dentist. Details are in APPENDIX C. Details for estimating risk are in the appendix for Cao et. al. [57].

5.2.4 Outcomes

We considered three outcomes: (i) *Met need*, defined as the number of additional children receiving care through the intervention, who are otherwise unserved; (ii) *Intervention cost*, estimated as the total cost of intervention implementation incurred by the state; and (iii) *Cost saving* from providing preventive care for children eligible for Medicaid/CHIP compared to treatment costs under no prevention. Cost saving is not the net cost and does not account for the intervention cost. Met need was further considered by sub-populations of family income. Met need is a measure for improvement in access to healthcare. For interventions focused on adding dentists to the system, we estimated that one dentist has the capacity to provide preventive services to approximately 1,076 children. Details are given in Cao et. al [57].

We estimated cost savings of a preventive care intervention as the difference in costs between children who received preventive care before they had caries and children who did not have preventive care before caries. In Georgia, Medicaid children aged 3-6 who received neither sealants nor fluoride before having a caries had total, costs of $209.23 per child per year over 7 years. For children who received sealants and fluoride before having caries, the annual total cost of care was $93.46 per child. Thus, the annual cost saving from providing preventive care was $115.77 per child [84]. We assumed that there were no cost savings for children below three and over six. Thus, the cost saving per child was $27.24 in the overall child population.

The cost saving for sealant programs was the difference in average Medicaid payment for dental care between children who received sealants and those who did not. Estimated averted treatment costs from sealants are $50.42 per child [85].

5.2.5 Dentist Loan Repayment

Loan Repayment programs can vary in the annual loan repayment amount and the percentage of the dentist's caseload involving Medicaid children. We considered annual loan repayments in the range $0 to $60,000 annually, in increments of $10,000.

The impact of a loan repayment program was scaled by the number of participating providers. The Georgia Dental Association (GDA) estimated that using loan repayments would encourage 8–12 dentists to practice in rural areas and accept publicly-insured children [82].

To estimate met need, we determined the available capacity of each dentist to provide preventive services to children. Details are given in Cao et al. [57].

Dental loan repayment programs range from total loan forgiveness after a specified period to a fixed amount per year in exchange for a short-term commitment to practice in shortage areas. The intervention cost was computed as the amount contributed annually by the program.

Potential cost savings were based on the additional number of publicly insured children served, based on the intervention setting and the publicly insured population in the service area. The cost saving equaled the number of eligible publicly insured children served multiplied by the potential savings per year per child for providing preventive services ($115.77).

5.2.6 Medicaid Reimbursement Rate

We used multivariate linear regression models to estimate the impact of fee-for-service reimbursement on state-level Medicaid acceptance rate or utilization of preventive care services (past year dental visit). We controlled for confounding from: (i) the structure of the Medicaid program in each state, including whether dental care was included in a state's managed care organizations (MCO), number of MCOs, and whether the state participated in Medicaid expansion; (ii) the dentist per 100,000 population ratio; (iii) the median family income; (iv) race/ethnicity; and (v) Medicaid enrollment.

Model selection including best subsets, forward and backward stepwise regression, and lasso regularized regression [86] was used to determine the final model. We considered various transformations of predictor variables. We normalized the data so that regression coefficients could be compared.

We determined the impact of raising Medicaid reimbursement rates by 10 percentage points (53% to 63% in Georgia). We estimated met need by the increase in utilization by taking the change in utilization multiplied by the number of publicly insured children. The intervention cost was the percentage increase in fees across the publicly insured children already utilizing preventive care plus the total increase in costs of the additional met need. We estimated cost savings by summing the potential savings across the met need satisfied through the provision of additional preventive services. Details are provided in APPENDIX C.

5.2.7 *Supervision of Dental Hygienists*

We estimated the impact of general supervision of dental hygienists based on its effect on school-based sealant programs (SBSP). We compared the cost of implementing a SBSP in Georgia public schools under direct and general supervision. We targeted schools with at least 60% of children participating in the free and reduced meal program. Sealant programs are aimed at all 2rd and 6th grade students (approximately ages 7-8 and 11-12) based on normal eruption times of first and second molars. We assumed students at each school were evenly distributed over each grade level. Screening and sealant times were 2 and 25 minutes respectively [87]. Each case assumed that 70% of the students screened received sealants [87].

We assumed that there were 60 minutes of combined set-up and teardown time. Sealant teams work 8.5 hours per day including drive time, the first 30 minutes of which was considered normal commuting time and not included in salary cost estimates. Similar to previous studies, we classified the drive time to be 30 minutes, 1 hour, and 1.5 hours for schools in cities and suburbs, towns, and rural areas respectively [87]. The mean hourly wages in Georgia of dentists, dental hygienists, and dental assistants were $85.36, $30.22 and $17.31, respectively [88], and equipment and supply costs per child were $2.74 and $6.93 respectively [89]. We used total costs, which included administrative costs spread across the costs provided. This provides a conservative cost estimate that would provide an upper bound as sealants are scaled to larger programs since administrative costs have economies of scale.

Under "direct supervision", the dentist undertook all screenings and ensured that sealants were placed correctly, while dental hygienists applied the sealants. Under "general supervision," the hygienists performed screenings and sealant placement. Most school sealant programs used two chairs due to space constraints in the schools. We assumed that each hygienist had a dental assistant. An additional dental assistant for the team performed equipment changes between procedures. Teams were assumed to visit (at most) one school per day.

We estimated cost savings from the number of children sealed and the averted treatment costs per child ($50.42). Cost savings to the state were based on students who qualified for free or reduced lunch (family income less than 185% of the FPL), which is below the requirement for Medicaid [90]. While sealants deteriorate over time, they remain largely effective for at least 4 years [85]. The impact of the school sealant programs was determined for all schools as well as targeting a specific percentage of schools.

5.3 Results

5.3.1 Dentist Loan Repayment

Approximately 1.49 million children were eligible for Medicaid/CHIP in Georgia. The impact of adding 8–12 dentists to underserved areas would have met needs for only an additional 8,610 to 12,915 children, even assuming 100% of the capacity was applied to publicly insured children.

We determined the intervention cost by the loan repayment amount and the number of providers. For eight providers, we estimated the intervention cost for a loan repayment amount of $20,000 and $50,000 to be $160,000 and $400,000 annually, respectively. The intervention cost per child served is $18.58 and $46.46 for loan repayment amounts of $20,000 and $50,000, respectively.

Based on $115.77 savings per child per year, $29,318 could be saved per provider if the provider had a 100% Medicaid caseload of children who would not otherwise receive preventive care. We conducted two-way sensitivity analysis showing the intervention cost and cost savings for one provider over a range of Medicaid capacity percentages and annual loan amounts (Table 14). For eight providers, we estimated the cost savings to range from $117,273 to $234,545 for 50% to 100% a public insurance capacity, respectively. For 12 providers, the cost savings would range from $175,909 to $351,818. The average cost savings per child is $27.24.

Table 14: Intervention cost and cost savings to Medicaid of implementing loan program per loan provided.

		% Medicaid children				
Loan Repayment	**Cost Type**	**10**	**20**	**30**	**40**	**50**
0	Intervention Cost	0	0	0	0	0
	Cost Savings	2,932	5,864	8,795	11,727	14,659
10,000	Intervention Cost	10,000	10,000	10,000	10,000	10,000
	Cost Savings	2,932	5,864	8,795	11,727	14,659
20,000	Intervention Cost	20,000	20,000	20,000	20,000	20,000
	Cost Savings	2,932	5,864	8,795	11,727	14,659
30,000	Intervention Cost	30,000	30,000	30,000	30,000	30,000
	Cost Savings	2,932	5,864	8,795	11,727	14,659
40,000	Intervention Cost	40,000	40,000	40,000	40,000	40,000
	Cost Savings	2,932	5,864	8,795	11,727	14,659
50,000	Intervention Cost	50,000	50,000	50,000	50,000	50,000
	Cost Savings	2,932	5,864	8,795	11,727	14,659
60,000	Intervention Cost	60,000	60,000	60,000	60,000	60,000
	Cost Savings	2,932	5,864	8,795	11,727	14,659

		% Medicaid children				
Loan Repayment	**Cost Type**	**60**	**70**	**80**	**90**	**100**
0	Intervention Cost	0	0	0	0	0
	Cost Savings	17,591	20,523	23,455	26,386	29,318
10,000	Intervention Cost	10,000	10,000	10,000	10,000	10,000
	Cost Savings	17,591	20,523	23,455	26,386	29,318
20,000	Intervention Cost	20,000	20,000	20,000	20,000	20,000
	Cost Savings	17,591	20,523	23,455	26,386	29,318
30,000	Intervention Cost	30,000	30,000	30,000	30,000	30,000
	Cost Savings	17,591	20,523	23,455	26,386	29,318
40,000	Intervention Cost	40,000	40,000	40,000	40,000	40,000
	Cost Savings	17,591	20,523	23,455	26,386	29,318
50,000	Intervention Cost	50,000	50,000	50,000	50,000	50,000
	Cost Savings	17,591	20,523	23,455	26,386	29,318
60,000	Intervention Cost	60,000	60,000	60,000	60,000	60,000
	Cost Savings	17,591	20,523	23,455	26,386	29,318

5.3.2 Medicaid Reimbursement Rate

Variables selected for the final model for Medicaid acceptance rate were (i) race/ethnicity, (ii) Medicaid enrollment, (iii) MCO program structure, (iv) median family income, and (v) Medicaid expansion. States with higher proportions of their population comprising non-Hispanic whites had higher acceptance rates than those with lower proportions. In addition, states with higher median family incomes, states with the dental care included in their MCO program type and states with higher Medicaid enrollment rates had lower acceptance rates, but the Medicaid enrollment results were not as significant statistically. States with Medicaid expansion had higher acceptance rates. FFS rates were not significantly associated with Medicaid acceptance rates.

The selected significant factors for predicting utilization of Medicaid services were Medicaid FFS percentage, the square of the Medicaid FFS percentage, and the number of dentists per 100,000 population. The association between utilization and Medicaid FFS was nonlinear in the model, so the effect was positive for lower values of FFS rates and negative for large FFS rates. States with higher concentrations of dentists had higher utilization of Medicaid. Both models are presented in Table 15.

Table 15: Regression models predicting Medicaid acceptance rate and Medicaid utilization using standardized data.

	Model 1 Response: Medicaid Acceptance Rate*		Model 2 Response: Medicaid Utilization†	
Predictor	Estimate	P value	Estimate	P value
Intercept	0.605	0.020	-0.015	0.951
White	0.389	0.034		
Dental Managed Care	-0.134	0.010		
Median Family Income	-0.536	0.023		
Medicaid Expansion	0.104	0.060		
Medicaid Enrollment	-0.209	0.171		
FFS Percentage			1.827	0.011
(FFS Percentage)^2			-1.232	0.029
Dentist per population			0.254	0.040

* N: 51, Adjusted R^2: 0.3051, Residual Standard Error: 0.1656

† N: 51, Adjusted R^2: 0.1915, Residual Standard Error: 0.1081

An increase of 10 percentage points in reimbursement rates in Georgia yielded an increase of 0.49% in utilization holding the dentists per population ratio constant, or approximately 7,366 additional children (details provided in APPENDIX C, Table 37). Increasing the reimbursement in Georgia from 53% to 63% increased Medicaid/CHIP costs by 18.9%. The intervention cost, therefore, comprised of the 18.9% increase for each child in addition to the total cost of any additional utilization added to the system. We estimated the intervention costs for current and new members as $36.9 million and $1.4 million, respectively. We estimated the intervention cost per child to be $5,205. This cost would be partially offset by the savings of $200,660 ($27.24 per child) resulting from the provision of preventive services.

5.3.3 General Supervision for Dental Hygienists

In Georgia, 1,129 schools met the targeting criteria. The intervention cost for SBSP in all target schools was approximately $5 million under direct supervision and $2.2 million under general supervision. The intervention costs using general supervision were on average 56% lower than direct supervision. The findings were similar across school sizes. Implementing a SBSP at all target schools has the potential to screen 151,047 students and provide sealants for 105,733 students each year. We estimated the intervention cost per child screened to be under $33 for direct supervision and $14.50 for general supervision. We estimated the cost saving per child screened was estimated to be $28.

Implementing SBSPs would improve outcomes and reduce costs to Medicaid/CHIP programs (Table 16). A program implemented in 10% of the target schools would reach 16,153 children annually. Sealing 70% of the children would yield cost savings of $452,197 to the state.

Table 16: Students Reached and Cost Measures for School-Based Sealant Programs.

	Met Need		Intervention Cost		Annual Cost Savings	
Percent of Target Schools	Screened per year	Sealed per year	Direct	General	Direct	General
10%	16,153	11,307	$529,394	$234,526	$452,197	$452,197
25%	38,853	27,197	$1,274,743	$566,129	$1,087,675	$1,087,675
50%	76,797	53,758	$2,521,672	$1,119,319	$2,149,902	$2,149,902
75%	115,113	80,579	$3,776,382	$1,677,658	$3,222,544	$3,222,544
100%	151,047	105,733	$4,965,490	$2,205,333	$4,228,502	$4,228,502

5.3.4 Comparison of the Three Interventions

Table 17 shows a comparison of the met need and costs associated with each intervention. We assumed a loan repayment for 12 dentists with a repayment of $50,000 annually per provider and that dentists allocated 50% of their workload capacity to publicly insured children. The reimbursement rate assumed a ten percentage point increase in the Medicaid FFS rates. Both SBSPs affected 25% of target schools and differed by supervision requirements.

Table 17: Comparison of interventions for loan repayment with 12 dentist at $50k repayment and 50% Medicaid caseload, 10 percentage point Medicaid rate increase, and supervision requirements based on implementation in 25% of target schools.

Intervention	Met Need	Intervention Cost	Annual Cost Savings
Loan Repayment	12,915	$400,000	$175,909
Reimbursement Rate	7,366	$38.3M	$200,660
Direct Supervision Sealant Program	27,197	$1,274,743	$1,087,675
General Supervision Sealant Program	27,197	$566,129	$1,087,675

5.4 Discussion

Overall, providing loan reimbursement and SBSPs under general supervision could be cost saving. Loan repayment was cost saving for smaller loan repayment amounts and higher Medicaid caseload percentages. SBSPs under general supervision were cost saving for implementation in any percentage of target schools. Changing the Medicaid reimbursement rate had a very high incremental cost compared to the resulting benefit.

Providing loan reimbursement for dentists in Georgia would increase the provision of preventive services for only 0.65% of children eligible for Medicaid/CHIP. However, there are additional benefits from this type of program. Some of the capacity of these providers could serve adults or be used for restorative care, allowing treatment options that dental hygienists or other mid-level providers cannot provide. Moreover, loan reimbursement will provide, if targeted, additional capacity to those who need it and is a cost saving intervention. We focused on the benefits of adding capacity through loan repayments programs and not on their effectiveness. Other studies have shown loan repayments to be one of the most successful ways to encourage generalist physicians to locate in underserved areas [91], though there is less success in the long term [92].

Additionally, we assumed providers would relocate given any of the loan repayment amounts varied in the analysis. In reality, we would expect more providers to be willing to relocate at higher repayment amounts. For the loan repayment to be cost saving, it would be necessary to have providers willing to relocate at some of the lower annual repayment amounts.

Adding providers through loan incentive programs also assumes those providers have sufficient patients to maintain their practice. Given the substantial need for Medicaid providers shown in Chapter 4, we believe these providers will not have difficulty in finding children in need of oral healthcare in these high need areas. The combination of substantial need across the state as well as targeted placements in high need areas benefits the practitioners as they bring in patients.

For the loan repayment programs analyzed here, since the results are annual results based on one loan provided, the structure of the loan repayment program in terms of the number of providers as well as the number of years of commitment can be left to the state to determine. For the sake of this analysis, there is no difference between locating two providers each with two-year commitments or locating four providers with one-year commitments in sequential years.

In our study, we found that in average over all states, Medicaid FFS reimbursement rates were not significantly associated with the Medicaid acceptance rates controlling for Medicaid system factors and for demographics and socio-economic factors. On the other hand, acceptance rates were lower for states with a higher non-Hispanic white population and for those with a higher median family income. Given the large cost of increasing the reimbursement rate, this is not likely to be as cost-effective as other interventions. Additionally, the projected increase in utilization would reach fewer children than loan repayment programs. Note that the relatively small increase in utilization we found is consistent with previous literature [93]. Changing the Medicaid FFS rates results in a very expensive intervention due to the system wide changes that occur. With the other interventions, the costs incurred by the intervention was only due to the children they reached through the intervention. Changing the Medicaid FFS rates affects all existing Medicaid children, resulting in substantial costs.

A recent study compared three states (Connecticut, Maryland, and Texas), which have increased the reimbursement rates between 2005 and 2012, to a control group of 14 states, which have not had significant changes in oral health policy for the Medicaid program during the same time period [94]. The study found that Connecticut and Texas have experienced a statistically significant increase in utilization of preventive dental care for Medicaid enrolled children compared to the control group of states. However, one limitation of this study is that it aggregates the data of all control states to compare the difference between the three states and the control states. If taken individually, some states have also experienced a significant change, e.g. Illinois from 25% in 2008 [95] to 47% in 2010 [96]. Other research has found that reimbursement rate increases are necessary but not sufficient to improve access. Reimbursement rates provide a foundation for encouraging provider acceptance, but there is also a need for administrative support and patient education [65, 97].

Another recent study by the American Dental Association estimated 94% of publicly insured children in Georgia live within 15 minutes of a Medicaid Dentist [98]. This result points to that geographic access is not a source concern for children on Medicaid in Georgia thus other barriers to utilization of dental care services may be more important. Implementing school based sealant programs remains particularly relevant even under this finding since children can be reached directly where they spent a good portion of their day. In this research, school-based programs were shown to be highly effective and can be cost saving under general supervision. Implementation of programs like school-based sealant programs along with access to dentists for restorative and additional preventive care would provide children with proper care.

There are a few issues with the reporting of Medicaid acceptance, however. Often Medicaid acceptance is reported in a binary form: yes if a provider takes Medicaid and no if a provider does not take Medicaid. The result of this form of measurement for Medicaid acceptance is that if a provider accepts one Medicaid child in their practice, they are listed as taking Medicaid despite the fact that they may see no other Medicaid children. The presence of a Medicaid dentist within 15 minutes of 94% of Medicaid children is Georgia is significant progress, but it does not answer the question of whether these children have access to care. These children and their parents still have to deal with the significant barriers to care discussed earlier including transportation, time off work, etc. Additionally, when the Medicaid capacity available at each provider (based on the Medicaid caseload they accept) are accounted for, the results could be very different.

Reducing supervision requirements for dental hygienists would both reduce costs and increase access to care for underserved. Moreover, the impact would not be limited to specific geographic locations because hygienists could reach populations where it may not be cost-effective for a dentist to operate. Additionally, it was found that stricter task-related regulations raised prices for dental care by 12% [99]. School-based sealant programs more than doubled sealant prevalence in the states in which they were implemented [71]. Schools also provide the additional benefit of removing many of the patient barriers to care known to exist including transportation and time off from work [65-67].

It is important to mention the difference in the stakeholders benefiting of the cost-savings from the three interventions. The costs for loan repayment included the amount paid by the state of Georgia to encourage providers to locate in underserved areas, but it did not include any reimbursements paid by Medicaid for increased dental care capacity for Medicaid of these new providers. Thus, the cost-savings for the state of Georgia may be lower if supporting additional Medicaid expenditure due to the increase in Medicaid capacity. The cost for SBSPs was developed from the perspective of the state of Georgia implementing a SBSP by hiring the staff and purchasing the supplies through the Georgia Department of Public

Health. For each child reached through the SBSP programs, we assume current Medicaid reimbursement rates for expenditure for care and cost-savings. For children with other forms of financial access, the cost-savings may be higher while for those without any financial access, the cost-savings will be lower. Overall, the cost-savings are of the state of Georgia estimated assuming Medicaid reimbursement rates. In contrast, when evaluating the impact of Medicaid reimbursement rates, the cost represents the expenditure of the Medicaid program due to the reimbursements paid to dental providers for treatments performed thus the cost-savings are those of the Medicaid program.

One factor that could affect the number of students actually sealed through these programs is the trading of capacity between dental offices and these sealant programs. While we did target high need schools, it is possible some of the children in these schools have already received sealants outside the school programs. In this case, the effect of the program will be reduced correspondingly by the number of children (Medicaid or non-Medicaid) who received outside care. While worth mentioning, this effect can be mitigated by focusing on target schools with high Medicaid populations where access to care is known to be limited.

There are several limitations to the study. Varying assumptions around the guidelines for care for low and high-risk patients will change the number of children seeking care. Cost savings are limited to young children in this study; however, cost savings could be higher if we had considered children of all ages. The estimates for Medicaid acceptance rates do not accurately reflect the capacity dedicated to publicly insured children since providers reported as accepting public insurance may only devote a small amount capacity to publicly insured children. The regression model also assumes a linear association between Medicaid reimbursement and Medicaid acceptance rates. However, this may not be linear once the reimbursement rates reach higher levels.

The findings have several important implications for oral healthcare policy in the US. Implementing loan repayment programs, raising Medicaid reimbursement rates, and loosening dental hygienist supervision can all improve access for underserved children. Moreover, both loan repayment programs and loosening supervision requirements were potentially cost saving.

The proposed methods can be generalized and applied more broadly in areas with similar dental programs. The loan repayment program assumes specific parameters on repayment, but are general for such programs in the USA. Second, analysis of the impact of reimbursement rates on Medicaid was based on all states, so the findings hold nationally in the USA based on the state level data presented. Third, the cost analysis of the supervision of dental hygienist in school-based programs can be generalized by using data on available providers or the school network in any area such as a state or region. Finally, other countries can learn from the findings on the loan repayment program and on staffing with different levels of expertise.

CHAPTER 6. POTENTIAL OF SILVER DIAMINE FLUORIDE TO REDUCE RESTORATIVE CARIES TREATMENT EXPENDITURES IN US CHILDREN

6.1 Introduction

Over 28% of US children aged 2 to 8 had dental caries in their primary teeth in 2012 [100]. Further, significant disparities exist for untreated dental caries for this population [3]. For example, non-Hispanic black 2 to 8 year olds had more than double the prevalence of untreated decay (20.5%) compared to their non-Hispanic white counterparts (10.1%) [100]. A contributing factor to oral health disparities is the limited access to dental care for children in low-income families even when they are eligible for Medicaid [101, 102].

Untreated tooth decay in young children can lead to pain, infections, and expensive emergency department (ED) visits and/or hospitalizations. In 2010, 0.65% of pediatric hospitalizations were due to non-traumatic dental conditions [103]. In 2011, $68 million in Medicaid payments were made for preventable dental conditions in operating rooms or ambulatory surgery centers, with 98% of those cases related to dental caries and 71% for children aged 1 to 5 years [104].

Silver diamine fluoride (SDF) has an antimicrobial effect on cariogenic biofilms and can slow down the demineralization of dentine [105-107]. The silver in SDF attacks harmful bacteria while the fluoride promotes remineralization of the tooth [108]. Recent systematic reviews show that the application of 38% SDF can arrest caries in the primary teeth of young children, though there is not consensus on the total number or frequency of applications that should be applied [109-111].

In young children, SDF has the potential to arrest caries in primary teeth, potentially removing the need for any restorative treatments until they are replaced by their permanent teeth. Further, SDF can reduce the use of anesthesia in very young children, either by eliminating the need for the restorative care or by postponing the potentially stressful dental procedures until the child is old enough to receive more standard restorative care options. Pediatricians in many states have been applying topical fluoride varnish on the teeth of young children to prevent caries, and potentially could begin using SDF for Medicaid-enrolled children with active caries lesions who have limited access to dental care.

We applied a simulation approach to quantify the cost impact of using SDF in young children (aged 0 to 5 years) with dental caries in three sub-populations: i) Medicaid-enrolled young children who had received caries related restorative care during 2010-2012, ii) all Medicaid-enrolled young children in 2010, and iii) all young children in the general population in 2010. States included in the analysis were Alabama (AL), Connecticut (CT), Massachusetts (MA), New Hampshire (NH), North Carolina (NC), South Carolina (SC), and Vermont (VT). We considered these states for two reasons. First, the data for Medicaid payments and dental care utilization in these states had relatively few missing values. Second, we wanted to compare states from two different regions of the US with different demographics and utilization of dental care services [112]. The outcomes of interest were the reduction in the number of children with preventable restorative care assuming SDF application and the reduction in the resulting system expenditures from using SDF from the payer perspective. The outcomes were determined for the three sub-populations for varying levels of penetration of SDF intervention defined as the percentage of children receiving SDF application (10%, 25%, and 50%) and of SDF effectiveness.

6.2 Methods

6.2.1 Data Sources

We analyzed data extracted from the 2010-2012 Medicaid Analytic Extract (MAX) files obtained from the Centers for Medicare and Medicaid Services (CMS) for seven states: three southeastern states (AL, NC, and SC) and four northeastern states (CT, MA, NH, and VT). The MAX claims data were used to extract procedure (CDT and CPT) codes, expenditures, and patient demographics including age, gender, and residence zip code. This study was approved by CMS (Data Use Agreement #23621) and by the Institutional Review Board of Georgia Tech (protocol #H11287).

We also used demographic data from the US Census Bureau to determine the proportions for each age, education level, household size, income, and sex at the census tract level for the general child population in the seven states.

