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THE ALLOCATION OF PUBLIC HEALTH RESOURCES TO ADDRESS DISPARITIES OF CARE

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ABSTRACT

Providing comprehensive health care services to all the members in a community is important for the achievement of health equity and for increasing a community members' quality of life. However, there are many disparities that exist in health care services that affect not only individuals but also the entire community. Two important reasons for disparities in health outcomes are a lack of access to care and a lack of insurance coverage. To address this issue, public awareness and understanding of which groups are most vulnerable, and which interventions are most effective is important. In this thesis, we develop effective interventions to reduce disparities in community health settings.

First, we develop an integrated model to examine the impact of both increasing the current government budget for Federally Qualified Health Centers (FQHCs) in Pennsylvania and expanding Medicaid through relaxing the income eligibility limits. We consider the geographic and demographic differences in our model, to consider the tradeoffs between these two policies. The objective of this research is to develop a methodology that will aid in finding a balanced investment between FQHC expansion and relaxing Medicaid eligibility to improve both access (by increasing the number of FQHCs) and coverage (by FQHC and Medicaid expansion). We develop a utility-based framework that we use in a multi-criteria optimization model. The comparison is achieved by integrating these models with publically available data sets that allow for specific estimations of healthcare need.

Oral health has been identified as having the greatest disparities for children's overall health. In the second part of the thesis, we study the consequences of access that lead to these disparities for children's oral health outcomes. We examine the association between differences in

insurance types and oral health outcomes. Specifically, our goal is to determine the factors that would best address the disparity gaps. Differences in oral health outcomes due to insurance comprehensiveness would imply that Medicaid-based policies could be effective at addressing oral health disparities.

Finally, we develop an integrated dental supply and demand estimation model for Medicaid children. The model is based on several factors at the county level including income, population density, and number of dentists. The model is tested using county-level data from the Center for Medicaid and Medicare Services (CMS). We use the supply and demand model to assess the two interventions of expanding Medicaid eligibility and increasing Medicaid reimbursement fees in order to increase oral health utilization, which is the key goal of the Oral Health Initiative of the Center for Medicaid and Medicare Services. Furthermore, using a non-linear programming model we develop, we find the optimal balanced investment between those two interventions for each state in the model. The framework developed can be used by policy makers to determine the best way to meet the Oral Health Initiative.

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CHAPTER 1

INTRODUCTION

1.1 Background

Healthy People 2020 [1] defines a *health disparity* as "a particular type of health difference that is closely linked with social, economic, and environmental disadvantage". Since the 1980s, the U.S. has made substantial progress in improving residents' health and reducing health disparities. To continue this improvement, public awareness and understanding which groups are most vulnerable and which interventions and policies are most effective are required [2]. Since health disparities are not only a socioeconomic injustice but also economic cost burden [3, 4], appropriate cost-effectiveness analysis is needed to consider the costs and the benefits of different interventions in order to provide better health outcomes. The method is used by decision makers to evaluate whether the improvement in health care outcomes from the intervention justifies the expenditures relative to other interventions.

Several government agency reports have been released that discuss the current status of health outcomes and related disparities. The *2010 National Healthcare Disparities Report* [5] examined more than 250 measures and found that overall health care quality is improving, while disparities for minority and low-income groups are increasing. The U.S. Department of Health and Human Services (HHS) released *Healthy People 2020* [1] that provided science-based, 10-year national objectives for improving the health of all Americans. One of its goals is to "achieve health equity, eliminate disparities, and improve the health of all groups". It strives to identify nationwide health improvement priorities and provide measurable objectives and goals that are applicable at the national, state, and local levels. The Centers for Disease Control and Prevention (CDC) released *the CDC Health Disparities and Inequalities in the United States-2011* [6], the first in a periodic series of reports examining disparities in selected social and health indicators. It consolidates the most recent national data available on disparities in mortality, morbidity, behavioral risk factors, health-care access, preventive health services, and social determinants of critical health problems in the United States by using selected indicators. Both the HHS and CDC reports reveal that health disparities remain a significant issue in the US.