We also used the demographic data from the US Census Bureau to determine the proportions for each age, education level of the parents, household size, income of the parents, and gender at the census tract in the seven states for the general child population. Census data came from four census tables: Single Years of Age and Sex: 2010 (DEC_10_SF2_QTP2), Household Type by Household Size (DEC_10_SF2_PCT20), Sex By Educational Attainment For The Population 25 Years And Over

(ACS_10_SF4_B15002), and Age By Ratio Of Income To Poverty Level In The Past 12 Months (ACS_10_SF4_B17024).

6.2.2 Study Population

As SDF is applied to existing caries lesions, we limited the population to children, aged 0 to 5 years, who would develop caries. For these children, we considered three populations/scenarios. Population 1 (P1) included all Medicaid-enrolled children who received a caries-related restorative dental procedure between 2010 and 2012; P1 reflects realized restorative dental care utilization in the Medicaid system for the 3 years considered. Population 2 (P2) included all Medicaid-enrolled children in 2010; P2 reflects potential dental care utilization in the Medicaid system. Population 3 (P3) included all children provided in the 2010 census data; P3 reflects potential dental care utilization for the general population.

6.2.3 Intervention and Comparison Group

For each population we assumed that caries would be treated with either SDF or a restoration. We assumed that a restoration would not fail within the study period. We also assumed only one caries incidence for children in P2 and P3 if they were determined to have caries.

6.2.4 Caries Prediction Model (Probability of Caries)

For the two populations, P2 and P3, without actual data on receipt of restorative dental care, we estimated the probability that a child aged 0 to 5 had at least one caries lesion within the past 24 months using a regression model [113]:

$P\{CARIES = 1|AGE, EDU, HHS, INC, FEMALE\} =$

$$1 - \exp(-\exp(-2.62183 + 0.52207 * AGE - 0.21811 * EDU + 0.07516 * HHS - 0.25528 * INC - 0.20061 * FEMALE))$$

where AGE is the age in months of the participant at the time of the examination, EDU is the household reference person's education level as shown in the numeric levels below matching the levels found in NHANES, HHS is the size (total number of people) pf the participant's household, INC is the ratio of family income to the federal poverty level (FPL), and FEMALE is an indicator variable set at 1 if the child was female and 0 otherwise.

For Medicaid-enrolled children in P2, we determined the age, sex, race, and zip code from the MAX claims data. Income, education level, and household size were simulated by using the demographic data from the 2010 Census Bureau, conditioned on the race of the child. For children in P3, all demographic variables used were simulated using the demographics data from the 2010 Census Bureau at the census tract level.

We used Monte Carlo simulation to simulate which children would develop caries.

6.2.5 Effectiveness of SDF

We used two distributions for the effectiveness of SDF. The first distribution was based on the 95% confidence interval (CI) for SDF effectiveness reported in the literature [105, 108] and heretofore referred to as the “main” distribution. Because this is based on the 95% CI, we assumed SDF effectiveness was uniform between 41.2% and 90.7% with 95% probability and between 0% and 100% with 5% probability. To test the sensitivity of lower SDF effectiveness, a second distribution was considered and referred to as the "lower" distribution. The lower distribution assumed SDF effectiveness was uniform between 20% and 60% with 95% probability and between 0% and 100% effective with 5% probability.

6.2.6 *Cost of SDF Application*

Because SDF is not reimbursed by Medicaid in all states, the actual SDF reimbursement amount is not available. As a proxy, we used 166% of the Medicaid reimbursement amount for topical fluoride in each state. For states that did reimburse SDF, some of them treated SDF as a standard fluoride. Other states reimbursed 50% to 100% more than fluoride. While the material cost is very low [114], SDF application is more expensive than fluoride, thus the final reimbursement amount used was chosen to be two-thirds higher than fluoride. The final expenditures used for SDF application are provided in Table 18 [115].

Table 18. Actual fluoride and estimated SDF reimbursement rates.

State	Fluoride rate ($)	Estimated SDF Rate ($)
AL	15.00	24.90
MS	22.42	37.22
SC	15.89	26.38
NC	15.61	25.91
NH	18.00	29.88
VT	15.00	24.90
MA	26.00	43.16
CT	20.00	33.20

6.2.7 *Costs of Restorative Dental Care*

We assumed costs of restorative dental care from the payer perspective using Medicaid expenditures for restorative dental care operations.

We estimated the Medicaid expenditures for dental care services by dividing the child population into three groups: children who received general or local anesthesia, children who received nitrous oxide, and children who received neither. For children who received nitrous oxide and children who received local or general anesthesia, we estimated both the total expenditures per-visit (all expenditures of restorative dental care as well as anesthesia and surgery related expenses) and the anesthesia expenditures per-visit (only the expenditures related to anesthesia and other surgery expenses).

For Medicaid-enrolled children with caries-related restorative procedures (P1) provided by the MAX claims data, we extracted claims for anesthesia (including nitrous oxide and local or general anesthesia) to identify children with caries related restorative procedures that were sedated by each type of anesthesia. The procedure codes used for caries related restorative care and anesthesia related procedures are shown in Table 19 and Table 20 respectively.

Table 19. Caries related restorative procedures codes used in cost analysis.

CDT Code	Description
D2140	1-Surface Amalgam, *Primary or* Permanent Tooth
D2150	2-Surface Amalgam, *Primary or* Permanent Tooth
D2160	3-Surface Amalgam, *Primary or* Permanent Tooth
D2161	4+ Surface Amalgam, *Primary or* Permanent Tooth
D2330	Composite Resin, One Surface, Anterior
D2331	Composite Resin, Two Surfaces, Anterior
D2332	Composite Resin, Three Surfaces, Anterior
D2335	Composite Resin, Four Surfaces or Incisal
D2391	Comp Resin, One Surf., Post., Perm or Prim (includes PRR)
D2392	Composite Resin, Two Surfaces, Post. (Perm or Primary)
D2393	Composite Resin, Three Surfaces, Post. (Perm or Primary)
D2394	Composite Resin, Four Surfaces, Post. (Perm or Primary)
D2930	Crown-Stainless Steel, Primary Tooth
D2931	Crown-Stainless Steel, Perm. Tooth
D2932	Crown-Prefab. Resin, Primary Tooth
D2934	prefabricated stainless steel crown with resin window
D2940	Sedative Filling
D2954	Post And Core (Prefab.), Excl Crown
D3220	Vital Pulpotomy, Primary or Perm. Tooth
D3221	Pulpal Debridement, Primary or Perm Tooth

Table 20. Anesthesia codes used in the cost analysis.

Code Type	Code	Description	Type
CPT	00100 - 00222	Anesthesia for Procedures on the Head	Anesthesia
CDT	D9210	Local anesthesia not in conjunction with operative or surgical procedures	Anesthesia
CDT	D9211	Regional block anesthesia	Anesthesia
CDT	D9212	Trigeminal division block anesthesia	Anesthesia
CDT	D9215	Local anesthesia	Anesthesia
CDT	D9220	Deep sedation/general anesthesia – first 30 minutes	Anesthesia
CDT	D9221	Deep sedation/general anesthesia – each additional 15 minutes	Anesthesia
CDT	D9230	Analgesia, anxiolysis, inhalation of nitrous oxide	Nitrous Oxide
CDT	D9241	Intravenous conscious sedation/analgesia – first 30 minutes	Anesthesia
CDT	D9242	Intravenous conscious sedation/analgesia – each additional 15 minutes	Anesthesia
CDT	D9248	Non-intravenous conscious sedation	Anesthesia

The statistical distributions of the total expenditures and anesthesia-only Medicaid expenditures per-visit were estimated for each state. Specifically, once we identified children who had received caries-related restorative care and anesthesia on the same day, the total healthcare expenditures per-visit per-child were determined by summing the Medicaid payment amounts across all procedures performed on the same day for each child.

For children with each type of anesthesia (local or general anesthesia or nitrous oxide) and each state, a distribution of total Medicaid payments and a distribution of anesthesia or surgery related payments were estimated using kernel density estimation (KDE) on the 10^{th} through 90^{th} percentiles of per-visit expenditure data. We removed 10%

on each tail of the distribution of the per-visit expenditure observations to exclude potential outliers.

For children in P1 who received any type of anesthesia during a visit, we used the actual reported Medicaid payments for all procedures. For children with visits that did not have any anesthesia claims, we added the Medicaid payment of nitrous oxide with probability 77.3% or the Medicaid payment of local or general anesthesia with probability 22.7% to the restorative dental care expenditure. This additional expenditure was added by sampling from the anesthesia payment distribution for the relevant state and anesthesia type.

For children in sub-populations P2 and P3, simulated costs were sampled from the total expenditure distributions for children who received nitrous oxide with probability 77.3% and for children who received local or general anesthesia with probability 22.7%. The total expenditure distributions include all restorative dental costs as well as the costs of anesthesia and other surgery related expenses. We used these Medicaid expenditures in all populations, including the general population P3. For P3, using Medicaid expenditures is a lower bound on the cost since private fee schedules would be higher.

6.2.8 Outcomes

We considered four outcomes: i) the number of caries-related visits that received SDF (*SDF applied*), ii) the number of averted caries lesions from those that would have needed restorative treatment (*SDF arrested*), iii) the averted expenditures by using SDF (*averted expenditures*), and iv) the realized expenditures. The *averted expenditures* is the expenditures for those prevented restorative procedures that would have been realized had

SDF not been used. The *realized expenditures* were the sum of the expenditures of restorative dental care for children whose caries was not prevented by SDF (either because they did not receive SDF or because it was not effective) plus the expenditure of applying SDF treatments. The averted expenditures is the expenditure saved by using SDF. The realized expenditures is the cost the system actually experiences.

6.2.9 Urban Classification

We used Rural Urban Continuum Codes (RUCC) to classify counties in the seven states as being metropolitan or non-metropolitan [83]. RUCC codes contain nine levels; counties with codes 1-3 were classified as metropolitan while counties with codes 4-9 were classified as non-metropolitan.

6.2.10 Simulation Model

We used Monte Carlo simulation to simulate restorations and costs over 100 runs. We simulated which children had caries (for sub-populations P2 and P3), which received SDF, and among those who received SDF, which had caries successfully arrested with SDF. The cost of SDF application was added regardless of its effectiveness for any child who received SDF treatment. We reported the mean and standard error for each outcome across the simulations.

For all three populations, we varied the percentage of children receiving SDF (SDF penetration) to 10%, 25%, and 50% of the population. Children were assigned to the SDF or other restorative treatment groups based on the penetration levels.

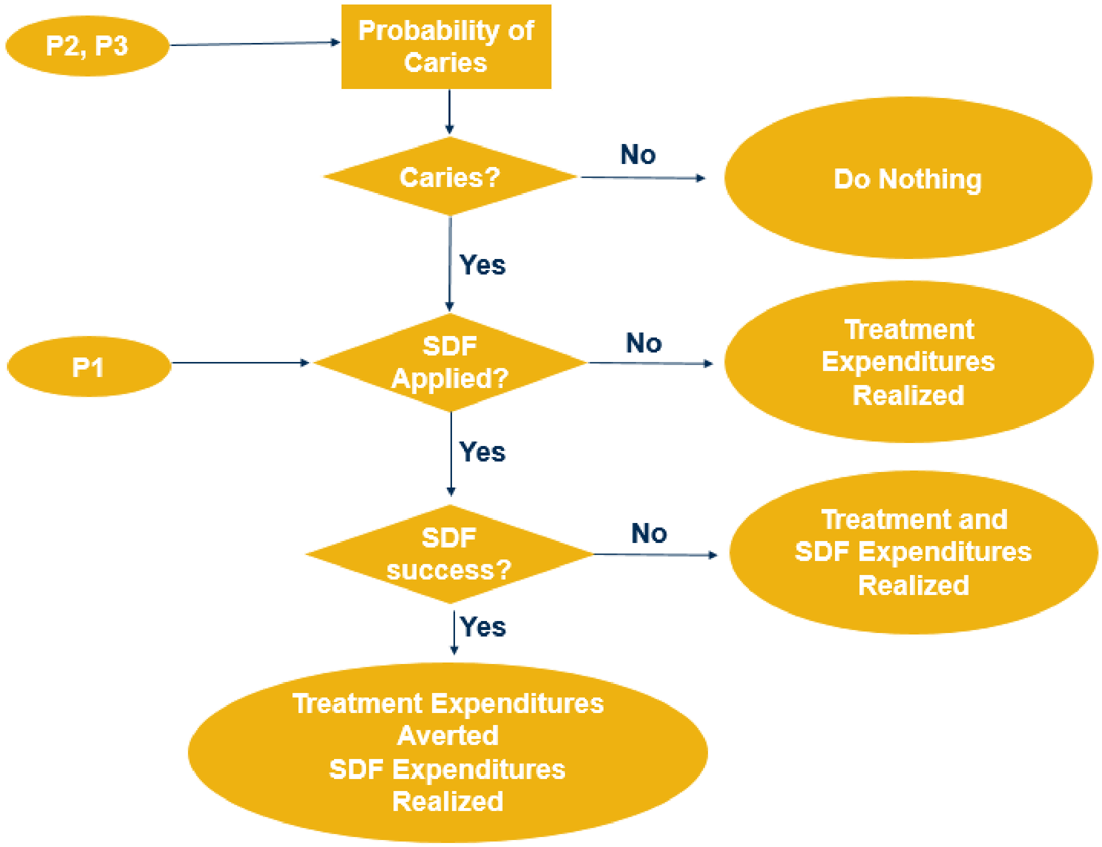

Figure 21. Diagram of Simulation Model.

To determine whether an SDF application was successful in arresting a child's caries, a Bernoulli distribution was sampled with the probability of success equal to the SDF effectiveness determined for each child who received SDF treatment. Figure 21 outlines the simulation process.

In the simulation process, any child who received SDF will have realized SDF expenditures. If a child does have caries but does not receive SDF or it is not effective, the child will have realized treatment expenditures. If a child has caries and SDF is effective, the treatment cost the child would have experienced is considered averted. These outcomes are defined more in the outcomes section.

Table 21. Description of each setting used in analysis.

Setting	SDF Penetration	Effectiveness
1	0.1	Lower
2	0.1	Main
3	0.25	Lower
4	0.25	Main
5	0.5	Lower
6	0.5	Main

The combination of three penetration and two effectiveness levels resulted in six simulation settings used in the analysis. Settings 1–2, 3–4, and 5–6 use 10%, 25% and 50% SDF penetration, respectively. Settings 2, 4, and 6 used our baseline distribution (main) of effectiveness while settings 1, 3, and 5 use the lower SDF effectiveness distribution. Each setting is described in Table 21.

6.3 Results

We initially considered 12 states for comparison. For each state, we evaluated the percentage of CDT codes compared to CPT codes as well as the proportion of each that was not missing (or non-zero) in the database to determine the quality of the Medicaid payment data in each state.

Table 22. Count of dental related restorative and anesthesia claims in Medicaid MAX data overall and with non-zero cost data.

State	CPT	CDT	Percentage CDT	CPT non-zero	CDT non-zero	Percentage CDT non-zero
AL	16753	397416	0.96	16753	397416	0.96
CT	16911	63989	0.79	5702	63843	0.92
GA	60006	600577	0.91	18002	53840	0.75
MA	8083	81603	0.91	6397	81535	0.93
MS	190468	294128	0.61	188979	291934	0.61
NC	184757	704420	0.79	184746	704420	0.79
NH	8047	39823	0.83	8047	39823	0.83
NJ	11221	159752	0.93	1559	1631	0.51
NY	18976	167292	0.90	4430	52469	0.92
SC	16937	349827	0.95	10074	349725	0.97
TN	46884	473367	0.91	2197	473347	1.00
VT	2080	33498	0.94	2080	33498	0.94

Table 22 presents overview results on Medicaid payment data in each of the 12 states initially considered. We found SC, MS, NC, AL, NH, VT, and MA all have low percentages of zero values (missing values) for Medicaid payment amounts in both the included CDT and CPT codes. Further, they generally have a high percentage of CDT codes among the total codes included.

NY, NJ, and GA were found to have poor cost data across the board. TN and CT had good CDT data but poor CPT data. However, looking at non-zero payment amounts in CT returned the ratio of CDT to CPT codes to similar values from other included states. Alternatively, TN was missing almost all payment data from CPT codes. In MS, there were very few nitrous oxide claims, all of which had a zero Medicaid payment.

The histogram of expenditures (blue) and KDE estimate (red) for the total payment in Alabama for children who received nitrous oxide and children who received local or general anesthesia is shown in Figure 22 and Figure 23, respectively. Additional expenditure distributions of the total expenditures by anesthesia type and state are shown in the Appendix.

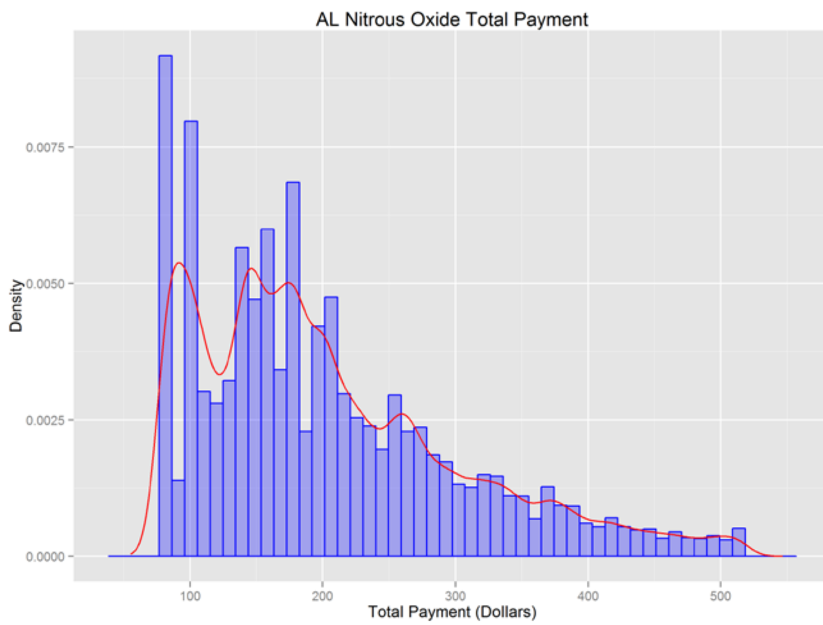

Figure 22. Histogram (blue) and KDE distribution (red) of total payment for children receiving only nitrous oxide anesthesia in Alabama.

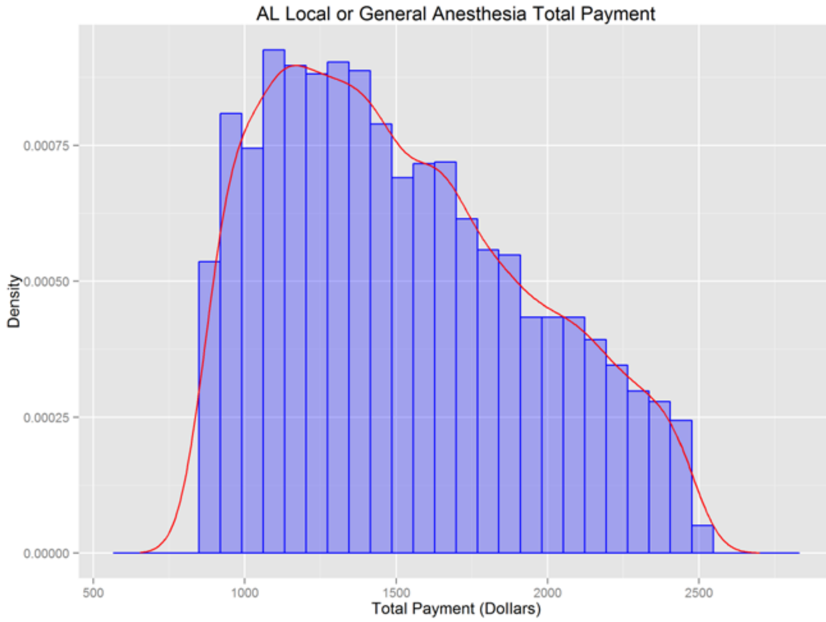

Figure 23. Histogram (blue) and KDE distribution (red) of total payment for children receiving local or general anesthesia in Alabama.

Figure 24 and Figure 25 show the distribution of anesthesia expenditure for children in AL who received local or general anesthesia and children who received nitrous oxide, respectively. Similarly, additional expenditure distributions of the anesthesia expenditures (including other surgical related expenditures) by children who received each anesthesia type and by state are shown in the Appendix. The difference between this distribution and the distribution shown in Figure 23 is the dental payments associated with the caries related restorative care performed.

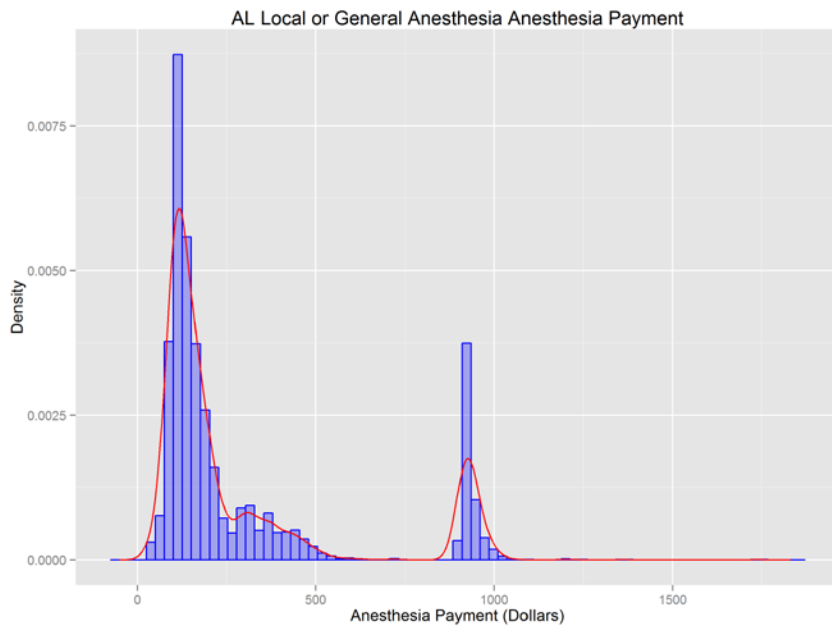

Figure 24. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving local or general anesthesia in Alabama.

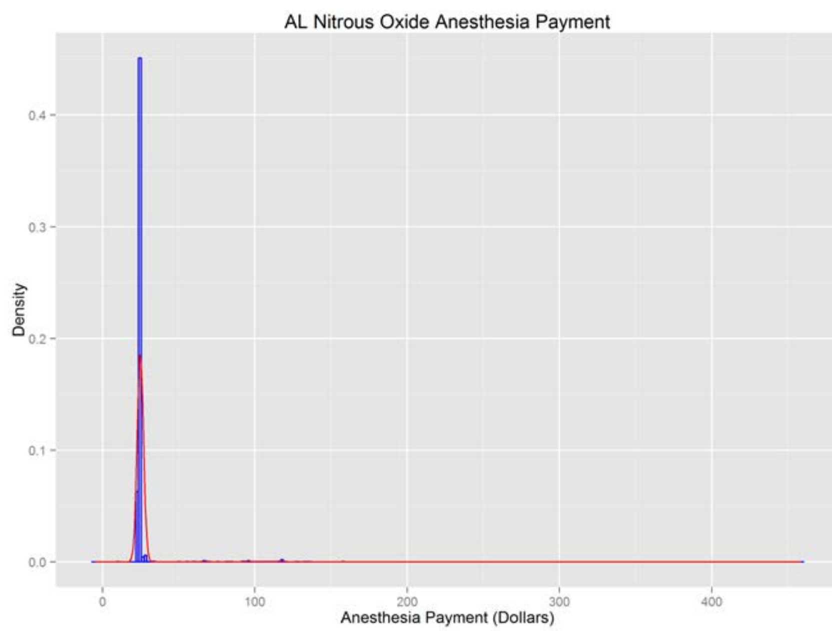

Figure 25. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving Nitrous Oxide anesthesia in Alabama.

Total payments for children who received nitrous oxide and children who received local or general anesthesia range between approximately $100 to $600 and $1000 to $5000 per visit, respectively. In CT, the total payment for children who received local or general anesthesia ranges even higher, from approximately $1000 to $8000 per visit.

Table 23. SDF applied, and SDF arrested for P1, P2, and P3.

		P1		P2		P3	
Setting	State	SDF Applied	SDF Arrested	SDF Applied	SDF Arrested	SDF Applied	SDF Arrested
1	AL	11,044	4,473	2,607	1,056	4,167	1,683
	CT	3,952	1,593	1,143	463	2,296	934
	MA	6,457	2,614	2,289	926	4,071	1,649
	NC	18,451	7,473	5,422	2,198	8,564	3,464
	NH	1,120	453	309	125	746	300
	SC	9,816	3,977	2,558	1,038	4,114	1,666
	VT	623	251	222	90	373	149
2	AL	11,055	7,243	2,603	1,710	4,182	2,741
	CT	3,965	2,605	1,146	751	2,295	1,504
	MA	6,455	4,240	2,301	1,513	4,078	2,675
	NC	18,466	12,120	5,396	3,536	8,566	5,616
	NH	1,115	729	309	203	752	491
	SC	9,815	6,437	2,547	1,669	4,122	2,703
	VT	620	406	224	147	373	245
3	AL	27,581	11,169	6,520	2,645	10,436	4,225
	CT	9,889	4,002	2,852	1,152	5,717	2,316
	MA	16,131	6,541	5,739	2,322	10,166	4,122
	NC	46,140	18,684	13,511	5,464	21,445	8,679
	NH	2,798	1,129	770	312	1,874	759
	SC	24,532	9,928	6,409	2,594	10,303	4,178
	VT	1,561	634	560	227	934	376
4	AL	27,584	18,101	6,496	4,259	10,451	6,849
	CT	9,901	6,498	2,849	1,868	5,727	3,749
	MA	16,125	10,579	5,738	3,763	10,189	6,676
	NC	46,125	30,248	13,490	8,849	21,437	14,045
	NH	2,800	1,836	769	503	1,868	1,227
	SC	24,517	16,075	6,397	4,198	10,295	6,758
	VT	1,557	1,021	561	368	924	606
5	AL	55,143	22,347	13,018	5,271	20,899	8,456
	CT	19,807	8,037	5,698	2,309	11,461	4,638
	MA	32,254	13,058	11,502	4,665	20,366	8,237
	NC	92,267	37,369	26,992	10,933	42,904	17,371
	NH	5,587	2,264	1,543	625	3,737	1,517
	SC	49,067	19,877	12,759	5,165	20,631	8,359
	VT	3,114	1,261	1,126	456	1,858	754

Table 23 (continued)

6	AL	55,182	36,180	13,047	8,551	20,871	13,689
	CT	19,785	12,960	5,713	3,750	11,432	7,496
	MA	32,246	21,156	11,495	7,542	20,344	13,332
	NC	92,278	60,521	26,981	17,692	42,895	28,147
	NH	5,589	3,663	1,548	1,013	3,745	2,450
	SC	49,050	32,158	12,809	8,395	20,637	13,536
	VT	3,120	2,045	1,125	738	1,858	1,218

The number of children who received an SDF application and the number of children who successfully averted treatment through SDF are reported in Table 23. The estimated number of caries related visits is shown in the Appendix.

The number of SDF applications and the number of children with caries arrested through SDF rose with the percentage of children who received SDF and the SDF effectiveness. In setting 1 for P1, VT and NC were able to arrest 251 and 7,473 of their Medicaid caries between 2010 and 2012 by applying SDF to 623 and 18,451 people, respectively. In setting 4, those numbers changed to arresting 1,021 and 30,248 caries lesions by applying SDF to 1,557, and 46,125 children, respectively. In P3 and setting 1, they could have arrested 149 caries lesions in VT and 3464 caries lesions in NC based on the 2010 census by applying SDF to 373 and 8,564 children, respectively. In setting 4, VT and NC could have arrested 606 and 14,045 caries lesions by applying SDF to 924 and 21,437 children, respectively. For comparison, in P2, VT and NC could arrest 368 and 8,849 caries lesions by applying SDF to 561 and 13,490 children, respectively. The lower numbers observed in some of the states (VT) are due to the smaller populations of children.

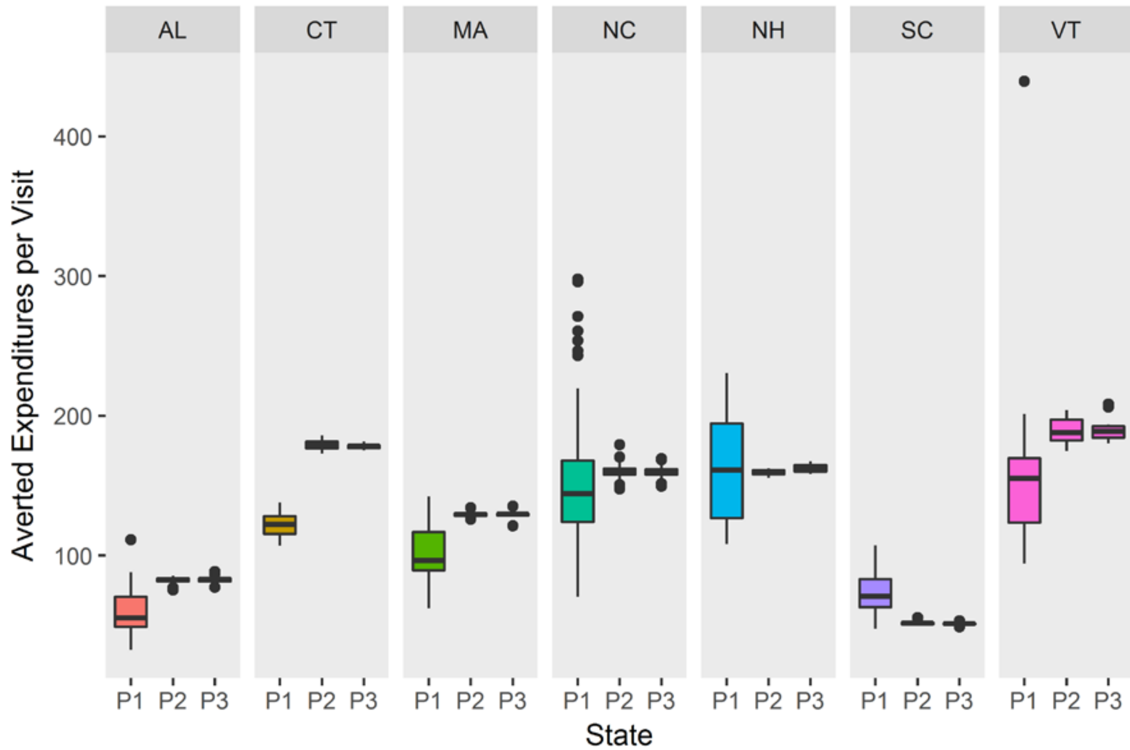

Figure 26: Box plot of averted expenditures per visit with caries for setting 4 by state and population group.

Figure 26 presents averted expenditures per visit with caries by state and population group for setting 4. Averted expenditures per visit ranged from \$75 to \$250 per-visit for setting 4. AL and SC had the lowest averted expenditures with values under \$100 per caries-related visit for all population groups while the expenditures in most other states ranged from \$100-\$200 per caries-related visit. NC, MA, and VT had the highest averted expenditures per-visit when looking across all population groups with mean averted expenditures per-child of \$152, \$162, and \$168 respectively for P1. CT also had high average averted expenditures per-child (\$200) for P2 and P3 but has lower values for P1.

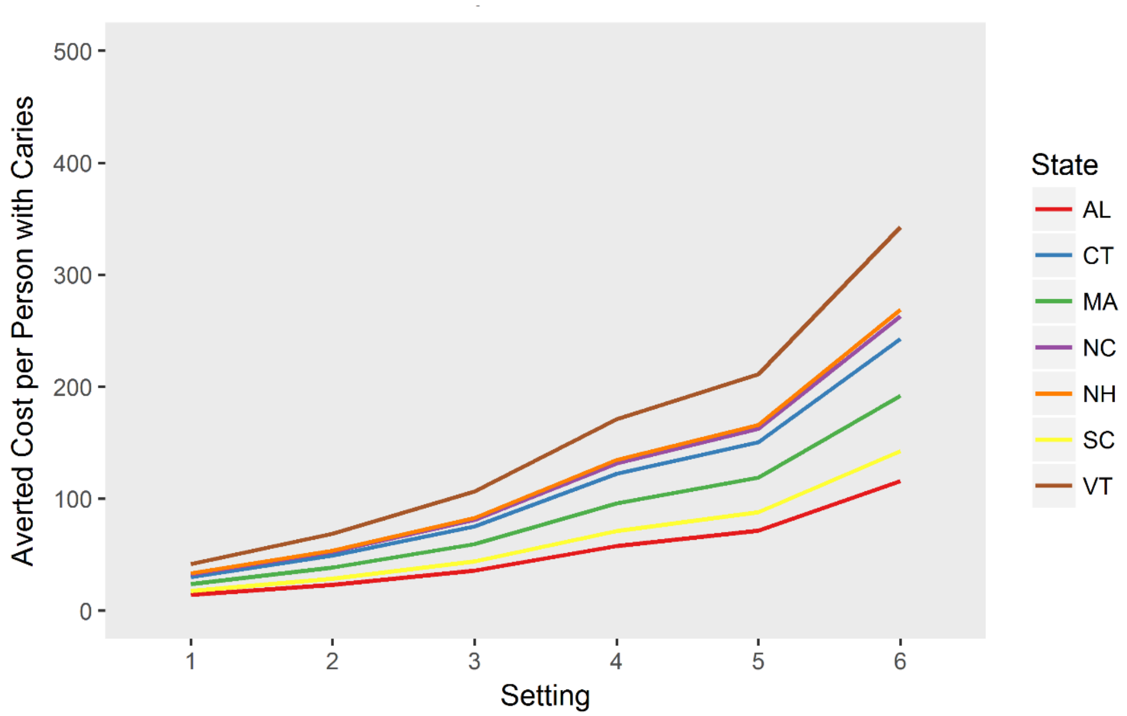

Figure 27. Averted expenditures per caries visit by state and setting for P1.

Figure 27 shows the difference in expenditures averted per person for P1 by state and setting. Higher expenditures averted per-child are found as SDF effectiveness rises and as more children received treatment from SDF. In P1, VT consistently had the highest averted expenditures per-child in all settings with AL at the bottom, followed by SC.

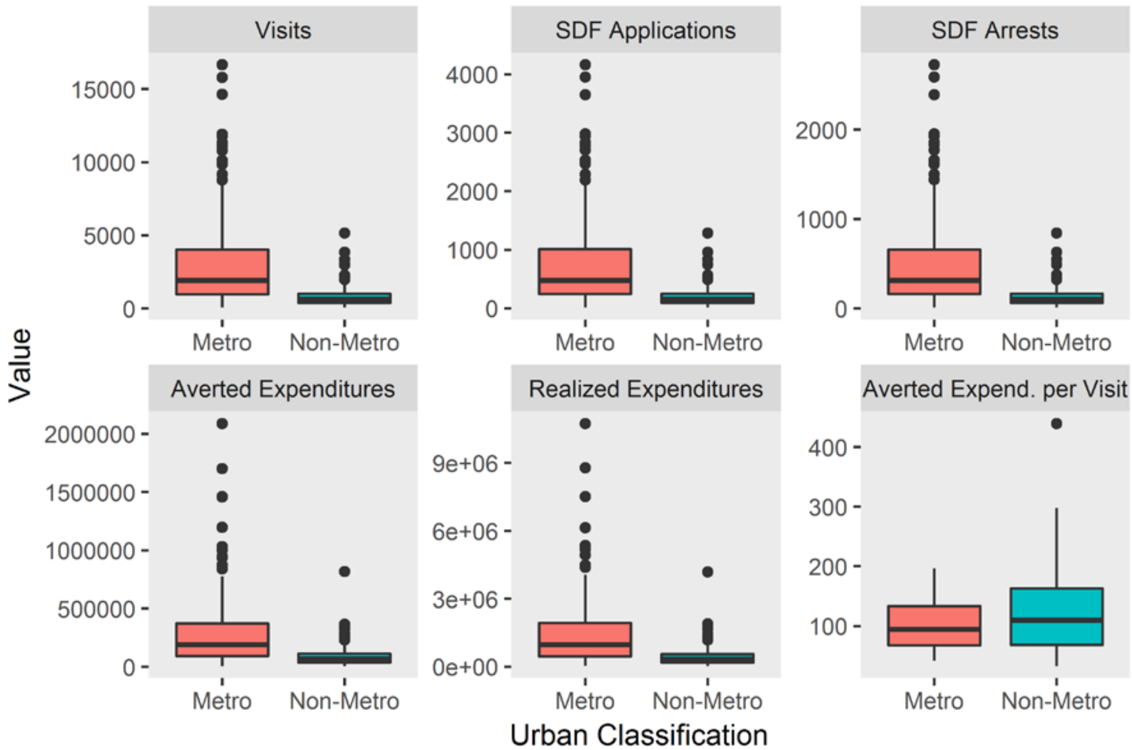

Figure 28. Box plot of outcome metrics by urban classification for setting 4 and P1.

Figure 28 shows the outcome measures across all states stratified by metropolitan counties and non-metropolitan counties for setting 4 and P1. The majority of the children in P1 lived in Metropolitan counties. As a result, we also found the majority of the SDF arrests, averted expenditures and realized expenditures occurred in the metropolitan counties. However, there were higher averted expenditures per-visit in the non-metropolitan counties.

Table 24. Averted and realized expenditures for P1.

		Averted Expenditures				Realized Expenditures		
Setting	State	Lower	Mean	Upper	Mean per Caries-Related Visit	Lower	Mean	Upper
1	AL	1,068,262	1,579,621	2,090,980	14.8	37,128,184	37,627,916	38,127,649
	CT	910,414	1,186,535	1,462,657	30.0	28,093,626	28,366,711	28,639,796
	MA	1,200,028	1,532,611	1,865,194	25.7	36,210,564	36,536,826	36,863,089
	NC	3,998,406	5,983,060	7,967,714	37.3	140,474,814	142,439,634	144,404,454
	NH	200,204	371,695	543,186	40.0	8,649,410	8,818,746	8,988,083
	SC	1,198,609	1,725,975	2,253,342	18.1	40,601,549	41,118,415	41,635,281
	VT	36,604	258,797	480,990	40.9	6,043,686	6,264,673	6,485,659
2	AL	1,899,881	2,560,932	3,221,983	23.9	36,003,393	36,646,857	37,290,321
	CT	1,584,814	1,944,025	2,303,236	49.0	27,254,468	27,609,641	27,964,813
	MA	2,071,543	2,489,464	2,907,385	41.1	35,171,255	35,579,914	35,988,574
	NC	7,189,632	9,723,469	12,257,306	60.7	136,192,349	138,699,607	141,206,866
	NH	380,550	600,260	819,970	64.0	8,372,786	8,590,010	8,807,234
	SC	2,124,485	2,793,739	3,462,992	29.3	39,396,169	40,050,626	40,705,084
	VT	154,247	427,475	700,703	68.2	5,824,261	6,095,923	6,367,585
3	AL	3,145,147	3,936,746	4,728,345	36.7	34,908,673	35,683,306	36,457,940
	CT	2,545,358	2,979,401	3,413,443	75.0	26,340,934	26,770,928	27,200,921
	MA	3,330,191	3,832,503	4,334,815	62.9	34,161,146	34,654,272	35,147,398
	NC	11,893,239	14,989,378	18,085,516	93.5	131,081,674	134,150,828	137,219,982
	NH	655,129	925,388	1,195,648	99.3	8,047,255	8,315,209	8,583,163
	SC	3,494,508	4,302,521	5,110,534	45.1	38,137,517	38,930,080	39,722,642
	VT	310,971	664,546	1,018,122	105.0	5,530,743	5,882,318	6,233,893
4	AL	5,403,176	6,385,119	7,367,062	59.6	32,277,784	33,235,006	34,192,228
	CT	4,313,652	4,834,644	5,355,636	121.3	24,400,761	24,916,080	25,431,400
	MA	5,571,988	6,179,226	6,786,465	101.5	31,711,654	32,307,321	32,902,989
	NC	20,472,050	24,258,573	28,045,097	152.1	121,131,280	124,881,231	128,631,181
	NH	1,165,285	1,501,991	1,838,697	161.5	7,405,601	7,738,678	8,071,754
	SC	5,996,724	6,981,769	7,966,814	73.3	35,286,427	36,250,423	37,214,418
	VT	645,604	1,065,552	1,485,499	168.2	5,063,282	5,481,210	5,899,138

Table 24 (continued)

5	AL	6,836,010	7,886,539	8,937,068	73.7	31,387,414	32,421,078	33,454,741
	CT	5,354,924	5,947,876	6,540,829	149.8	23,542,142	24,131,688	24,721,233
	MA	6,979,667	7,652,524	8,325,381	125.7	30,867,624	31,529,836	32,192,048
	NC	25,857,011	29,953,998	34,050,986	187.3	116,311,410	120,381,474	124,451,538
	NH	1,484,519	1,853,835	2,223,150	198.9	7,103,329	7,470,170	7,837,011
	SC	7,541,159	8,622,912	9,704,665	90.5	34,189,592	35,256,905	36,324,218
	VT	875,044	1,316,148	1,757,253	206.9	4,830,150	5,269,447	5,708,744
6	AL	11,523,817	12,772,589	14,021,362	119.1	26,311,124	27,536,007	28,760,891
	CT	8,910,332	9,611,242	10,312,151	241.3	19,772,049	20,467,593	21,163,136
	MA	11,594,024	12,386,990	13,179,957	203.3	26,015,322	26,794,997	27,574,672
	NC	43,702,309	48,504,998	53,307,687	303.0	97,067,980	101,830,772	106,593,564
	NH	2,566,316	3,001,236	3,436,156	322.8	5,891,959	6,322,847	6,753,735
	SC	12,714,952	13,974,397	15,233,843	146.9	28,667,031	29,904,964	31,142,896
	VT	1,618,741	2,135,730	2,652,719	335.1	3,935,749	4,450,013	4,964,278

Table 24 shows the averted expenditures and realized expenditures CI as well as the average averted expenditure per-visit with caries for P1. Under all settings, states averted expenditures. In setting 1, mean averted expenditures varied between $259,000 for VT and $6M for NC. In setting 4, the mean averted expenditures for all states was over $1M and up to $24M in NC. The mean averted expenditures per caries visit was between $60 and $170 in setting 4 and between $119 and $335 in setting 6, where total mean averted expenditures varied between $2M and $48.5M.

6.4 Discussion

For young children aged 0 to 5 years, using SDF has the potential not only to arrest caries but also to avert dental care expenditures. For the youngest children, SDF has the potential to avert the dental care expenditures associated with dental care involving general anesthesia. For these children, SDF can either prevent more invasive restorative treatments entirely if the caries remain arrested until permanent teeth replace the affected primary teeth, or it can delay the treatment until the child is sufficiently old enough that they do not need to be treated under general anesthesia or conscious sedation. For slightly older children, SDF has the potential to prevent restorative procedures on the primary teeth until they are replaced by healthy permanent teeth.

We evaluated the impact of using SDF though Monte Carlo simulation. We considered three subpopulations of children; the first (P1) captures the realized utilization and the second (P2) captures the potential utilization for Medicaid-enrolled young children while the third (P3) captures the potential utilization for all young children. P2 and P3 represent conservative estimates of utilization since we used the probability of developing at least one caries lesion during a two–year period. In reality, it is possible that these children could have repeated visits, each of which would avert additional expenditures if SDF were used.

Providing SDF as a caries management strategy for young children has the potential to save states dental care expenditures by averting more expensive caries treatment options. Assuming the main SDF effectiveness distribution and 25% of children with caries receive SDF, states were able to save in the range of $59.6-168.2, $51.5-189.5, and $51.1-$190 per-visit with caries in the three sub-populations P1, P2, and P3, respectively. In all three sub-populations and in all levels of SDF penetration and SDF effectiveness, the benefit of providing SDF outweighed the expenditures associated with its application. In young children, the high rate of using local or general anesthesia was costly to the healthcare system. With 22% of claims using the significantly higher cost distribution associated with local or general anesthesia, the potential to avert even a few of these cases could result in cost savings to Medicaid or other dental care systems. Mean total averted expenditures under these assumptions ranged from $1M in VT to $24M in NC. AL, MA, and SC had mean total averted expenditures greater than $6M. Note that differences in expenditure outcomes between states were likely the result of the different Medicaid reimbursement amounts and the proportion of different procedures given in each state, in particular for anesthesia.

This study has several limitations. First, we assumed a range in the effectiveness of SDF. While there have been systematic reviews on the effectiveness of SDF in arresting caries, previous studies have been critical of the methods used in these systematic reviews [105, 108], pointing out the lack sufficient control groups or lack of details on the specific application timing and dosage of SDF necessary to obtain the quoted level of effectiveness [109]. The lack of more specific information regarding optimal treatment guidelines for using SDF is a limitation in this study. Other limitations include using only Medicaid payment data and using the proportion of anesthesia found in the Medicaid claims data to extrapolate to the general young child populations. In the general population, the fee schedules for these procedures are likely different but we have pulled all payment data from distributions determined by Medicaid payments. Changing the proportion of anesthesia claims among children will have a large impact on expenditure outcomes because these procedures are expensive. A more detailed analysis that included the number of children who receive different types of anesthesia in the different populations could potentially provide a more robust analysis.

Additionally, since differences in expenditure distributions cause the majority of differences between states, another potential issue could be data issues with states coding specific procedures different from expected. Based on the distributions, it is difficult to determine if a state does not use the more expensive anesthesia types and other expensive treatment procedures or if they potentially use a different coding scheme. If procedures used for dental care were different from those we listed, their cost would have been missed in our expenditure distributions.

It is important to note the stakeholders benefiting from the cost benefit analysis. In P1 and P2, the benefit is to the Medicaid population while in P3 the benefit is to the general population. Further, it is important to mention the difference between P1 and the other populations. P1 consisted of the caries related expenditures in the Medicaid population and the potential averted expenditures based on all caries related Medicaid claims between 2010 and 2012. P2 and P3 used a national level estimate for the probability of a child having caries within 24 months based on demographic factors. Since many children will have more than one caries related visit, the estimates for P2 and P3 are very conservative. At minimum, we can compare P1 and P2. P1 had more caries related visits than P2 despite P1 consisting only of Medicaid children with caries related visits and P2 consisting of the Medicaid population in 2010.

Using the probability of caries also created a difference in timeframes between the populations. P1 represented the caries related expenditures over 3 years (2010-2012) for the Medicaid population. P2 and P3 represented conservative estimates of the expenditures for caries related visits over 2 years for the children aged 0-5 in 2010. Naturally, we would expect the expenditures to be higher for P1 both because of the timeframe of the analysis and the conservative nature of the caries estimation.

In the simulation, we assumed that children who received SDF were randomly selected. It may be possible to obtain better results by targeting areas known to have more problems with children having caries or more severe oral health outcomes. For example, while the majority of the expenditures averted comes from metropolitan counties, we found non-metropolitan counties had higher expenditures averted per visit with caries than did their metropolitan counterparts. Targeting children in more rural areas who may have less access to preventive care and potentially higher treatment expenditures could provide even higher averted expenditures than shown here.

6.5 Conclusion

Overall, SDF provides a relatively inexpensive caries management option for young pediatric populations experiencing dental caries. If used in the Medicaid-enrolled population, SDF potentially can save state Medicaid programs between \$15 on the very low end and \$330 on the high end per caries-related visit. In additional to lower expenditures, using SDF could also prevent stressful restorative dental procedures for young children.

CHAPTER 7. CONCLUSION

Evaluating the impact of policy decisions is crucial to effective policymaking. The ability to consider multiple policy options and the impact of each before they are implemented gives policymakers knowledge to make informed decisions. This thesis aimed to address a selection of current policy issues in healthcare and health systems, ranging from the global health supply chain design to the potential impact of using new treatments in oral health.

First, we considered the impact of geographic distance on patients with cystic fibrosis. Beginning with the hypothesis that patients with better access to the specialized care necessary to treat CF would have better health outcomes, we used patient level health data from the Cystic Fibrosis Foundation and incorporated geographic distance in addition to the standard covariates that have been used in past literature to predict a patient's lung function. This study helps doctors understand the impact travel distances have on a patient's health and whether better access to care is helpful in providing better service to patients. We found evidence patients moved throughout the course of the study and determined that when using realized distances, there is little evidence that patients who are closer to care are in fact healthier. Alternatively, we found that for older adults who moved during the study period, the heathiest patients lived farther away from care centers, potentially meaning that patients who could manage to live farther away based on their health condition chose to do so. To understand better the impact of patient mobility, it would be beneficial to study the temporal relationship between patient movements and lung function as well as to better characterize patient movement, potentially evaluating which patients are moving closer to and farther from a care facility. It would also be beneficial to study the impact of alternative care centers for patients who may see a standard doctor to supplement care at CF care centers.

Second, the impact of the USAID malaria supply chain on malaria health in the countries it operates was studied. Variables known to predict malaria mortality were combined with variables demonstrating the performance of the USAID supply chain to determine which aspects of supply chain design impacted malaria health. This study demonstrates the value of supply chain organizations within health systems, not only to provide the commodities necessary to implement health programs, but also to contribute to the patients overall health by understanding the impact of supply chain design and the choices made in supply chain organizations. This type of analysis can show the value of the choices available to supply chain organizations. In this study, we found adaptable supply chains capable of responding to changes in demand and uncertain conditions could save lives. Particularly in the context of donor driven commodities, the ability to respond to other donors missed shipments or to a sudden shift in demand is important in maintaining a fully functioning malaria supply chain. Expanding on this scope of this study, it would be interesting to see how the results hold using other health commodity types or looking at other parts of the world. With malaria, there are very specific health needs from bed nets to antimalarial medications. Other diseases or health concerns could potentially be benefitted from a different supply chain optimization strategy.