Kilbourne et al. [7] suggest key potential determinants of health disparities from the perspective of health services researchers, including individual, provider, and health care system factors. Individual factors, such as race/ethnicity, gender, age, poverty level, culture, and education, are all important when seeking to understand the origins of health disparities. Most health services research has focused on the effect of these individual factors and on emerging issues such as individual preferences or possible biological or genetic factors. Provider factors can also influence health and health care disparities. This includes bias or stereotyping, especially within busy health care settings, which in turn can adversely affect patient engagement in care. Organization, financing, and delivery within health care systems also play a role in disparities. This includes level of provision, financial incentives to providers, and health care system factors.

Three barriers that lead to disparities where defined in Healthy People 2020 [1]: (a) lack of coverage, (b) lack of facilities, and (c) workforce shortages. To gain entry into the health care system, particularly for catastrophic care, people typically need to own some type of insurance. However, the number of people without health insurance across the nation is rising. Census data shows that 50.7 million Americans were uninsured in 2009, an increase of 4.4 million from 2008. The percentage of uninsured persons in 2010 was 16.4 % in the U.S. and 11.0% in Pennsylvania

[8]. This lack of adequate coverage makes it difficult for people to get the health care they need and, when they do receive that care, burdens them financially. To ensure health equity, current policy efforts focus on the provision of government insurance coverage. Medicaid is the nation's principal safety-net health insurance program, covering health and long-term care services for nearly 60 million low-income Americans, most of whom would otherwise be uninsured. Medicaid's enrollees include children and parents in working families, people with disabilities, and seniors. The eligibility rules for Medicaid differ by state, however most states offer coverage for adults with children at some income level. In addition, beginning in 2014, most adults under age 65 with individual incomes up to about $15,000 per year will qualify for Medicaid in every state [9]. Although many researchers have found that coverage status affects various health outcomes, and assert the necessity for expanding public insurance like Medicaid, there is scant research that presents approaches for how to best expand it.

The lack of access to health services is another important issue. It is well known that having access to primary care has many health benefits including improvements in health status [10, 11], fewer hospitalizations [12], more physician visits [13], more control over treatable diseases [14, 15], and fewer preventable hospitalizations [16, 17]. However, there are many people that do not have a source of primary care. This may be due to a lack of insurance, the fact that not all doctors take Medicaid patients, or because of a limited supply of primary care physicians where they live. According to Kaiser Health Facts, the population that lives in primary care shortage areas in 2010 was 11.8% in the U.S. and 5.9% in Pennsylvania [8]. Federally Qualified Health Centers (FQHCs) are one measure the government uses to address this issue. The FQHC Initiative is designed to improve access to primary care, particularly for needy populations. These centers provide primary and preventive healthcare, outreach, dental care, some mental health and substance abuse treatments, and prenatal care, especially for people living in rural and medically underserved communities. Over 90% of FQHC patients have incomes below 200% of the federal poverty limit (FPL), and over 40% of FQHC patients are uninsured. Expanding the number of FQHCs could potentially increase access to primary care for those who currently do not have one. In addition, it could increase the availability of free or lower cost services for those who are uninsured, which means it would have the effect of increasing both access to primary care and provision of insurance. As a result of healthcare reform, $11 billion will be provided to expand community health centers over the next 5 years (2013 to2017) [18].

Workforce shortages are one of the most challenging barriers to the adequate provision of health services. The relationship between the number of primary care physicians and various health measures has been studied at the state level. States with more primary care physicians have lower mortality rates for a number of diseases and greater life expectancy, even after controlling for income [19]. Many states are working to address their workforce recruitment and retention problems while anticipating increasing shortages when newly insured people seek care as a result of health care reform.

The *2010 National Healthcare Disparities Report* [5] identified seven populations with special concerns: (a) racial and ethnic minorities, (b) low-income groups, (c) women, (d) children, (e) older adults, (f) residents of rural areas, and (g) individuals with disabilities or special health care needs. Figure 1 summarizes the vulnerable population groups experiencing health care disparities, barriers leading to disparities, and public safety nets measures to address these disparities.

Figure 1. Vulnerable populations, barriers, and public safety nets.

1.2 Research Objectives

Understanding the key factors that lead to disparities, while important, is insufficient for making appropriate changes to address disparities. In this dissertation, our goal is to develop decision making tools and strategies that provide guidance to policy makers in order to help address disparities in health care in public health settings. This includes the development of appropriate measures and objectives, supply and demand models, health utility functions, and resource allocation models. In each case we apply the developed methods to publically available healthcare models, and show the corresponding improvements that would be achieved by the various interventions.