Next, we evaluated the need for pediatric preventive dental care in Georgia and looked at three potential policy interventions to improve access to pediatric preventive dental care, including dental loan repayment programs, changing the Medicaid reimbursement rate, and relaxing the supervision requirements of dental hygienists. First, this study provided an optimization model to evaluate capacity in healthcare systems. We showed there is a strong need for Medicaid capacity currently in Georgia. Second, we evaluated interventions to improve access to care. This study provides a methodology to compare vastly different policy interventions ranging from targeted community level interventions to system wide changes. Specifically, we evaluated each policy in terms of met need and cost. We found dental loan repayment programs and relaxing the supervision levels of dental hygienists (specifically looking at implementing a school based sealant program) to be cost saving interventions, while Medicaid reimbursement would affect utilization but would not substantially increase acceptance of Medicaid among providers. Loan repayment programs provide targeted complete care to specific areas; alternatively, relaxing the supervision requirements would enable hygienists to provide a basic level of preventive services across the state. Currently, this work focused on the impact of these policies in Georgia. Practically, it was used by the Georgia Dental Hygienists Association to promote legislation that has since successfully passed through the Georgia legislature relaxing the supervision requirements of dental hygienists. Now, other states have become interested in quantitative methods to evaluate the impact of similar policies in their states. This paper provides a framework for such analysis and future work based on this paper could include similar analyses of these interventions on other states. Additionally, it would be possible to evaluate other interventions using a similar approach to understand the impact of a larger set of policy changes.

Last, we evaluated the impact of using silver diamine fluoride to treat caries in young children. SDF provides an advantageous and cost effective way to address caries in very young children. Given the unique combination of ease of application, cheap materials, and high effectiveness at arresting caries, promoting SDF treatments to arrest caries in young children has the potential to save states between $60 and $170 per child with caries when it is applied 25% of the time with the normal effectiveness range reported in the literature. Depending on the size of the state, this can translate into savings between $1M in Vermont and $24M in North Carolina. With the current lack of access to oral healthcare among Medicaid patients, SDF could provide Medicaid programs a cost effective way to increase services to a large number of children who currently do not have access to care, or to provide a cheaper and simpler alternative for those already receiving care. This study allows seven states to observe the potential impact of using SDF under a variety of scenarios to aid in decision making.

Overall, we have evaluated a number of healthcare policies including distance to care with cystic fibrosis, supply chain impact and design with the USAID malaria supply chain, access to pediatric preventive dental care, and the use of SDF to treat caries in young children. The analysis and methods presented will aid policymakers both in understanding how to evaluate potential options as well as in the specific impacts of the policies presented.

APPENDIX A. SUPPLEMENTAL MATERIAL FOR CHAPTER 2

The following plots in Figure 29 through Figure 32 show additional information about the distribution of visits overall and in removed data to understand the nature of the included and removed data in the dataset.

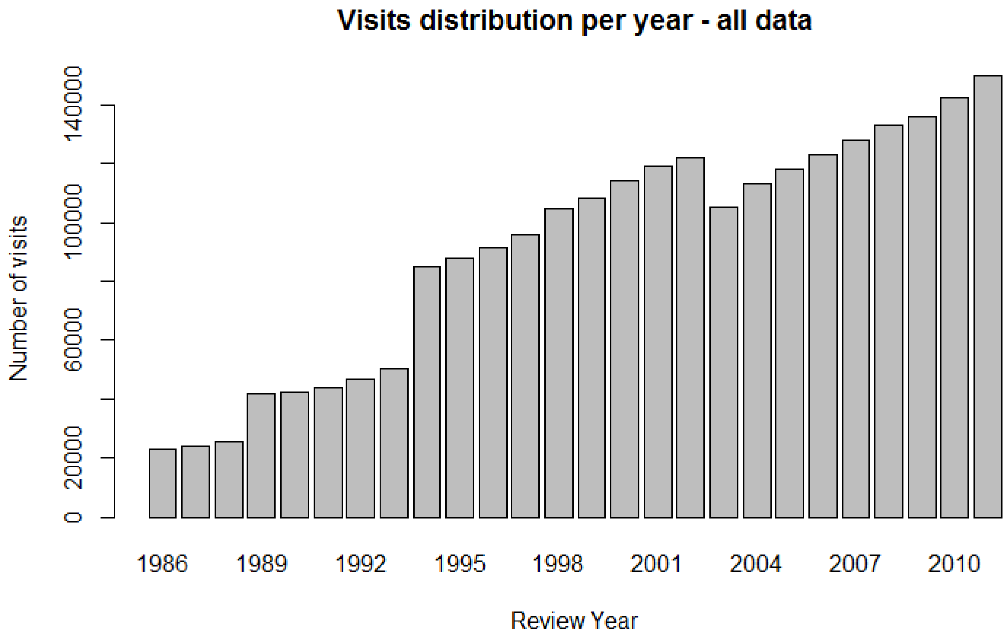

Figure 29: Visits distribution per year for all data prior to any filtering.

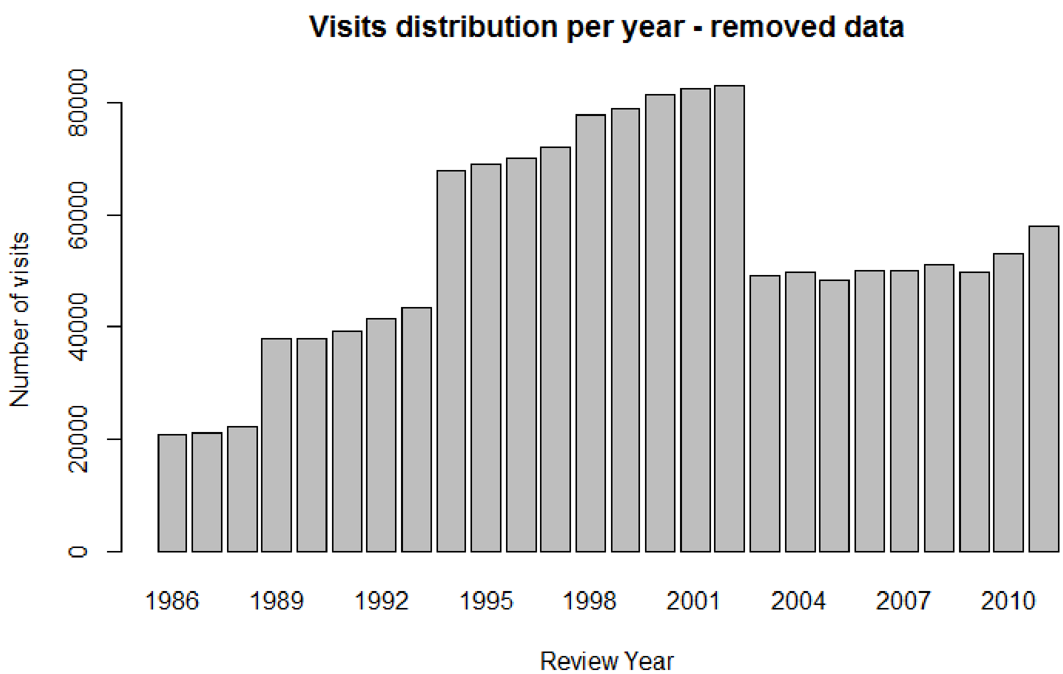

Figure 30. Visits distribution per year for all data removed with filtering.

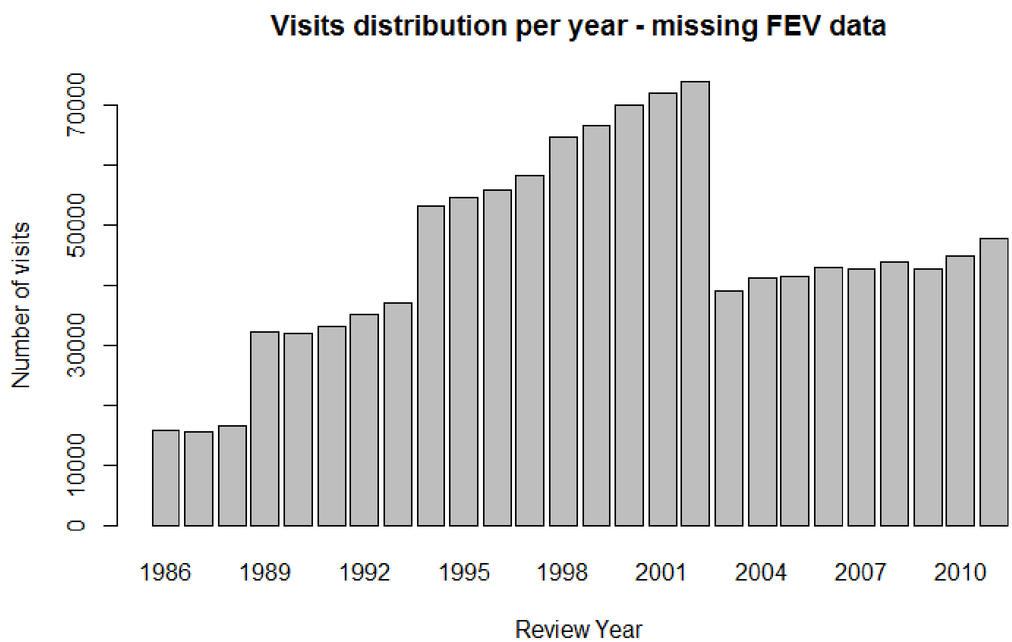

Figure 31: Visits distribution per year for data with missing %FEV_1.

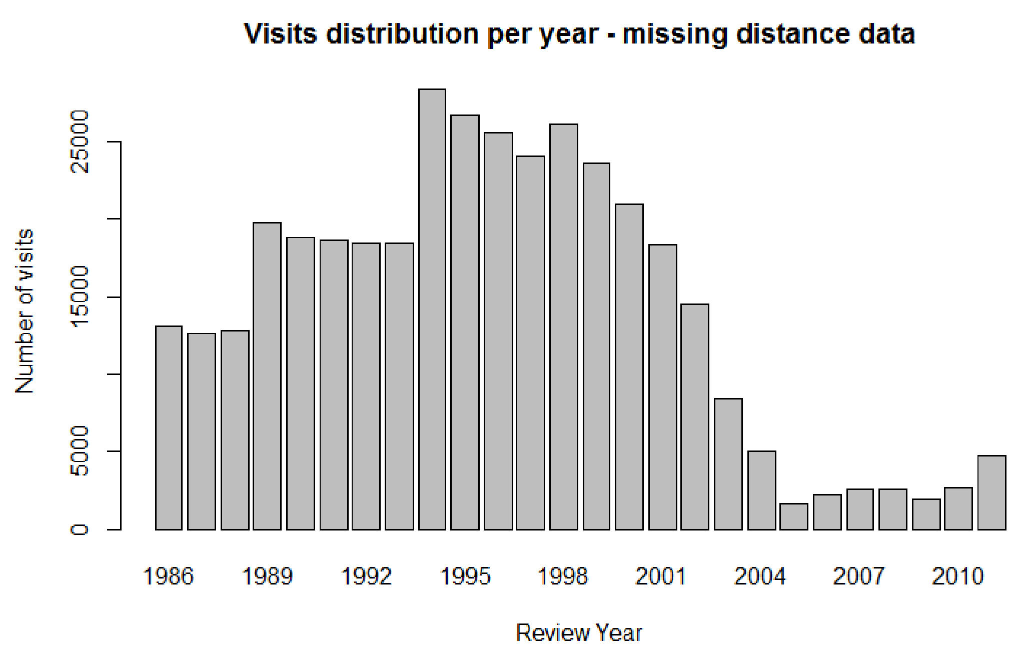

Figure 32: Visits distribution per year for data with missing distance data.

APPENDIX B. SUPPLEMENTAL MATERIAL FOR CHAPTER 4

B.1 Data

The data elements listed here were used in the optimization model. Note that existing facilities were assumed to have a fixed cost of zero since they are already open.

$I = \{1, \ldots, m\}$: Client locations

$J = \{1, \ldots, n\}$: Facility locations

$\hat{J} \subset J$: Facilities that do not accept Medicaid

$E \subset J$: Existing facilities

P: Provider types (dentist or hygienist)

R: Risk classes (low (L), high (H))

c^R: Yearly cost of providing service to a patient of risk class R

F_j: Fixed cost of opening a new facility.

d_{ij}: Distance between client i and facility j

n_i^{AR}: Number of pediatric preventive dental care patients with financial access other than Medicaid in census tract i with risk R.

n_i^{MR}: Number of pediatric preventive care Medicaid patients in census tract i with risk R.

$n_i = n_i^{AL} + n_i^{AH} + n_i^{ML} + n_i^{MH}$: Number of pediatric preventive care patients in census tract i.

$\overline{N_i^R}$: Average number of hours per year needed for one patient of risk class R in census tract i, weighted by the number of people in each age class.

CAP: Number of hours available to one provider during the year

M: Maximum providers allowed at a facility

B: Maximum budget allowed

NP: Maximum number of new providers allowed

AD_j: Binary data indicating whether facility j accepts new dentists or not.

S_j^M: Medicaid supply at facility j (existing)

S_j^T: Total supply at facility j (existing)

Sal: Salary need for provider

B.2 Decision Variables

x_{ij}^A: Percentage of need met (in people) in census tract i at facility j for patients who have financial access other than Medicaid

x_{ij}^M: Percentage of need met (in people) in census tract i at facility j for Medicaid patients

y_j: Decision variable for opening new locations

z_j: Number of new providers to locate at an open facility

B.3 Model

Objective Function: maximize the number of people served

$$\sum_{i \in I} \sum_{j \in J} \sum_{r \in R} \left(n_i^{AR} x_{ij}^{AR} + n_i^{MR} x_{ij}^{MR} \right)$$

Constraints:

Budget constraint:

$$\min \sum_{j \in J} \left(F_j y_j \right) + \sum_{i \in I} \sum_{j \in J} \sum_{r \in R} c^R \left(n_i^{AR} x_{ij}^{AR} + n_i^{MR} x_{ij}^{MR} \right) \leq B$$

Maximum number of new providers:

$$\sum_{j \in J} z_j \leq NP$$

Max supply from a census tract is 1 for non-Medicaid patients:

$$\sum_{j \in J} x_{ij}^{AR} \leq 1 \quad \forall i \in I, r \in R$$

Max supply from a census tract is 1 for Medicaid patients

$$\sum_{j \in J} x_{ij}^{MR} \leq 1 \quad \forall i \in I, r \in R$$

No patient can travel farther than 45 miles.

$$x_{ij} = \ 0 \quad \forall\, d_{ij} > 45 \quad \forall \ AL, AH, ML, MH$$

We cannot staff additional providers unless a facility is open.

$$z_j \leq M\, y_j \quad \forall j \in J$$

We cannot staff additional providers unless a facility takes additional providers.

$$z_j \leq M\, AD_j \quad \forall j \in J$$

Capacity limit:

$$\sum_{i \in I} \sum_{r \in R} \overline{N_i^R} \left(n_i^{AR} x_{ij}^{AR} + n_i^{MR} x_{ij}^{MR} \right) \leq S_j^T + \ CAP\ z_j \ \forall j \in J$$

Medicaid Capacity limit:

$$\sum_{i \in I} \sum_{r \in R} \overline{N_i^R} \left(n_i^{MR} x_{ij}^{MR} \right) \leq S_j^M + \ CAP\ z_j \ \forall j \in J$$

All existing facilities must be open. Note there is no cost to open new facilities.

$$y_j = 1 \ \ \forall \ j \ \in \ \ E$$

You can only locate a new provider if sufficient revenue is generated to support them

$$\sum_{i \in I} \sum_{r \in R} c^R \left(n_i^{AR} x_{ij}^{AR} + n_i^{MR} x_{ij}^{MR} \right) \geq Sal * z_j \quad \forall j \in J$$

Sign constraints:

$x_{ij}^A \in [0,1]$

$x_{ij}^M \in [0,1]$

$z_j \in \mathbb{Z}^+$

$y_j \in \{0,1\}$

APPENDIX C. SUPPLEMENTAL MATERIAL FOR CHAPTER 5

C.1 Additional Data Sources

Detailed data was used in the analysis. This appendix provides links to smaller additional data elements used to throughout each intervention to create the necessary definitions for each.

Table 25: Additional Data Sources.

Medicaid Learning Labs [116]	http://www.medicaiddental.org/learninglabs
ADA Dental Loan Repayment [117]	https://www.ada.org/~/media/ADA/Education%20and%20Careers/Files/dental-student-loan-repayment-resource.pdf
Dental Hygienist Practice Acts [118]	https://www.adha.org/resources-docs/7511_Permitted_Services_Supervision_Levels_by_State.pdf
Medical Expenditure Panel Survey [15]	http://meps.ahrq.gov/mepsweb/
Kaiser Family Foundation – Medicaid Data [119]	http://kff.org
Medicaid Coverage [120]	http://files.kff.org/attachment/tables-managed-care-medicaid
School Population Data [37]	http://nces.ed.gov/
Medicaid Eligibility [121]	https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-eligibility-levels/index.html
School Program Information [122]	https://www.benefits.gov/benefits/benefit-details/1960
Federal Poverty Guidelines [123]	https://dch.georgia.gov/sites/dch.georgia.gov/files/2016_Federal_Poverty_Guidelines.pdf

C.2 Supply and Met Need

Met need is defined by the proportion of the time required to serve children that can be satisfied by the time that providers have available for dental care. Dental loan repayment programs and changing the Medicaid reimbursement rate affect dentists overall in the state, either by encouraging new dentists to open practices in underserved areas or by opening up additional capacity by encouraging providers to take additional Medicaid children.

C.2.1 Supply

First, the annual time a dentist has for pediatric primary care is determined. Based on the 2010 Survey of Dental Practice [124], male and female dentists work an average of 35.2 and 33.6 hours/week respectively with 49 work weeks during the year. The total annual time is 1,715 hours/year. This time is dedicated to adult and pediatric patients, and to preventive and treatment care.

The capacity for dental hygienists is added to account for the support provided. We assume dental hygienists have the same caseload of a dental provider [125]. We assume a dentist in Georgia will have an average of two hygienists under their supervision [125]. Thus, each standard provider has an additional 3,430 hours of support available. This capacity is the total available for both children and adults as well as preventive care and restorative and other treatment procedures. The distribution of procedures performed in dental offices by age was obtained from the Medical Expenditure Panel System (MEPS) database [15]. To determine the supply available for pediatric cases, we need to remove supply used for adult need from the total capacity. The time necessary to perform each procedure was used to compute the total time used for each procedure in each age group.

For example, the times used for preventive procedures performed in dental offices are shown in Table 26 [126].

Table 26. Time required for preventive procedures.

Procedure	Time (mins)
Oral exam	11.7
Fluoride rinse	2
Fluoride varnish	20.4
Cleaning	33
Sealants	11.5
X-rays	9.8

The procedures were split into preventive/evaluation care (which from this point on we simple refer to as preventive care) and restorative care (treatment). Preventive care procedures included exams, cleaning, x-rays, topical fluoride applications, and sealants. Other procedures were placed into the treatment category including fillings, crowns, root canals, etc. The proportion of time spent on each category was computed as shown in Table 27. Assuming a constant distribution across providers, each provider on average spends 21.97% of their time on pediatric preventive care.

Table 27. Percent of time spent by age and procedure type.

	Preventive	Treatment	Total
Pediatric	21.97%	4.21%	26.18%
Adult	39.10%	34.72%	73.82%
Total	61.07%	38.93%	100.00%

Applying the proportion to the total time available for each additional provider (including support staff), each provider has the capacity for 1,130.5 hours available each year for pediatric primary care. By using this proportion, the assumption is made that the dentist is not specifically targeting children or one particular treatment type.

C.2.2 Met Need

Risk class was estimated as described in Cao et. al. [57]. Next, the time required to provide care for one child is needed. This is computed using the age breakdown, the risk level, the recommended dental guidelines for care by risk class and each age category, and the time required for each of the recommended procedures as described above.

The population by age for each census tract in Georgia was obtained from census data. Children in each age group were broken down by the level of access (privately insured, publicly insured, and without financial access) as described above and risk level (low risk or high risk). The details for this procedure are supplied in the section on estimating risk in Cao et. al. Guidelines for each age group and risk class were determined from the American Academy of Pediatric Dentistry [127, 128]. Guidelines used in the analysis are shown in Table 28. In this analysis, the choice of guidelines was selected to allow access for as many children as possible. For example, when the recommended guidelines recommended a recall internal of between 6 months and 1 year, the guidelines used here would be a recall interval of 1 year.

Table 28: Number of procedures recommended by age group and risk level.

	Low Risk - Procedures per year					High Risk - Procedures per year				
Age	**1-2**	**3-4**	**5**	**6**	**7+**	**1-2**	**3-4**	**5**	**6**	**7+**
Oral exam	1	1	1	1	1	2	2	2	2	2
Fluoride rinse	0	0	0	0	1	0	0	0	0	2
Fluoride varnish	1	1	1	1	0	2	2	2	2	0
Cleaning	0	1	1	1	1	0	2	2	2	2
Sealants	0	0	1	0	0	0	0	1	0	0
X-rays	1	1	1	0.5	0.5	2	2	2	1	1

The number of procedures for each age group and the time for each procedure were used to compute the total time required to provide recommended care for each age group and each risk class. This measure was then applied to the breakdown of population by age and risk class to determine the time needed to meet the necessary need in each category. A weighted average was used to find the final average time needed for the annual recommended preventive care to be 1.05 hours.

The number of children each additional provider can serve is then the annual time available (1,130 hours) divided by the average time necessary to serve one child in Georgia (1.05 hours). Each additional provider added through an intervention can meet the need of 1,076 children.

For the remaining intervention, school based sealant programs, met need for is computed differently and is included in the additional text under that intervention.

C.3 Additional Regression Results and Impact Calculation

C.3.1 Regression Data

Data used for the regression are shown in Table 29. Dental inclusion in managed care programs, number of managed care organizations (MCOs), and Medicaid expansion information were obtained from the Kaiser Family Foundation [119]. Medicaid acceptance rate, fee for service as a percentage of private rates, dentists per population ratio, and utilization were obtained from the ADA Oral Health System state analysis [81]. Median family income was obtained from the US Census Bureau.

Table 29: Regression Data.

State	Medicaid Acceptance Rate	Medicaid Utilization Rate 2013	Dental Managed Care	Number of MCO's	Medicaid FFS Percentage	Dentists per population 2013	Median Family Income
AK	43	48	0	0	62	78.3	71829
AL	74	54	0	13	54	44	41657
AR	61	54	0	0	67	40.9	41264
AZ	32	50	1	13	55	54.5	49928
CA	29	45	0	22	29	76.6	61489
CO	53	54	1	2	45	68.7	59448
CT	46	64	0	15	67	76.2	69899
DC	27	54	1	4	58	89.2	69235
DE	55	49	0	2	81	45.4	60231
FL	30	30	1	17	37	50.7	47212
GA	28	53	1	3	54	47	49342
HI	36	57	0	5	47	75.2	68201
IA	86	54	0	3	42	51.9	52716
ID	48	60	0	0	45	57.8	47334
IL	30	55	1	12	33	66.7	57166
IN	50	44	0	3	56	47.4	48737
KS	26	49	1	3	47	50.5	51872
KY	39	48	1	5	44	56.6	43342
LA	43	51	0	5	61	48	44991
MA	39	58	0	6	58	78	67846
MD	25	58	0	8	48	71.9	74149
ME	42	43	0	0	44	52.2	48804
MI	92	41	0	11	33	61.4	49087
MN	69	43	1	9	27	60.6	60828
MO	23	39	1	3	40	48	47764
MS	55	52	1	2	48	42.6	39464
MT	72	53	0	0	53	58.9	46766
NC	27	52	0	0	48	47.9	46693
ND	83	33	0	1	63	54.4	55579
NE	61	56	0	3	43	64.4	52400
NH	45	60	0	2	40	64	65986
NJ	24	50	1	5	69	81.2	72062

Table 29 (continued)

NM	53	55	1	4	49	50.9	44968
NV	42	46	1	2	48	51.9	52205
NY	38	43	1	25	37	73.5	58687
OH	20	42	1	5	41	51.9	48849
OK	52	51	0	0	55	50.4	46235
OR	39	45	1	16	33	68.9	50521
PA	68	45	1	9	43	60.2	53115
RI	45	47	0	2	28	53.7	56423
SC	48	53	0	6	53	47.9	45003
SD	65	45	0	0	51	54.1	50338
TN	35	53	1	4	54	50	44621
TX	48	64	1	19	60	50.5	52576
UT	60	53	0	4	43	65.2	59846
VA	31	52	0	6	47	62.8	64792
VT	76	60	0	0	50	58.2	54447
WA	29	59	0	5	41	71	60294
WI	36	28	0	20	32	56	52738
WV	71	52	1	4	70	48	41576
WY	73	45	0	0	61	53	58252

State	Medicaid Expansion	White	Black	Other	Hispanic	Enrollment
AK	Yes	0.665	0.035	0.3	0.062	158453
AL	No	0.691	0.264	0.045	0.04	885046
AR	Yes	0.783	0.155	0.062	0.067	889082
AZ	Yes	0.789	0.042	0.17	0.301	1699635
CA	Yes	0.621	0.059	0.32	0.382	11902445
CO	Yes	0.84	0.04	0.12	0.209	1353757
CT	Yes	0.776	0.102	0.122	0.143	753413
DC	Yes	0.402	0.496	0.102	0.099	258918
DE	Yes	0.697	0.216	0.087	0.086	236248
FL	No	0.762	0.161	0.077	0.233	3620085
GA	No	0.604	0.309	0.087	0.091	1744095
HI	Yes	0.252	0.019	0.729	0.096	340829
IA	Yes	0.914	0.031	0.055	0.053	613386
ID	No	0.918	0.006	0.076	0.117	289858
IL	Yes	0.725	0.144	0.131	0.163	3088044

Table 29 (continued)

IN	Yes	0.844	0.091	0.065	0.063	1473414
KS	No	0.853	0.058	0.09	0.11	422549
KY	Yes	0.877	0.079	0.043	0.032	1223869
LA	Yes	0.628	0.321	0.05	0.046	1308428
MA	Yes	0.8	0.07	0.13	0.102	1660518
MD	Yes	0.581	0.295	0.125	0.088	1226309
ME	No	0.951	0.011	0.038	0.014	270827
MI	Yes	0.792	0.14	0.069	0.046	2273394
MN	Yes	0.852	0.054	0.094	0.049	1026023
MO	No	0.828	0.115	0.057	0.038	961073
MS	No	0.593	0.373	0.033	0.028	687219
MT	Yes	0.894	0.005	0.103	0.032	239250
NC	No	0.696	0.215	0.09	0.087	1984599
ND	Yes	0.892	0.015	0.092	0.026	89460
NE	No	0.883	0.047	0.071	0.097	234836
NH	Yes	0.938	0.012	0.049	0.031	185735
NJ	Yes	0.687	0.135	0.178	0.186	1749400
NM	Yes	0.732	0.02	0.249	0.47	761033
NV	Yes	0.701	0.083	0.216	0.272	609435
NY	Yes	0.65	0.156	0.194	0.182	6372384
OH	Yes	0.826	0.122	0.052	0.033	2941236
OK	No	0.733	0.073	0.195	0.094	787331
OR	Yes	0.851	0.018	0.131	0.121	1019340
PA	Yes	0.819	0.109	0.072	0.061	2834129
RI	Yes	0.813	0.063	0.124	0.133	283838
SC	No	0.672	0.276	0.051	0.053	987147
SD	No	0.854	0.015	0.131	0.032	119252
TN	No	0.78	0.168	0.053	0.048	1628196
TX	No	0.747	0.119	0.135	0.382	4708051
UT	No	0.88	0.011	0.109	0.133	306857
VA	Yes	0.693	0.193	0.115	0.084	966932
VT	Yes	0.951	0.01	0.038	0.016	178142
WA	Yes	0.782	0.036	0.182	0.117	1775882
WI	No	0.867	0.062	0.07	0.062	1045160
WV	Yes	0.936	0.032	0.032	0.013	572107
WY	No	0.908	0.01	0.082	0.094	63618

C.3.2 Full Models

Full models used for model selection including all predictor variables are included below.

Table 30: Medicaid Acceptance Full Model.

Coefficient	Standardized Estimates	Std. Error	t	Sig.	
Intercept	-0.675	40.546	-0.02	0.987	
Number of MCO's	0.126	0.149	0.85	0.403	
Medicaid FFS Percentage	0.185	0.207	0.89	0.377	
Dentists per population	0.01	0.407	0.03	0.980	
Utilization 2013	0.027	0.248	0.11	0.913	
Median Family Income	-0.593	0.406	-1.46	0.153	
Medicaid Expansion	0.098	0.06	1.63	0.112	
Dental Managed Care	-0.126	0.06	-2.09	0.044	*
White	1.51	38.579	0.04	0.969	
Black	0.519	20.129	0.03	0.980	
Other	0.919	29.566	0.03	0.975	
Hispanic	-0.071	0.177	-0.4	0.692	
Enrollment	-0.249	0.237	-1.05	0.299	

N	51
Adjusted R^2	0.2069
Resid. Std. Error	0.1769

Table 31: Medicaid Utilization Full Model.

Coefficient	Standardized Estimates	Std. Error	t	Sig.	
Intercept	-19.388	25.867	-0.75	0.458	
Number of MCO's	-0.081	0.098	-0.83	0.415	
Medicaid FFS Percentage	0.025	0.105	0.24	0.810	
Dentists per population	1.505	0.881	1.71	0.096	.
Utilization 2013	0.266	0.268	0.99	0.328	
Median Family Income	-0.022	0.283	-0.08	0.939	
Medicaid Expansion	0.025	0.042	0.6	0.554	
Dental Managed Care	-0.046	0.04	-1.13	0.265	*
White	18.522	24.623	0.75	0.457	
Black	9.747	12.845	0.76	0.453	
Other	14.137	18.872	0.75	0.459	
Hispanic	0.175	0.11	1.59	0.120	
Enrollment	-0.072	0.154	-0.46	0.646	
Medicaid FFS Percentage^2	-1.063	0.691	-1.54	0.133	

N	51
Adjusted R^2	0.1069
Resid. Std. Error	0.1136

C.3.3 Model Selection

Final models were selected using best subsets, forward and backward stepwise regression, and Lasso. Best subsets of variables were used to identify best models of different sizes. Models were selected using forward and backward stepwise regression using the *step* function in the R statistical software. The selected models from backward and forward stepwise regression were compared. If both methods selected the same predictors, the models were validated using Lasso variable selection method using the R statistical software and chosen as the final model. If the methods chose different predictors, they were compared to see which predictors were overlapping. Lasso was then used to identify which predictors were selected for the final model. Final models selected were the most consistent models selected using each method. Differences between best subset results and stepwise regression results are due to best subsets using the BIC criterion while stepwise regression uses the AIC criterion for model selection.

C.3.4 Medicaid Acceptance

The best subsets plot is shown below in Figure 33.

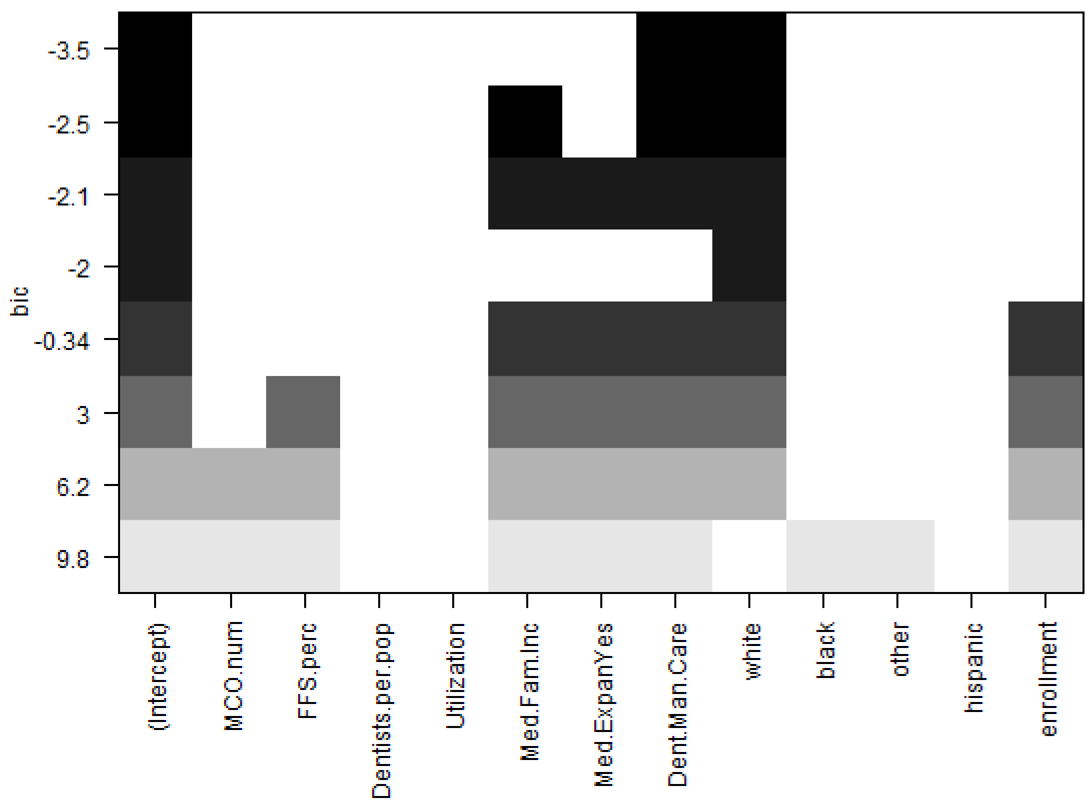

Figure 33. Best subsets for Medicaid acceptance model.

After the best subsets models were considered, forward stepwise regression was conducted. The final model chosen by forward stepwise regression included white, dental managed care, median family income, Medicaid expansion, and enrollment. Next, backward stepwise regression was compared. The results of each step in the stepwise regression for forward stepwise regression and backward stepwise regression are shown in Table 32 and Table 33 respectively. In the tables, + indicated the variable was added in the specified step, - indicated it was subtracted, and the ● indicated the variable was included in the step.

Table 32. Results of each step in forward stepwise regression for predicting Medicaid acceptance.

	Step					
Coefficient	**1**	**2**	**3**	**4**	**5**	**Final**
Intercept	●	●	●	●	●	●
Number of MCO's						
Medicaid FFS Percentage						
Dentists per population						
Utilization 2013						
Median Family Income			+	●	●	●
Medicaid Expansion				+	●	●
Dental Managed Care		+	●	●	●	●
White	+	●	●	●	●	●
Black						
Hispanic						
Enrollment					+	●

Table 33. Results of each step in backward stepwise regression for predicting Medicaid acceptance.

	Step						
Coefficient	**1**	**2**	**3**	**4**	**5**	**6**	**Final**
Intercept	●	●	●	●	●	●	●
Number of MCO's	●	●	●	●	-		
Medicaid FFS Percentage	●	●	●	●	●	-	
Dentists per population	-						
Utilization 2013	●	-					
Median Family Income	●	●	●	●	●	●	●
Medicaid Expansion	●	●	●	●	●	●	●
Dental Managed Care	●	●	●	●	●	●	●
White	●	●	●	●	●	●	●
Black	●	●	●	-			
Hispanic	●	●	-				
Enrollment	●	●	●	●	●	●	●

This resulted in final model consisting of the same variables. Due to agreement between the methods, this model was chosen as the final model. Lasso variable selection was also checked for consistency and is shown below.

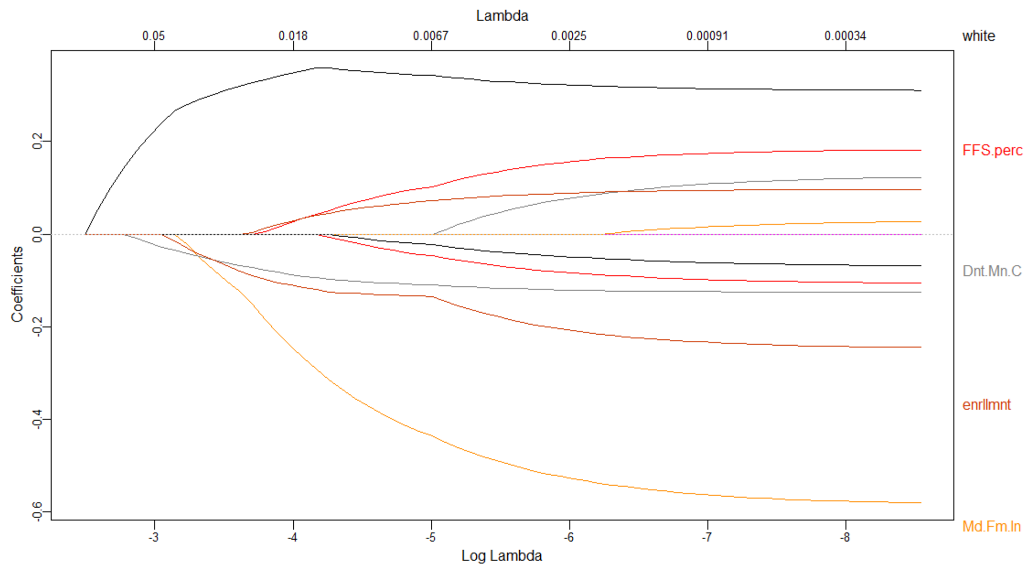

Figure 34. Lasso for Medicaid acceptance model.

Figure 34 Legend: FFS.perc is the Medicaid FFS percentage. Dnt.Mn.C is Dental Managed Care. Enrllmnt is enrollment. Md.Fm.In is median family income.

C.3.5 Medicaid Utilization

For Medicaid utilization, the best subsets plot is shown below.

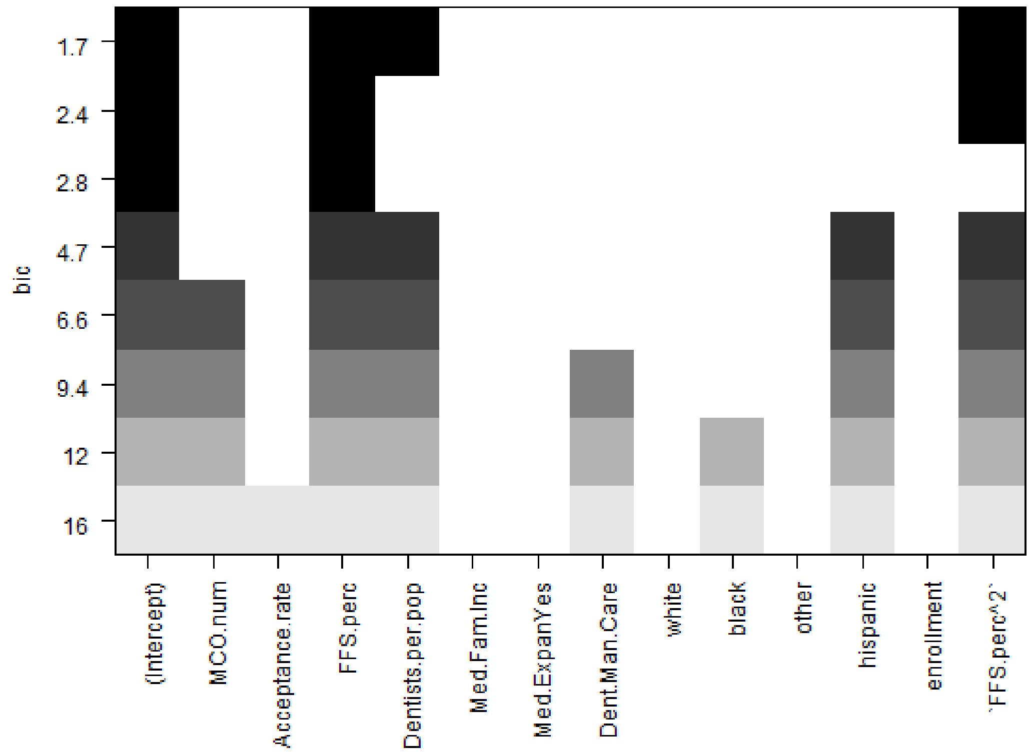

Figure 35. Best subsets for Medicaid utilization model.

After considering best subsets, forward and backward stepwise regression were performed. Forward stepwise regression resulted in the Medicaid FFS percentage, Medicaid FFS percentage squared, and the dentist per population ratio as the final variables selected. Backward stepwise regression resulted once again in the same set of variables. The results of each step in the stepwise regression for forward stepwise regression and backward stepwise regression are shown in Table 34 and Table 35, respectively. In the tables, + indicated the variable was added in the specified step, - indicated it was subtracted, and the ● indicated the variable was included in the step.

Table 34. Results of each step in forward stepwise regression for predicting Medicaid utilization.

Coefficient	Step 1	2	3	Final
Intercept	●	●	●	●
Number of MCO's				
Medicaid FFS Percentage	+	●	●	●
Dentists per population			+	●
Medicaid Acceptance Rate				
Median Family Income				
Medicaid Expansion				
Dental Managed Care				
White				
Black				
Hispanic				
Enrollment				
Medicaid FFS Percentage^2		+	●	●

Table 35. Results of each step in backward stepwise regression for predicting Medicaid utilization.

Coefficient	1	2	3	4	5	6	7	8	9	Final
Intercept	●	●	●	●	●	●	●	●	●	●
Number of MCO's	●	●	●	●	●	●	●	-		
Medicaid FFS Percentage	●	●	●	●	●	●	●	●	●	●
Dentists per population	●	●	●	●	●	●	●	●	●	●
Medicaid Acceptance Rate	●	-								
Median Family Income	-									
Medicaid Expansion	●	●	●	●	-					
Dental Managed Care	●	●	●	●	●	●	-			
White	●	●	●	-						
Black	●	●	●	●	●	-				
Hispanic	●	●	●	●	●	●	●	●	-	
Enrollment	●	●	-							
Medicaid FFS Percentage^2	●	●	●	●	●	●	●	●	●	●

This set became the final model choice after being selected by both methods and being the best choice among the best subsets regression. For consistency, lasso variable selection was again used and is included below.

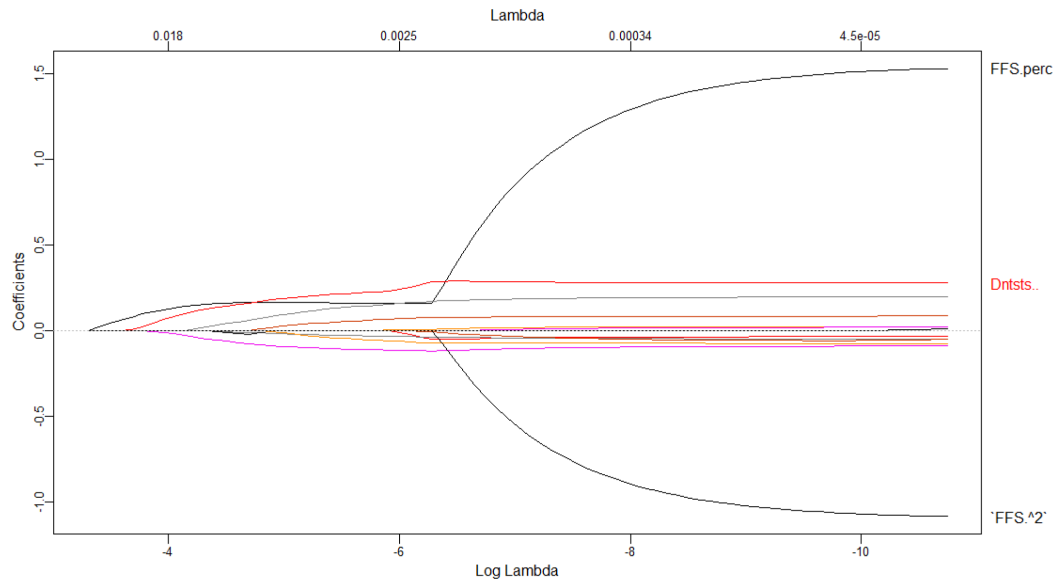

Figure 36. Lasso for Medicaid utilization model.

Figure 36 legend: FFS.perc is the Medicaid FFS percentage. Dntsts is the dentists per population ratio. FFS.^2 is the square of the Medicaid FFS percentage.

C.3.6   Final Models

The models presented in the paper use normalized data so that coefficients can be compared accurately to determine their relative impact.

The model predicting Medicaid utilization using non-standardized data is used to get a proper estimate of the impact of changing the Medicaid reimbursement rate. The model is shown in Table 36.

Table 36. Model predicting Medicaid utilization with non-standardized data.

Coefficient	Estimates	Std. Error	t	Sig.	
Intercept	-0.932	15.026	-0.06	0.951	
FFS Percentage	1.444	0.547	2.64	0.011	*
(FFS Percentage)^2	-0.012	0.005	-2.26	0.029	*
Dentists per population	0.182	0.086	2.11	0.040	*

N	51
Adjusted R^2	0.1915
Residual Std. Error	6.919

The prediction intervals used for estimated the impact of changing the FFS percentage are shown in Table 37.

Table 37. Prediction and prediction intervals for estimating change in FFS percentage on Medicaid utilization.

Dentists per population	FFS Percentage	fit	lower	upper
47	53	50.39	36.13	64.65
47	63	50.88	36.53	65.24

C.3.7 Impact of Changing Reimbursement Rate

The total costs per-member-per-year used are shown in Table 38 [129].

Table 38. Georgia Medicaid expenditures per-member-per-year (pmpy).

Fluoride	11.36
Sealants	8.19
Evaluations	23.63
Prophylaxis	23.59
Caries Restorations	92.71
Total Cost (pmpy)	159.48

The impact of the rate increase is then determined for current members and the 7366 estimated new members from the increase in utilization. The intervention cost per child is the rate increase for the current members and the full cost including the rate increase for new members as shown in Table 39.

Table 39. Invention Cost by current and new members for changing the reimbursement rate.

	Number of Children	Cost per Child	Total Cost
Current Members	1,227,855	30.09	$36,946,852
New Members	7366.365039	189.57	$1,396,446

C.4 Example School Data

Table 40. Example School Data.

School Name	County Name	Urban-centric Locale	School Level Code	Total Free and Reduced Lunch Students	Total Students
A. S. CLARK ELEMENTARY SCHOOL	CRISP COUNTY	41-Rural: Fringe	1-Primary	329	404
ABBOTTS HILL ELEMENTARY SCHOOL	FULTON COUNTY	21-Suburb: Large	1-Primary	116	792
ACADEMIC ENHANCEMENT PROGRAM	BROOKS COUNTY	41-Rural: Fringe	3-High	61	64
ACADEMY OF RICHMOND COUNTY HIGH SCHOOL	RICHMOND COUNTY	12-City: Mid-size	3-High	703	1283
ACWORTH INTERMEDIATE SCHOOL	COBB COUNTY	21-Suburb: Large	1-Primary	500	816
ADAIRSVILLE ELEMENTARY SCHOOL	BARTOW COUNTY	31-Town: Fringe	1-Primary	414	693
ADAIRSVILLE HIGH SCHOOL	BARTOW COUNTY	41-Rural: Fringe	3-High	487	952
ADAIRSVILLE MIDDLE SCHOOL	BARTOW COUNTY	41-Rural: Fringe	2-Middle	431	742
ADAMSON MIDDLE SCHOOL	CLAYTON COUNTY	41-Rural: Fringe	2-Middle	491	617
ADAMSVILLE ELEMENTARY SCHOOL	FULTON COUNTY	11-City: Large	1-Primary	363	381
ADDISON ELEMENTARY SCHOOL	COBB COUNTY	21-Suburb: Large	1-Primary	196	581

APPENDIX D. SUPPLEMENTAL MATERIALS FOR CHAPTER 6

D.1 State Confidence Interval

We reported expenditures with lower bound, mean, and upper bound of the confidence intervals for each state in the analysis. To obtain the confidence interval for the state, the 95% confidence interval was created for each county. The confidence interval listed for each state is the sum of each lower bound, mean, and upper bound of the confidence intervals for all counties in the state.

D.2 Additional Expenditure Distributions

Figure 37 through Figure 50 show the distributions of expenditures by state, service type for total payments (anesthesia and dental expenditures combined).

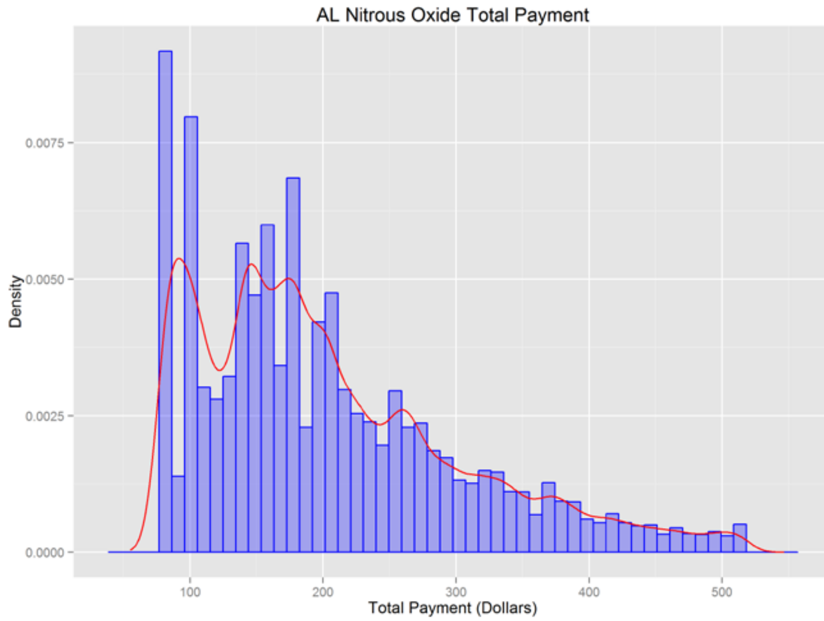

Figure 37. Histogram (blue) and KDE distribution (red) of total payment for children receiving only nitrous oxide anesthesia in Alabama.

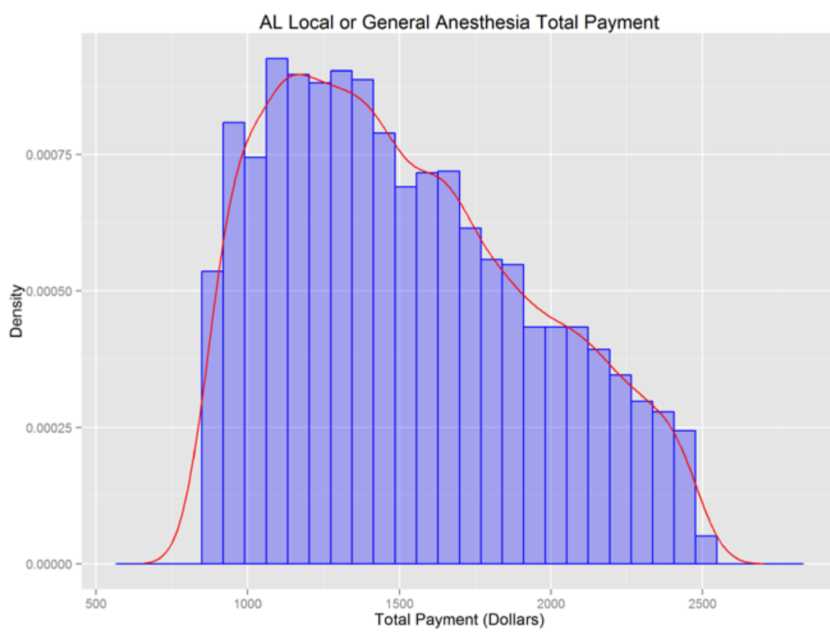

Figure 38. Histogram (blue) and KDE distribution (red) of total payment for children receiving local or general anesthesia in Alabama.