In order to achieve this goal, three key research challenges need to be addressed. They are:

1. *Determining an appropriate quantitative objective that will be used to drive the decision making model*. The challenge is two-fold. First, in public health settings a social perspective is used, which includes actual expenses, quality of life, and the burden of future conditions. In theory we would like an objective that maximizes the overall social health and wellness of the population of interest. Unfortunately, there is no clear definition of what this means in practice. Second, most

research in public health examines conditions individually. However, whenever resource allocations need to be made, it is across a portfolio of health conditions. We therefore need to be able to make quantitative tradeoffs between conditions. For example, what is the tradeoff for applying resources to address type II diabetes versus cardiovascular disease? We need to be able to describe in a quantitative way how to make those tradeoffs in any objective that we use.

2. *Developing a framework that allows access and insurance to be measured on the same scale*. As mentioned previously, there are two approaches that can be used to help improve health for at-risk populations: improving access to care and providing insurance for care. For example, access to care for a community could be increased through the location of federally qualified health centers in their geographic vicinity while insurance could be provided through Medicaid expansion. However, there are four states that an individual can be in: no access, no insurance, access but no insurance, and insurance by no or limited access. There is a value, or utility, of being in each of these states. A quantitative approach must be developed that quantifies the utility of an individual in each of those four states. Otherwise it is not possible to budget both interventions simultaneously in a meaningful way.

3. *Estimating the interaction between supply and demand*. Many intervention studies assume that base conditions do not change. For example, if Medicaid fees are increased for dental procedures, the focus is on supply elasticity. However, supply and demand are related in complex ways. An accurate decision support model will not work well unless these interactions are characterized well.

Throughout the dissertation, these challenges will continually arise. The novelty of the work presented here depends on how well these three challenges are addressed.

In this dissertation we focus on three problems in allocating resources in public health settings. In particular, health care disparities arising from the lack of access and coverage are addressed. Table 1 shows the scope of the research. In each chapter, addressing one of more of the key research challenges will be key.

Table 1. Scope of Research.

Disparity	Disparities of Health Care Access and Coverage	Disparities of Children's Oral Health Outcomes	
Chapter	CHAPTER 2	CHAPTER 3	CHAPTER 4
Target Population	• Low income • Rural residents	• Children	• Low income children
Barriers	• Lack of Coverage • Lack of Facilities	• Lack of Coverage	• Lack of Coverage • Workforce Shortages
Public Measures	• FQHCs • Medicaid	• Medicaid	• Medicaid
Interventions	• Optimal location of FQHCs • Balanced investment between Medicaid and FQHCs	• Fluoride • Medicaid Utilization	• Expanding Medicaid enrollees • Increasing Medicaid Reimbursement rates
Goal	Improve coverage and access for vulnerable populations	Reduce the gap of dental health status between children’s groups	Maximize children’s dental Medicaid beneficiaries

Two important interventions for improving disparities of health care are increasing access to care and/or providing insurance to at-risk populations. In Chapter 2, we construct a multi-criteria optimization model to find optimal FQHC locations and corresponding service selection in order to improve health outcomes for vulnerable populations of US adults. FQHCs and Medicaid expansion have both been associated with reduced health disparities. Previous literature has not addressed how to consider investments in both options simultaneously. The key is the development of a quantitative set of objectives. We develop a statistical technique to weight the importance of various conditions as well as a local estimation method for prevalence. Combining these factors with an estimate of the likelihood of a FQHC visit allows for a comprehensive objective. A combination of supported health care and comprehensive health insurance can most effectively reduce health disparities. We also develop a utility-based framework to equivalently measure the value of access and insurance for at-risk populations. This allows us to optimally balance the investment between FQHC and Medicaid expansion. The analysis is done from the perspective of the state of Pennsylvania. The approach is generalizable to other states where cost data exists.

In Chapter 3, disparities in children's oral health outcomes are addressed. Oral health improvements are unequal among subgroups of the U.S. population defined by socioeconomic status, disability status, race or ethnicity, and other factors. We analyze which interventions with respect to coverage work for different subgroups, and determine how to best reduce these gaps. Important in this analysis are the combination of supply and demand factors. We see that health outcomes are positively impacted by Medicaid expansion policies.