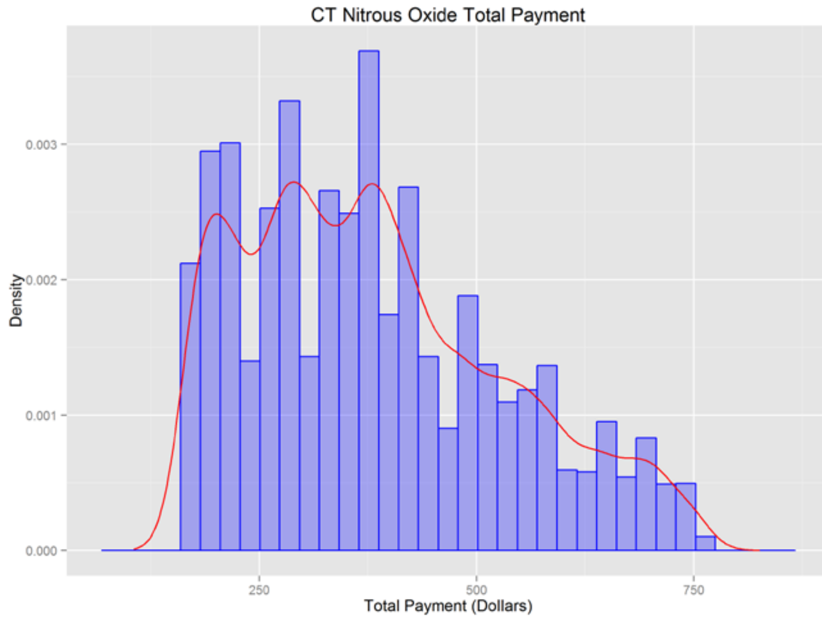

Figure 39. Histogram (blue) and KDE distribution (red) of total payment for children receiving only nitrous oxide anesthesia in Connecticut.

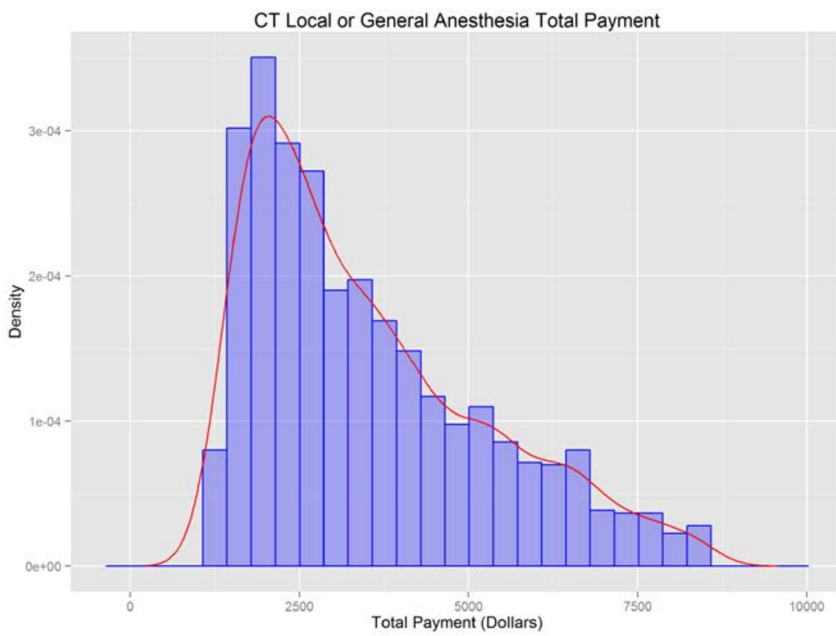

Figure 40. Histogram (blue) and KDE distribution (red) of total payment for children receiving local or general anesthesia in Connecticut.

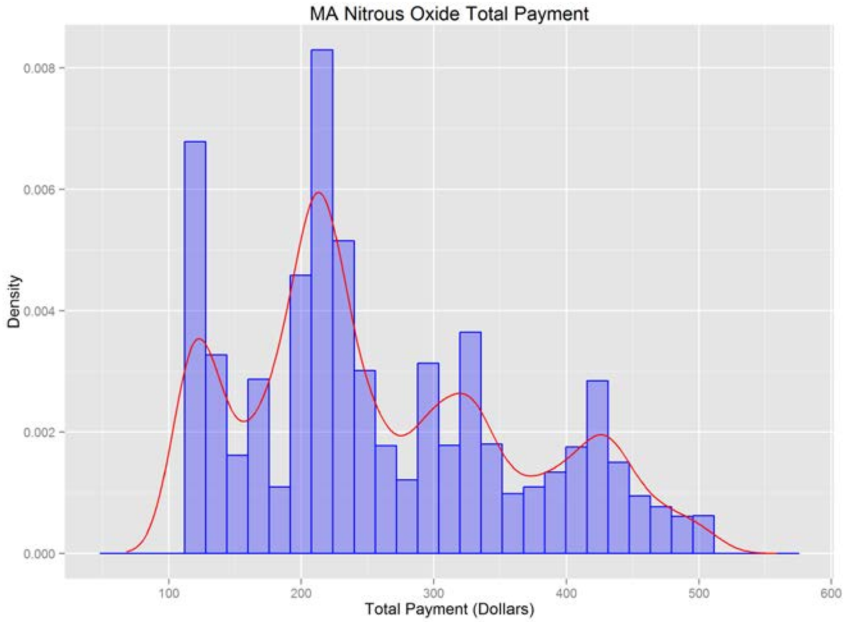

Figure 41. Histogram (blue) and KDE distribution (red) of total payment for children receiving only nitrous oxide anesthesia in Massachusetts.

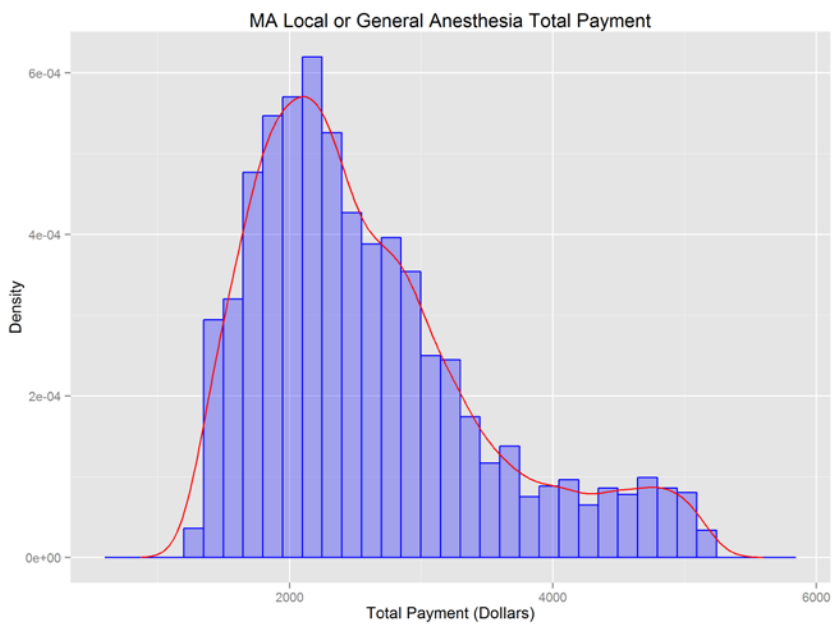

Figure 42. Histogram (blue) and KDE distribution (red) of total payment for children receiving local or general anesthesia in Massachusetts.

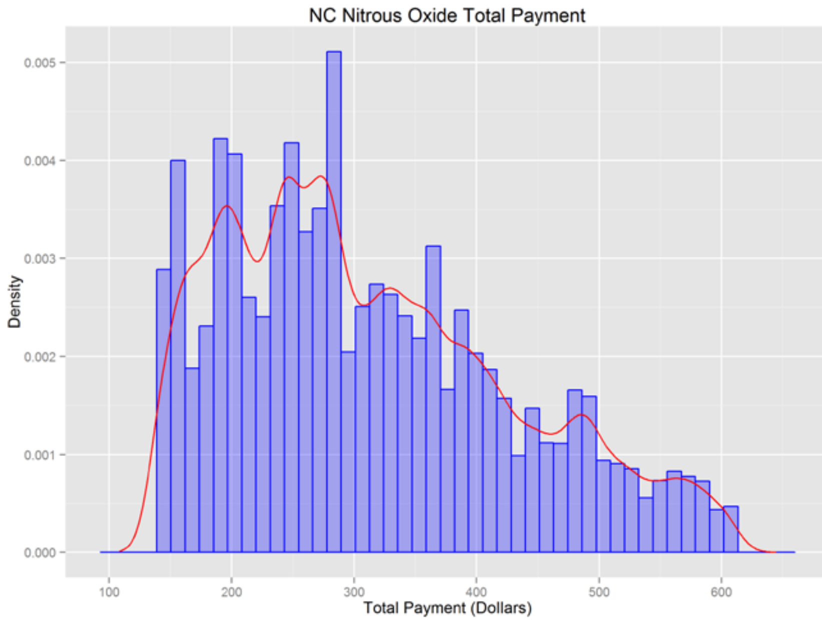

Figure 43. Histogram (blue) and KDE distribution (red) of total payment for children receiving only nitrous oxide anesthesia in North Carolina.

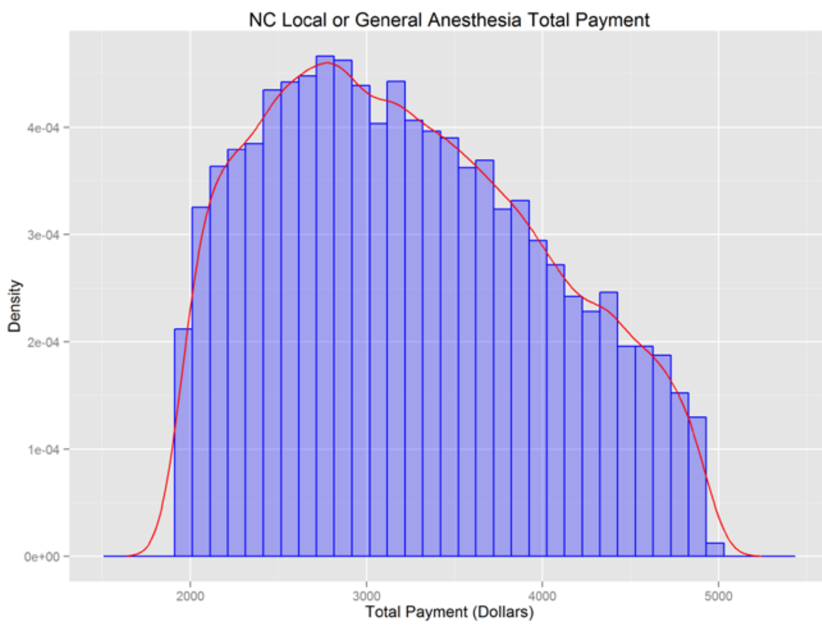

Figure 44. Histogram (blue) and KDE distribution (red) of total payment for children receiving local or general anesthesia in North Carolina.

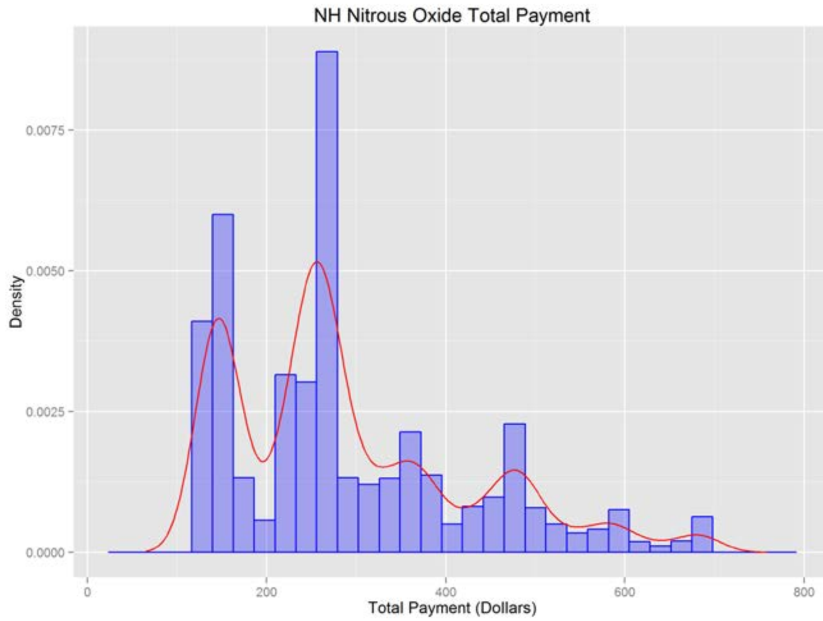

Figure 45. Histogram (blue) and KDE distribution (red) of total payment for children receiving only nitrous oxide anesthesia in New Hampshire.

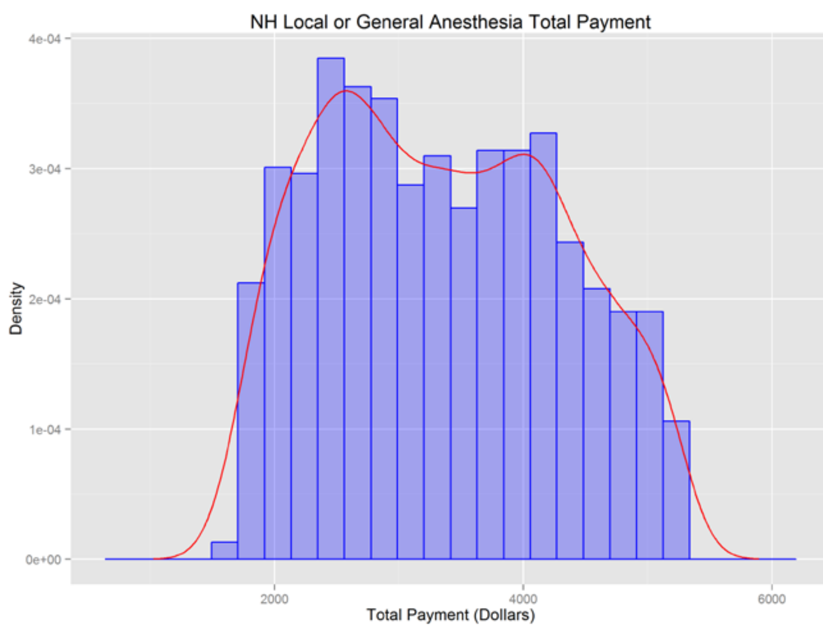

Figure 46. Histogram (blue) and KDE distribution (red) of total payment for children receiving local or general anesthesia in New Hampshire.

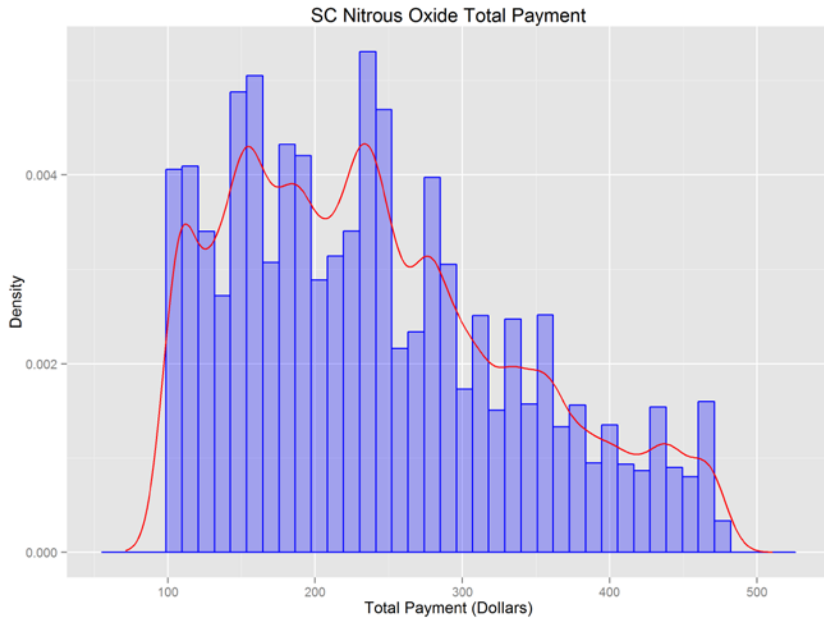

Figure 47. Histogram (blue) and KDE distribution (red) of total payment for children receiving only nitrous oxide anesthesia in South Carolina.

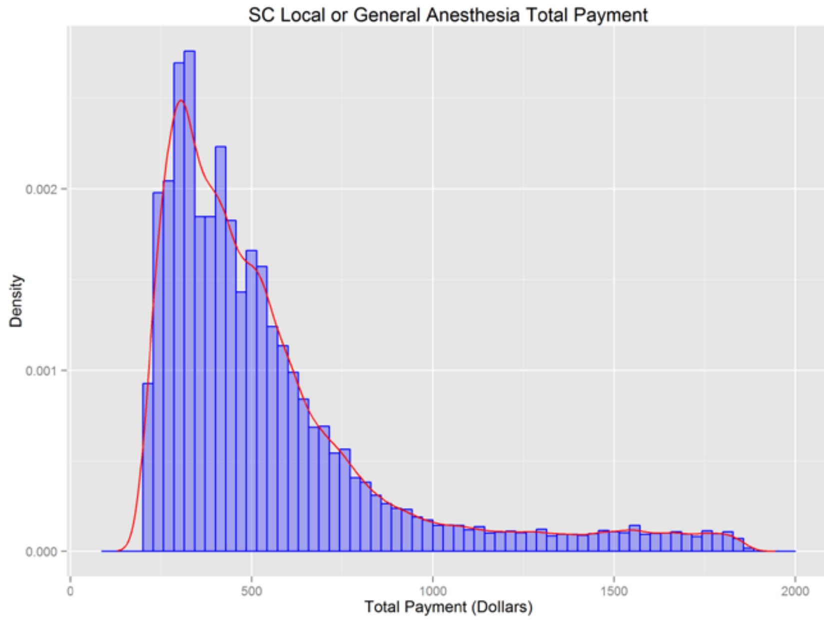

Figure 48. Histogram (blue) and KDE distribution (red) of total payment for children receiving local or general anesthesia in South Carolina.

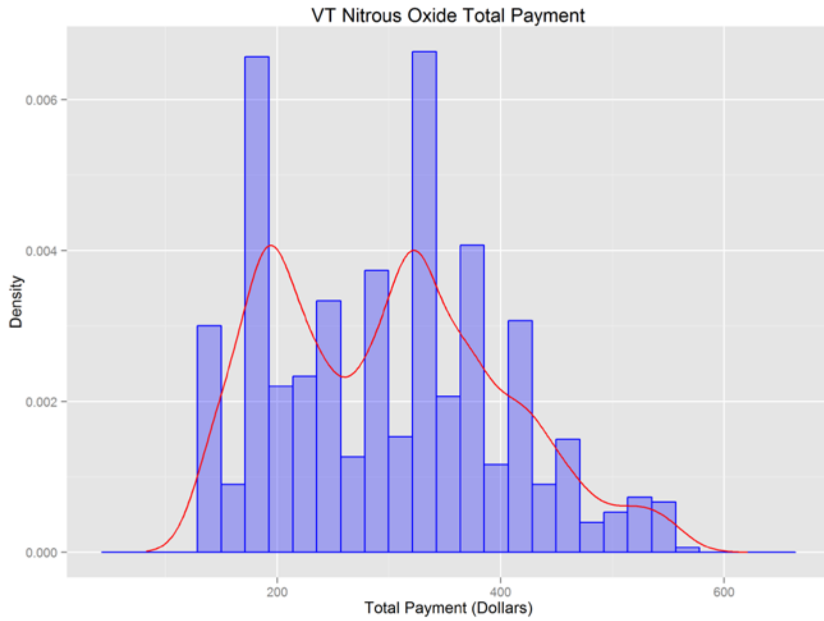

Figure 49. Histogram (blue) and KDE distribution (red) of total payment for children receiving only nitrous oxide anesthesia in Vermont.

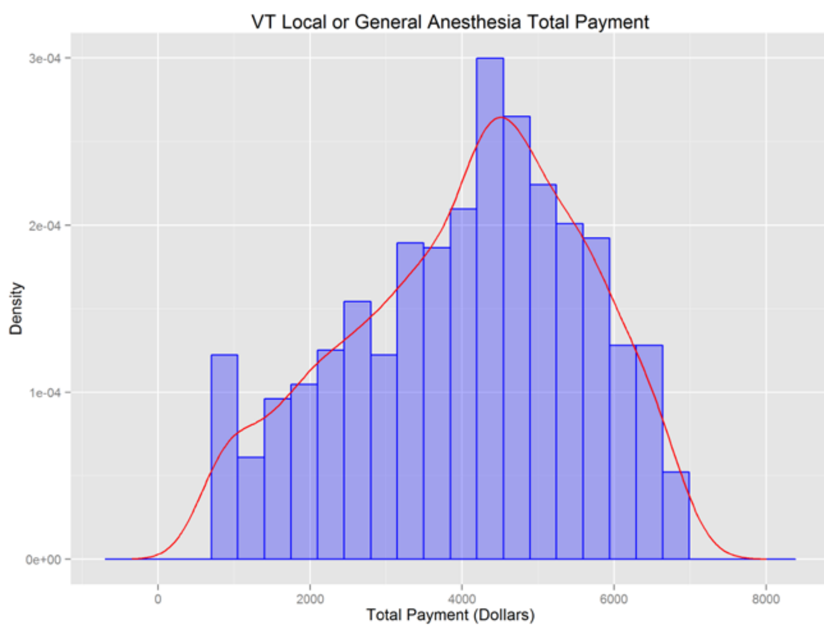

Figure 50. Histogram (blue) and KDE distribution (red) of total payment for children receiving local or general anesthesia in Vermont.

Figure 51 through Figure 64 show the distributions of anesthesia expenditures by state and service type for anesthesia payments (expenditures for anesthesia and any other surgery expenditures).

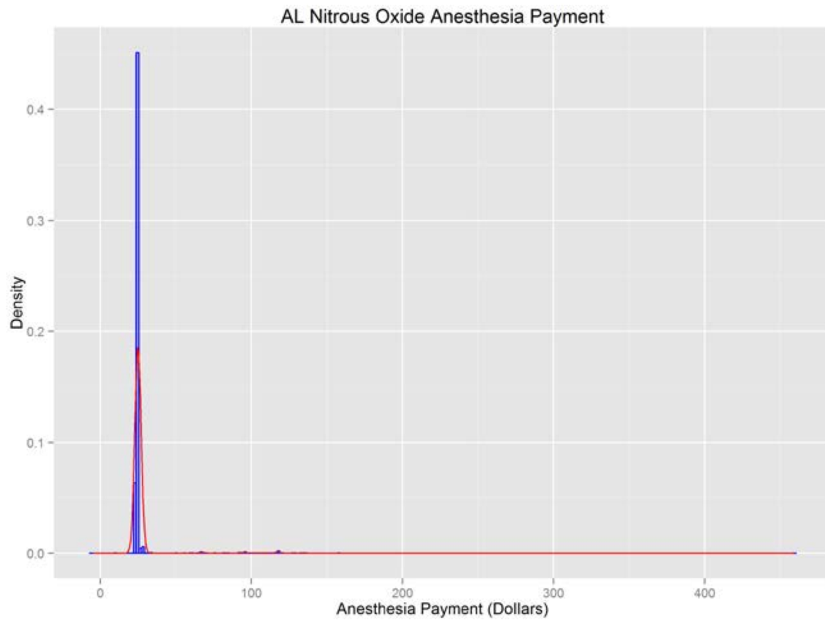

Figure 51. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving only nitrous oxide anesthesia in AL.

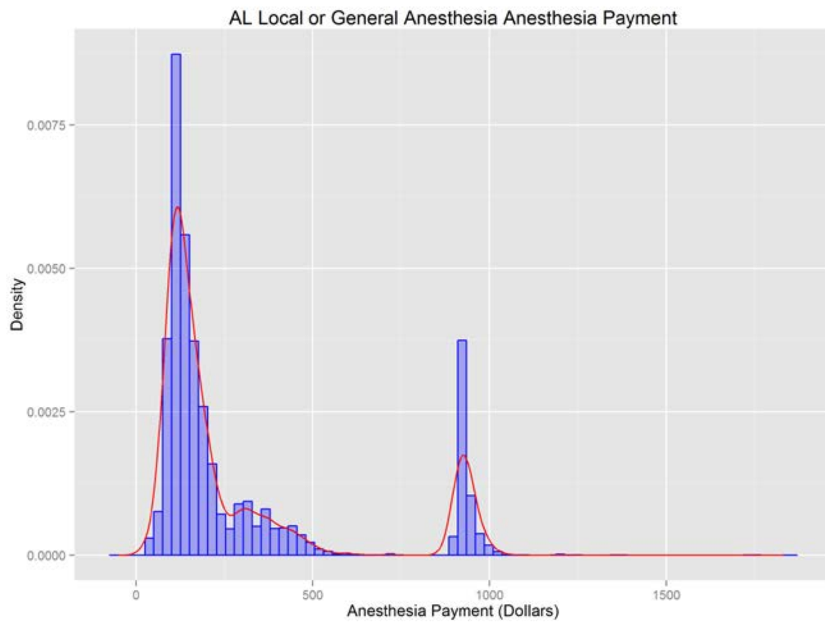

Figure 52. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving local or general anesthesia in AL.

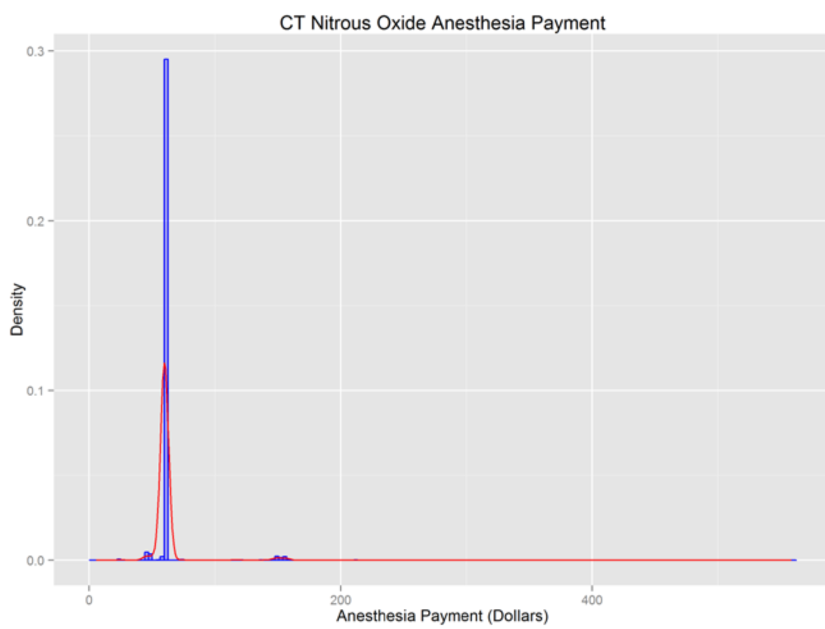

Figure 53. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving only nitrous oxide anesthesia in CT.

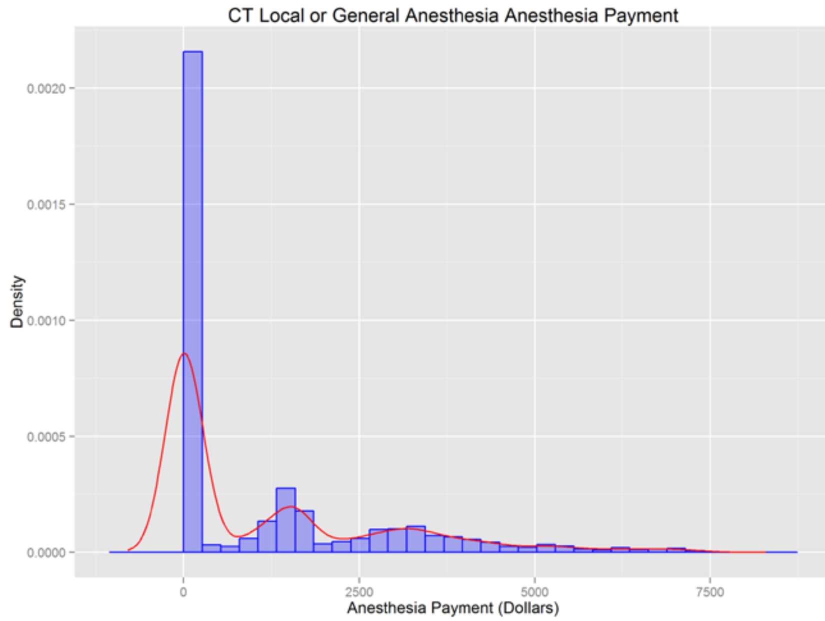

Figure 54. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving local or general anesthesia in CT.

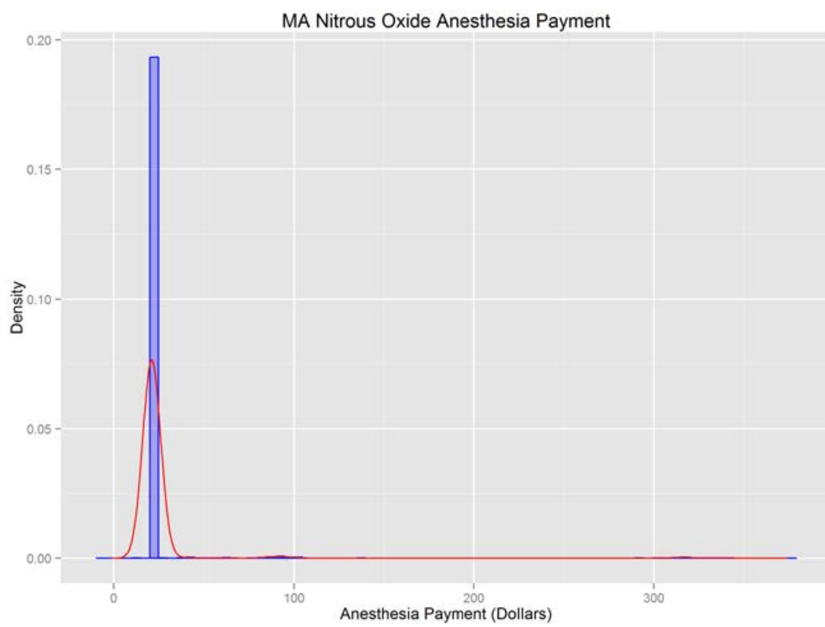

Figure 55. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving only nitrous oxide anesthesia in MA.

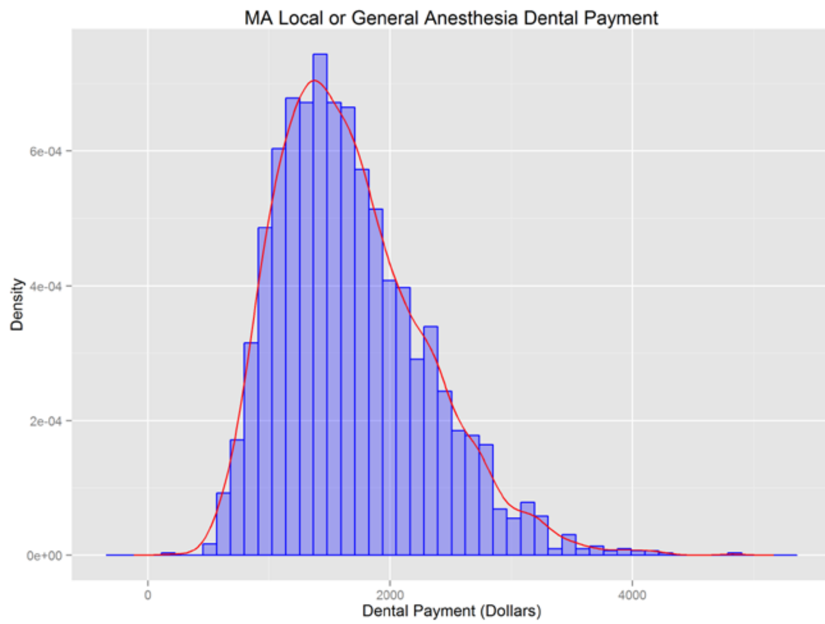

Figure 56. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving local or general anesthesia in MA.

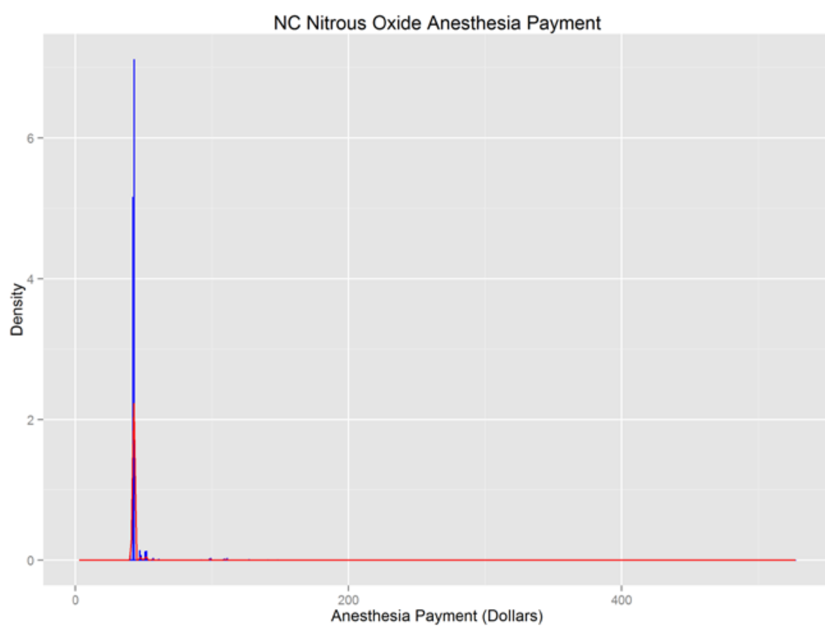

Figure 57. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving only nitrous oxide anesthesia in NC.

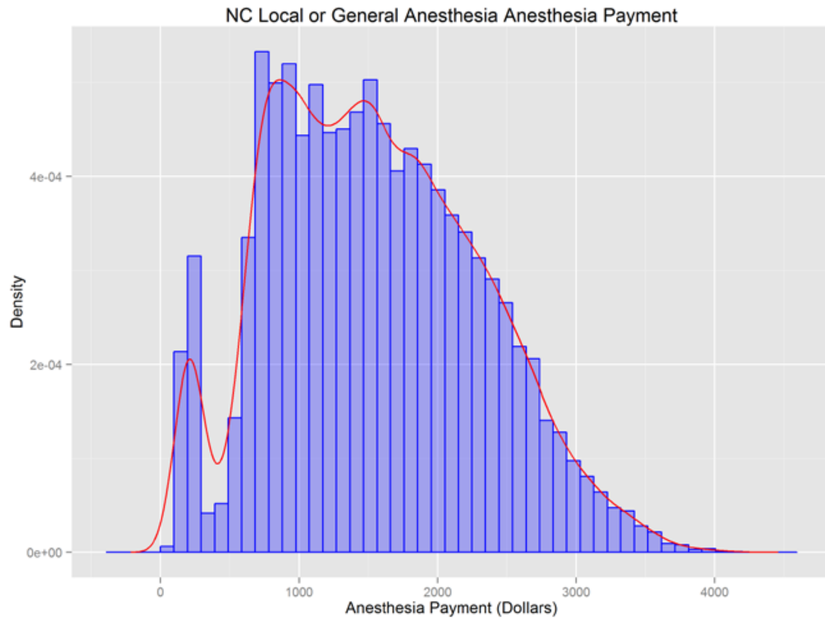

Figure 58. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving local or general anesthesia in NC.

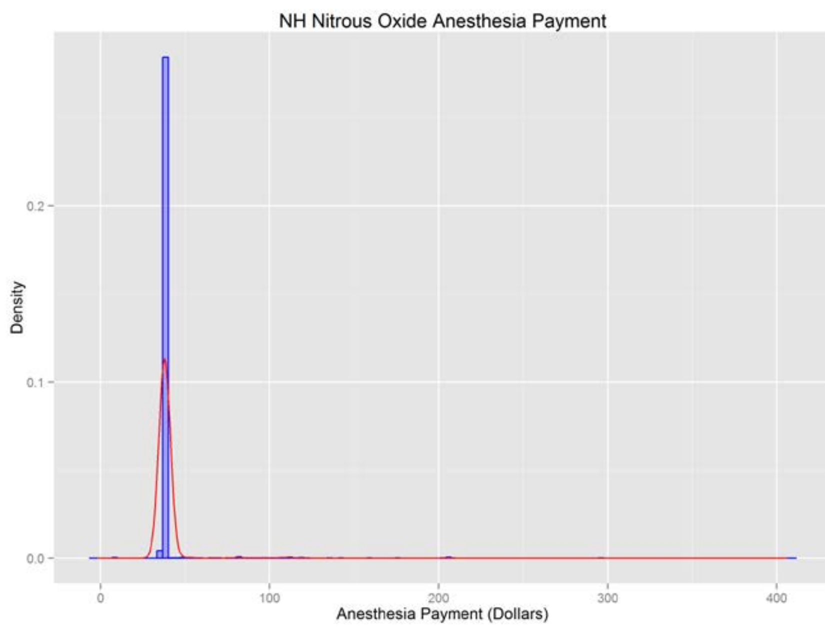

Figure 59. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving only nitrous oxide anesthesia in NH.

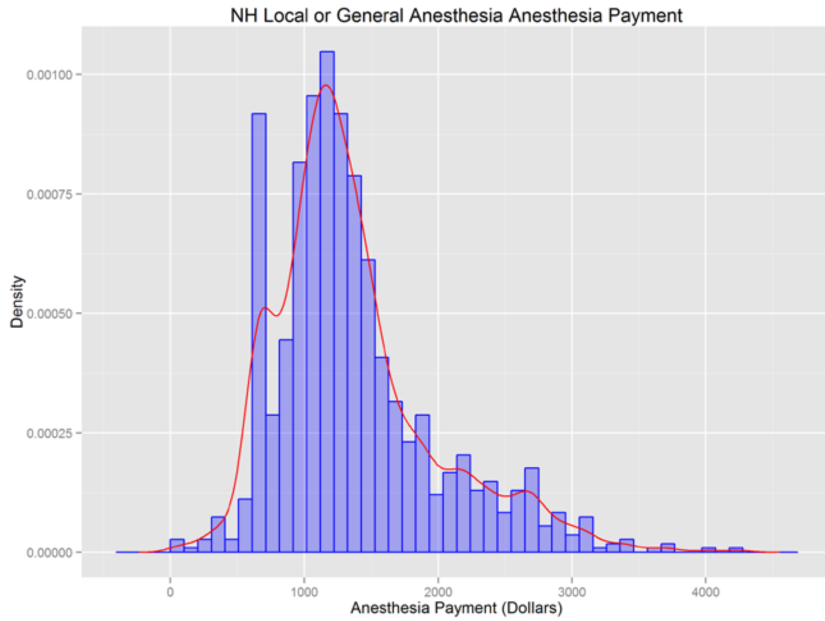

Figure 60. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving local or general anesthesia in NH.

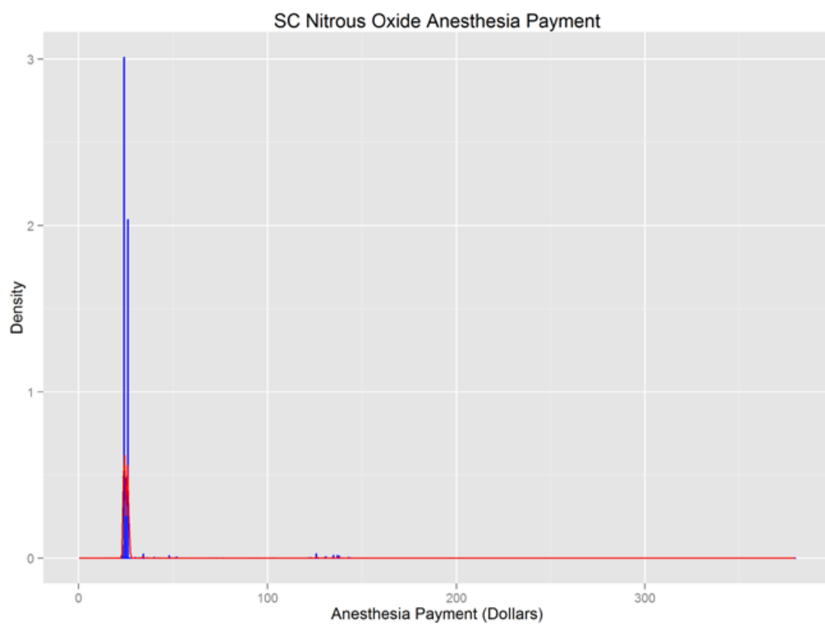

Figure 61. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving only nitrous oxide anesthesia in SC.

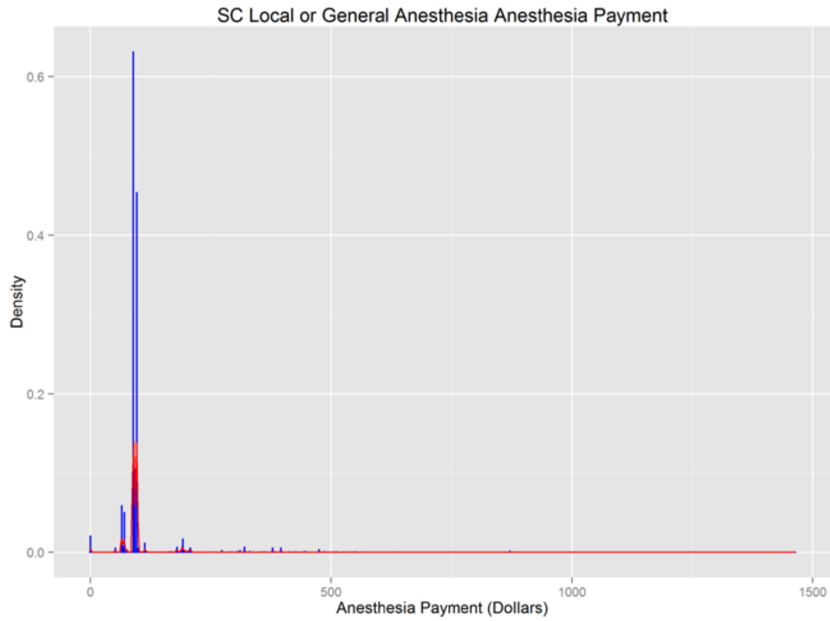

Figure 62. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving local or general anesthesia in SC.

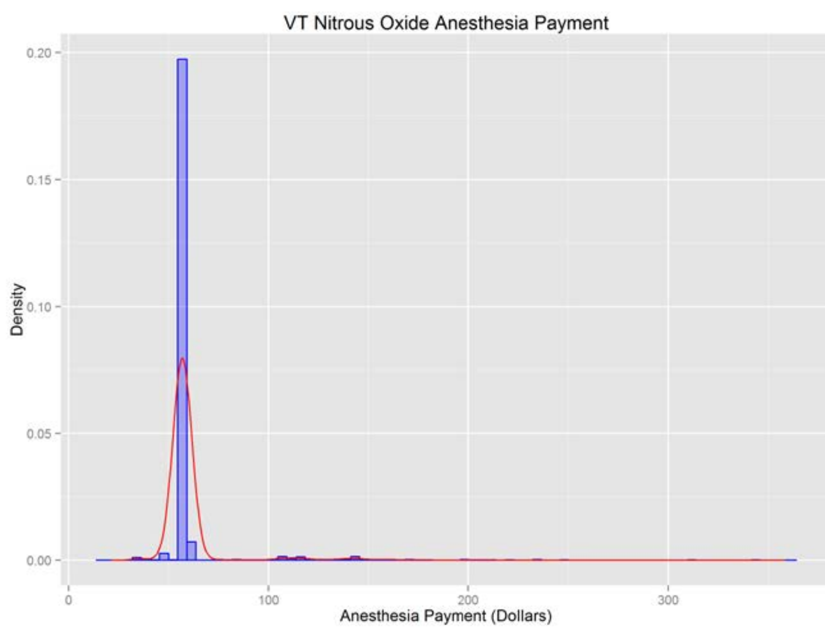

Figure 63. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving only nitrous oxide anesthesia in VT.

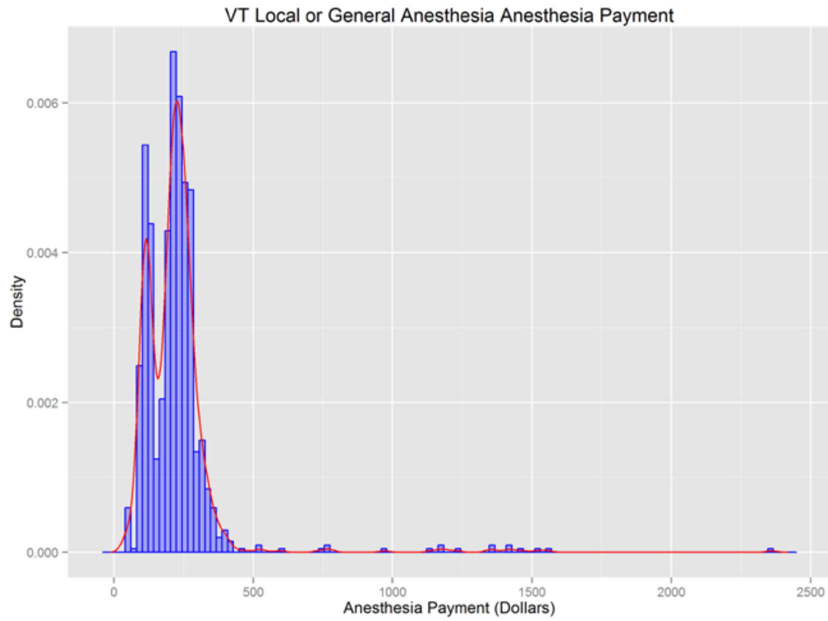

Figure 64. Histogram (blue) and KDE distribution (red) of anesthesia payment for children receiving local or general anesthesia in VT.

D.3 Population Results

Table 41 shows the estimated caries visits for P1, P2, and P3.

Table 41. Estimated caries visits for P1, P2, and P3.

		Caries Visits		
Setting	State	P1	P2	P3
1	AL	110,358	26,038	41,770
	CT	39,580	11,420	22,936
	MA	64,498	22,933	40,700
	NC	184,550	54,065	85,820
	NH	11,169	3,095	7,489
	SC	98,108	25,564	41,218
	VT	6,235	2,246	3,725
2	AL	110,358	26,038	41,816
	CT	39,580	11,433	22,936
	MA	64,498	22,961	40,751
	NC	184,550	54,016	85,776
	NH	11,169	3,095	7,490
	SC	98,108	25,554	41,213
	VT	6,235	2,242	3,724
3	AL	110,358	26,055	41,793
	CT	39,580	11,438	22,911
	MA	64,498	22,990	40,707
	NC	184,550	54,050	85,802
	NH	11,169	3,087	7,501
	SC	98,108	25,587	41,245
	VT	6,235	2,247	3,733
4	AL	110,358	26,025	41,797
	CT	39,580	11,433	22,923
	MA	64,498	22,967	40,730
	NC	184,550	54,001	85,773
	NH	11,169	3,094	7,484
	SC	98,108	25,564	41,246
	VT	6,235	2,248	3,715

Table 41 (continued)

5	AL	110,358	26,055	41,792
	CT	39,580	11,412	22,914
	MA	64,498	22,986	40,730
	NC	184,550	54,027	85,812
	NH	11,169	3,087	7,489
	SC	98,108	25,539	41,293
	VT	6,235	2,248	3,719
6	AL	110,358	26,078	41,763
	CT	39,580	11,424	22,890
	MA	64,498	22,972	40,711
	NC	184,550	53,984	85,817
	NH	11,169	3,091	7,483
	SC	98,108	25,582	41,243
	VT	6,235	2,245	3,722

D.4 Expenditure Results

Figure 65 through Figure 69 show the averted expenditures per visit by state and population group for settings 1, 2, 3, 5, and 6.

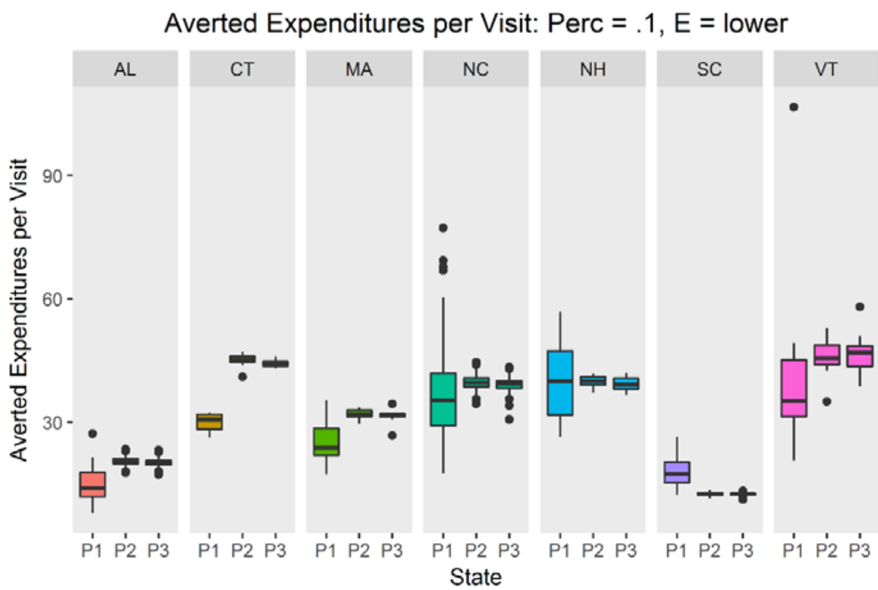

Figure 65: Box plot of averted expenditures per caries visit for setting 1 by state and population group.

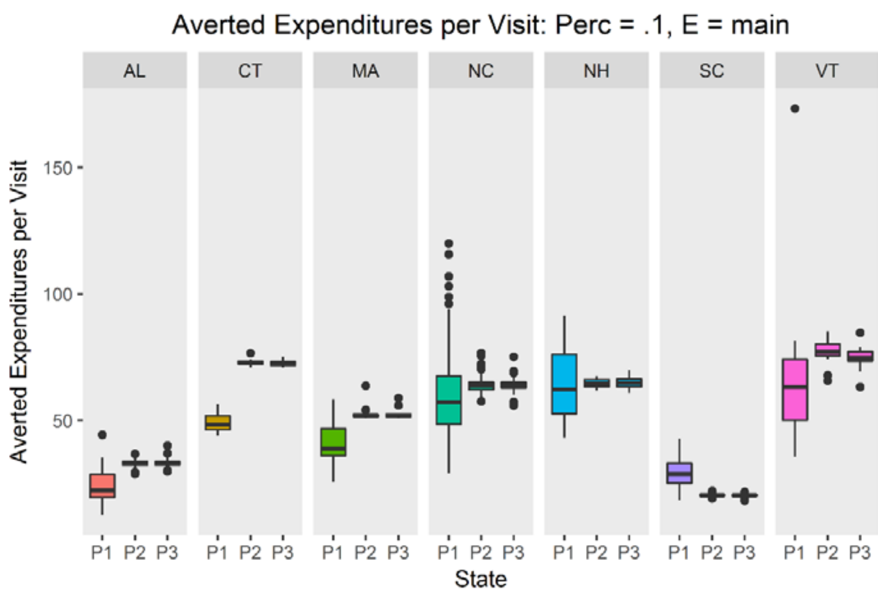

Figure 66: Box plot of averted expenditures per caries visit for setting 2 by state and population group.

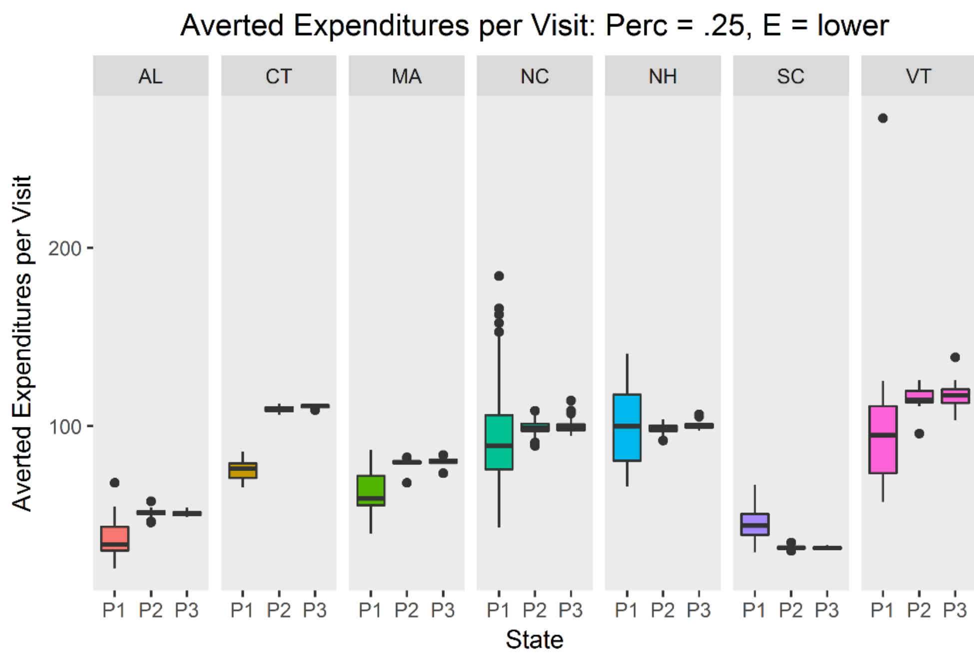

Figure 67: Box plot of averted expenditures per caries visit for setting 3 by state and population group.

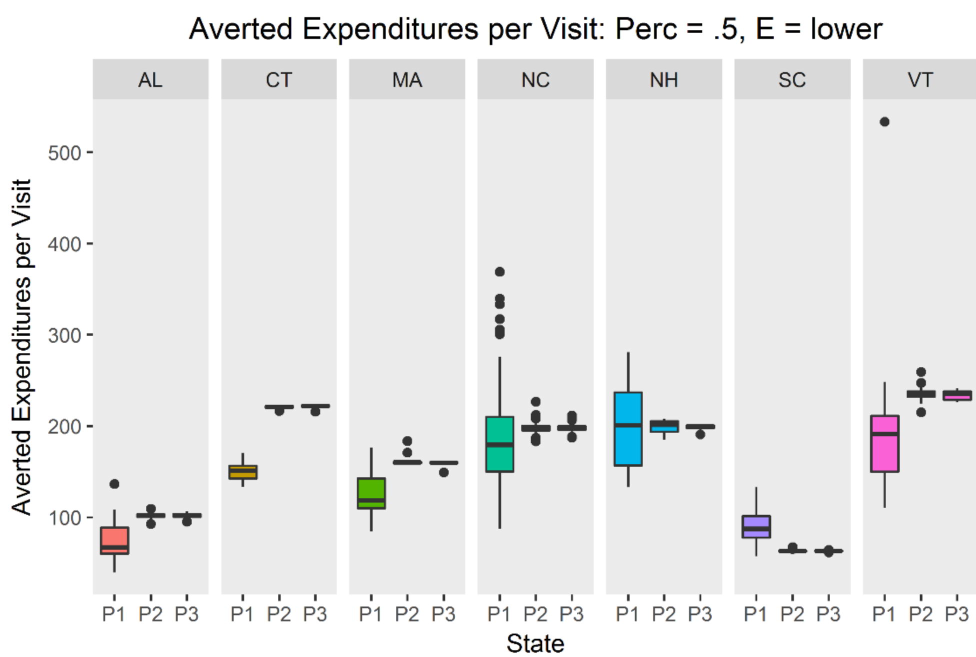

Figure 68: Box plot of averted expenditures per caries visit for setting 5 by state and population group.

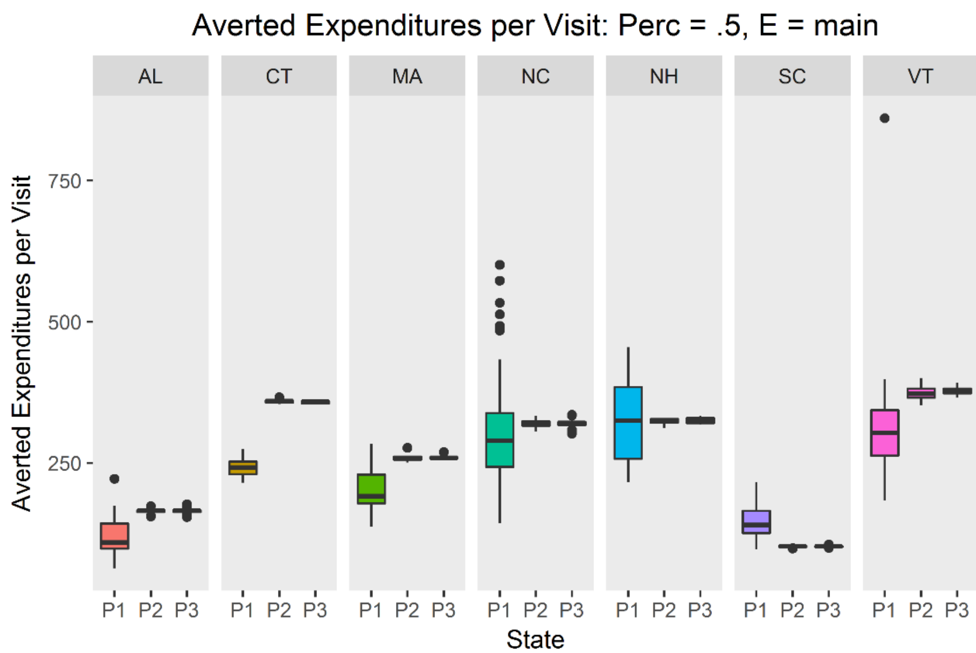

Figure 69: Box plot of averted expenditures per caries visit for setting 6 by state and population group.

Figure 70 and Figure 71 show the averted expenditures per caries visit by state and setting for P2 and P3.

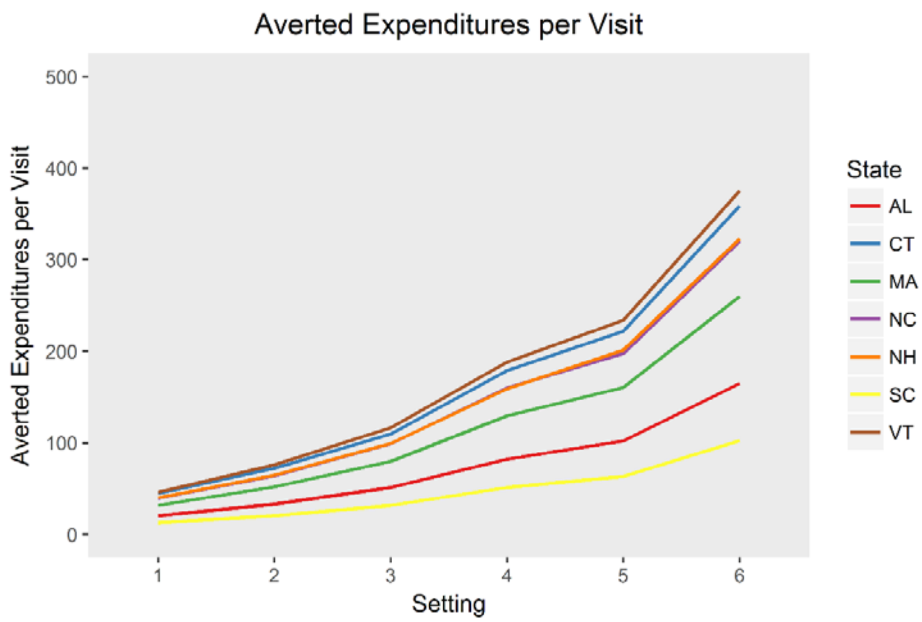

Figure 70. Averted expenditures per caries visit by state and setting for P2.

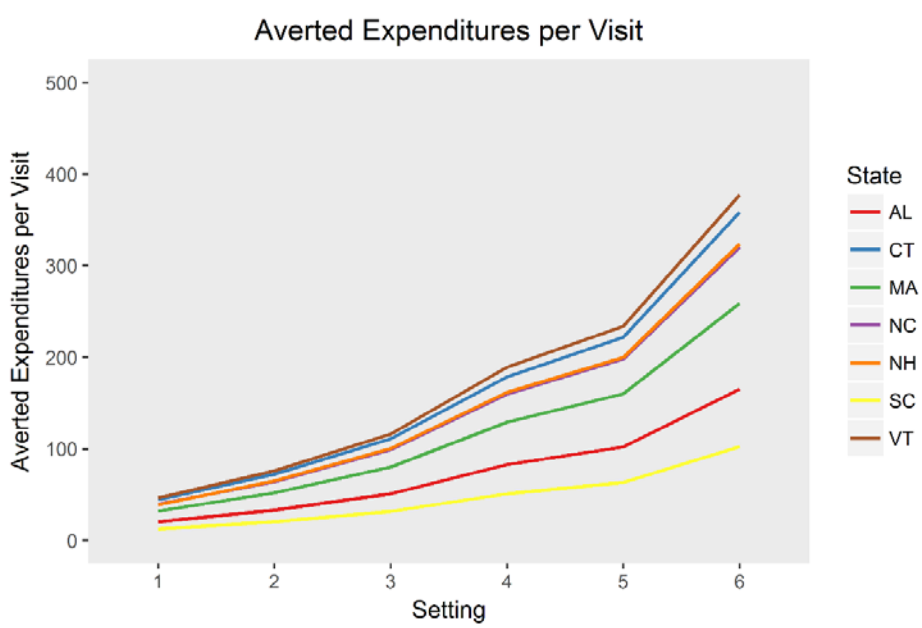

Figure 71. Averted expenditures per caries visit by state and setting for P3.

Table 42 and Table 43 show the averted and realized expenditures for P2 and P3.

Table 42. Averted and realized expenditures for P2.

		Averted Expenditures				Realized Expenditures		
Setting	State	Lower	Mean	Upper	Mean per Caries Visit	Lower	Mean	Upper
1	AL	171,481	533,698	895,915	20.5	10,998,582	12,650,625	14,302,668
	CT	322,459	510,385	698,310	45.0	11,167,651	12,037,016	12,906,381
	MA	472,142	728,753	985,364	32.1	16,283,666	17,513,862	18,744,057
	NC	852,541	2,141,995	3,431,448	39.7	44,725,855	50,823,585	56,921,315
	NH	9,786	123,678	237,571	40.0	2,412,709	2,934,190	3,455,670
	SC	175,552	323,487	471,422	12.6	7,029,582	7,711,219	8,392,857
	VT	-37,941	103,708	245,357	46.0	1,797,534	2,484,383	3,171,232
2	AL	407,281	858,178	1,309,076	33.0	10,654,885	12,316,729	13,978,572
	CT	575,658	823,396	1,071,134	73.0	10,812,365	11,741,798	12,671,230
	MA	865,956	1,195,005	1,524,053	52.9	15,845,552	17,031,289	18,217,026
	NC	1,817,792	3,457,477	5,097,163	64.0	43,455,124	49,444,422	55,433,720
	NH	58,215	199,885	341,555	64.7	2,332,931	2,866,340	3,399,748
	SC	329,234	520,560	711,887	20.4	6,851,489	7,513,485	8,175,480
	VT	-6,999	170,570	348,140	77.0	1,756,455	2,405,853	3,055,251
3	AL	764,992	1,331,709	1,898,426	51.3	10,322,298	11,937,546	13,552,794
	CT	942,155	1,254,990	1,567,825	109.4	10,476,439	11,346,129	12,215,820
	MA	1,429,129	1,834,536	2,239,943	79.0	15,383,518	16,564,834	17,746,151
	NC	3,301,585	5,350,490	7,399,394	99.0	41,877,145	47,825,831	53,774,517
	NH	128,554	306,938	485,323	98.5	2,261,560	2,767,364	3,273,168
	SC	571,882	808,233	1,044,583	31.6	6,646,571	7,332,253	8,017,936
	VT	37,988	261,331	484,674	115.1	1,704,394	2,334,569	2,964,743
4	AL	1,424,450	2,138,292	2,852,134	82.1	9,544,768	11,115,757	12,686,746
	CT	1,657,731	2,045,109	2,432,487	179.1	9,706,545	10,569,367	11,432,189
	MA	2,471,194	2,969,955	3,468,715	129.4	14,250,974	15,396,880	16,542,786
	NC	6,044,827	8,646,222	11,247,618	160.0	38,710,329	44,468,894	50,227,460
	NH	274,098	491,764	709,431	159.2	2,105,305	2,586,485	3,067,665
	SC	1,016,676	1,309,179	1,601,681	51.5	6,198,615	6,829,179	7,459,743
	VT	145,274	422,800	700,327	189.5	1,564,527	2,175,304	2,786,082

Table 42 (continued)

5	AL	1,861,669	2,656,316	3,450,963	101.9	9,237,516	10,771,390	12,305,265
	CT	2,095,252	2,529,288	2,963,324	220.7	9,257,923	10,142,645	11,027,366
	MA	3,114,145	3,681,745	4,249,346	162.2	13,802,217	14,955,268	16,108,319
	NC	7,809,499	10,668,634	13,527,770	198.0	37,254,505	42,791,677	48,328,848
	NH	371,854	620,440	869,026	199.1	2,006,952	2,481,042	2,955,132
	SC	1,276,650	1,610,573	1,944,495	63.1	6,046,366	6,683,436	7,320,506
	VT	210,692	525,414	840,136	235.2	1,476,190	2,086,021	2,695,851
6	AL	3,291,058	4,301,401	5,311,743	164.8	7,708,979	9,141,860	10,574,742
	CT	3,532,188	4,098,547	4,664,906	359.2	7,803,336	8,581,914	9,360,492
	MA	5,243,339	5,967,003	6,690,667	259.2	11,599,167	12,660,416	13,721,665
	NC	13,659,868	17,278,879	20,897,891	319.7	31,001,836	36,167,902	41,333,967
	NH	690,593	997,876	1,305,159	323.5	1,652,861	2,094,951	2,537,042
	SC	2,200,498	2,614,086	3,027,674	102.2	5,114,492	5,690,377	6,266,262
	VT	445,004	841,963	1,238,922	373.9	1,223,409	1,767,971	2,312,534

Table 43. Averted and realized expenditures for P3.

		Averted Expenditures				Realized Expenditures		
Setting	State	Lower	Mean	Upper	Mean per Caries Visit	Lower	Mean	Upper
1	AL	407,146	848,381	1,289,616	20.2	18,167,198	20,282,671	22,398,143
	CT	726,070	1,017,229	1,308,388	44.3	22,839,960	24,227,075	25,614,189
	MA	950,510	1,298,102	1,645,695	31.6	29,295,169	30,987,809	32,680,450
	NC	1,789,752	3,380,282	4,970,812	39.2	73,040,692	80,719,195	88,397,698
	NH	130,838	290,755	450,672	39.4	6,306,607	7,104,038	7,901,468
	SC	330,706	519,624	708,541	12.6	11,574,864	12,440,080	13,305,296
	VT	-11,219	173,557	358,333	46.8	3,270,957	4,119,101	4,967,245
2	AL	809,621	1,376,400	1,943,179	33.0	17,716,423	19,765,859	21,815,295
	CT	1,286,932	1,657,430	2,027,928	72.6	22,180,742	23,532,260	24,883,778
	MA	1,665,462	2,116,468	2,567,473	52.5	28,617,064	30,235,666	31,854,268
	NC	3,439,876	5,478,132	7,516,388	63.9	71,066,714	78,523,829	85,980,944
	NH	266,438	487,119	707,800	65.0	6,168,550	6,948,079	7,727,608
	SC	606,372	842,324	1,078,275	20.4	11,233,230	12,104,533	12,975,836
	VT	51,680	282,322	512,965	74.8	3,208,835	4,012,775	4,816,714
3	AL	1,430,155	2,128,427	2,826,698	51.0	17,114,955	19,180,180	21,245,404
	CT	2,075,915	2,538,541	3,001,166	111.1	21,337,948	22,730,617	24,123,285
	MA	2,714,982	3,255,442	3,795,902	79.9	27,712,774	29,325,767	30,938,760
	NC	5,934,841	8,485,680	11,036,518	99.6	68,621,446	75,952,751	83,284,056
	NH	489,174	752,753	1,016,333	100.8	5,939,374	6,729,832	7,520,290
	SC	1,003,403	1,300,957	1,598,512	31.6	10,973,618	11,822,626	12,671,634
	VT	155,505	433,006	710,508	117.5	3,045,963	3,881,839	4,717,714
4	AL	2,548,598	3,454,049	4,359,501	82.5	15,873,451	17,863,515	19,853,578
	CT	3,497,009	4,093,547	4,690,085	178.0	19,821,717	21,196,419	22,571,121
	MA	4,590,849	5,263,826	5,936,804	129.2	25,749,236	27,345,627	28,942,018
	NC	10,501,618	13,702,714	16,903,810	159.8	63,385,443	70,615,260	77,845,078
	NH	866,082	1,209,258	1,552,433	162.6	5,473,458	6,221,215	6,968,973
	SC	1,737,112	2,103,329	2,469,545	51.1	10,181,237	11,016,296	11,851,356
	VT	342,130	702,788	1,063,446	190.0	2,825,378	3,601,899	4,378,420

Table 43 (continued)

5	AL	3,255,851	4,258,552	5,261,253	101.9	15,314,889	17,301,256	19,287,623
	CT	4,454,976	5,080,434	5,705,892	221.3	19,125,766	20,418,989	21,712,212
	MA	5,708,455	6,509,889	7,311,323	159.0	24,975,994	26,516,940	28,057,885
	NC	13,428,388	17,006,305	20,584,222	198.2	61,113,138	68,001,906	74,890,673
	NH	1,122,757	1,496,167	1,869,578	198.5	5,308,114	6,007,350	6,706,586
	SC	2,189,831	2,607,419	3,025,008	63.1	9,975,471	10,806,243	11,637,015
	VT	466,109	869,779	1,273,448	233.9	2,691,795	3,442,431	4,193,067
6	AL	5,651,743	6,892,664	8,133,586	165.0	12,880,741	14,669,322	16,457,904
	CT	7,402,134	8,203,544	9,004,954	357.3	16,057,108	17,264,692	18,472,276
	MA	9,550,675	10,530,279	11,509,883	259.3	21,109,373	22,491,449	23,873,524
	NC	23,014,898	27,485,235	31,955,572	319.6	51,034,834	57,466,547	63,898,260
	NH	1,943,996	2,423,130	2,902,264	325.2	4,388,773	5,077,349	5,765,924
	SC	3,693,349	4,214,781	4,736,214	102.2	8,435,456	9,173,942	9,912,427
	VT	909,191	1,404,031	1,898,871	377.0	2,223,234	2,920,663	3,618,092

D.5 General Results

Figure 72 and Figure 73 show several outcome results for setting 4 and P2 and P3.

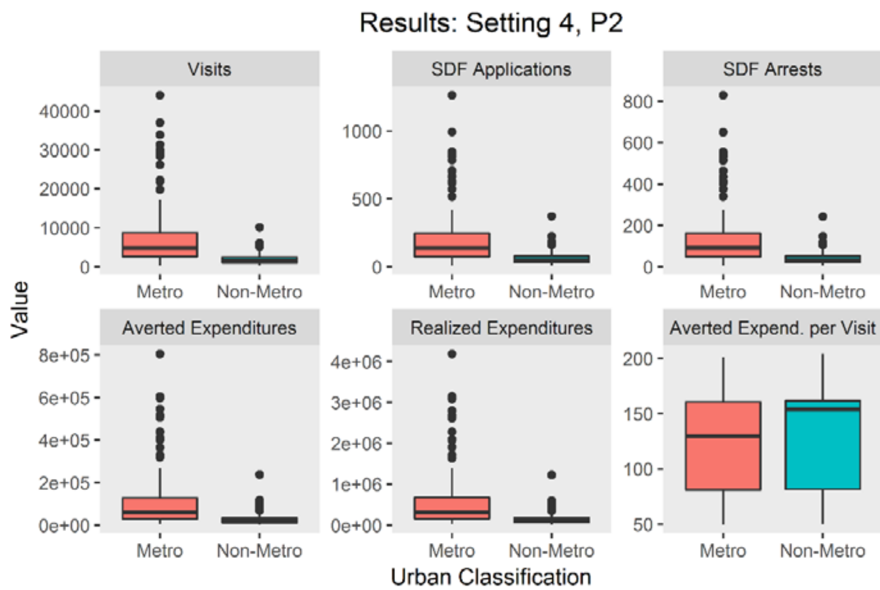

Figure 72. Box plot of outcome metrics by urban classification for setting 4 and P2.

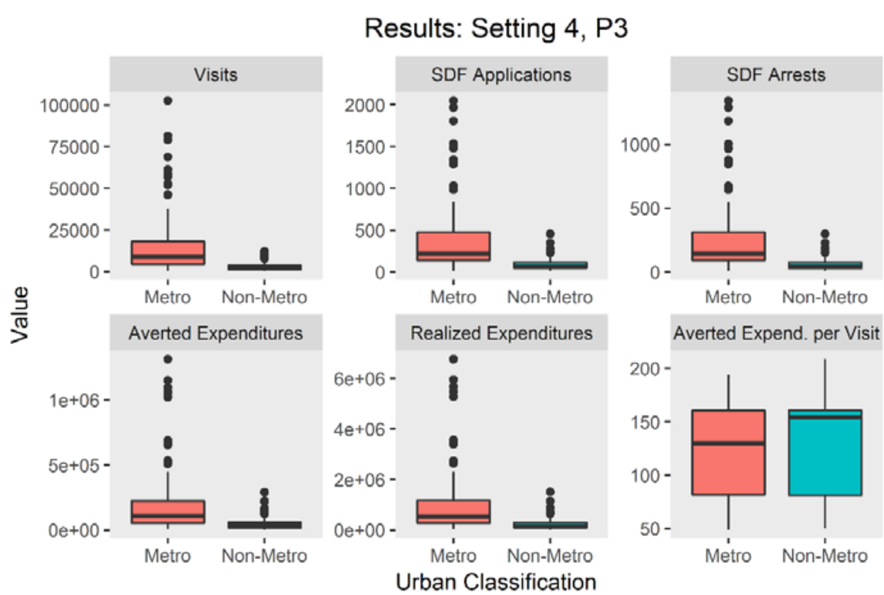

Figure 73. Box plot of outcome metrics by urban classification for setting 4 and P3.

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