In Chapter 4, we develop an integrated dental supply and demand model for Medicaid children to assess: (1) expanding Medicaid eligibility and (2) increasing Medicaid reimbursement levels. An empirical econometric model is developed, and parameter estimates are found using data from the Center for Medicaid and Medicare Services (CMS), controlling for socio-demographic factors. We test the validity of the model by using later data not used in the parameter estimation models. A nonlinear programming framework is then developed and applied to determine the optimal balanced investment between those two interventions. We see that there are significant state effects. The importance of this is that the best policy for one state is not necessarily a good policy for another state.

Discussion of conclusions and future research are discussed in Chapter 5. Details of data and model development are provided in various appendices.

CHAPTER 2

THE IMPACT OF FEDERALLY QUALIFIED HEALTH CENTERS & MEDICAID ON DISPARITIES OF CARE

In this Chapter, we address the problem of finding the best mix of community health policies using federally qualified health center (FQHC) and Medicaid expansion from the state perspective. The specific focus is to support vulnerable populations and address disparities of care. Section 2.1 presents the background and literature review around this topic. Section 2.2 presents the FQHC location and service location multi-criteria optimization model for a given budget and applies it to the state of Pennsylvania as an example. In Section 2.3, a utility-based model is developed to find the best balanced investment in FQHC and Medicaid expansion. The previous example for the state of Pennsylvania is used to illustrate.

2.1 Literature Review

By many measures, FQHCs are improving the healthcare of many persons in the community. Research has found that they reduce hospitalizations, reduce mortality, reduce usage of emergency rooms, and increase utilization [13, 20, 21]. It has also been found that quality of service in FQHCs is comparable to other types of primary care [22], and that they are cost-effective for Medicaid patients as compared to other sources of care [21, 23]. Although 75% of uninsured persons in the United States report that they have a source of primary care, this number increases to approximately 99% for FQHC users [24]. In addition, with the passage of health care reform (i.e., the Affordable Care Act), the importance of FQHCs is growing as an integral component [25].

To maximize the benefit from FQHCs, Griffin, et al.[26] developed an optimization model to determine the best FQHC locations, the services to offer at each, and the corresponding capacity level of those services. Their method determines the best resource allocation over a network, and takes into consideration that demand for a service differs by location. The model incorporates the fixed cost of opening a facility, the variable operating cost according to the level of capacity chosen, and the demand for services from the surrounding area. The objective of the optimization model is to maximize the number of patients served at FQHCs (i.e., that receive a primary source of care). Since the objective is to increase the number of patients regardless of their current status, some of the new persons served may not be part of a medically underserved population and switch from hospital care to a primary care physician at the FQHC. The solution, therefore, may not address health care disparities for needy populations. In order to consider medical need, we estimate the local demand according to current access and insurance status, and define special target groups. In addition, we develop a multi-objective approach to maximize health care access, coverage, and FQHC utilization in order to help reduce the aforementioned disparities in outcomes.

There are a few studies that explicitly consider how delivering care through FQHCs compares to other alternatives. Okada, et al. [13] studied the effect of FQHCs and Medicaid service on health care throughout surveys, and Cunningham, et al. [27] used data from the Community Tracking Study and FQHC reports to compare the impact of expanding FQHCs to increased insurance coverage. Shi and Stevens [28] also compared the primary care experiences of FQHC uninsured and Medicaid insured. Using three aspects of primary care experience: access, longitudinality, and comprehensiveness, they found that FQHCs could fill an important gap in primary care for Medicaid and uninsured patients. They also report that Medicaid insurance remains fundamental to high quality primary care access, even when FQHCs are used.

These comparisons of delivery alternatives, however, do not take into account the specific location of FQHCs to improve a particular measure based on geographical and demographic differences in communities, and do not allow the policy maker to evaluate prescriptive alternatives or to compare simultaneously different policy options. We develop an integrated model to examine the impact of both increasing the current government budget for FQHCs in Pennsylvania and expanding Medicaid through relaxing the income eligibility limits. We consider the geographical and demographic differences in our model and find a balanced investment between these two policies.

2.2 Multi-objective Model for FQHC Locations

The objective of previous work for finding the best FQHC locations is to maximize the total number of people who can be served throughout the FQHC network in a state. However, in order to address disparities in health outcomes (in our case, utilization), the population would be categorized according to current access and coverage status. Different groups should be given different priorities based on their vulnerability.

Table 2. Population group by access and coverage.

Coverage / Access	No Insurance	Public Insurance	Private Insurance
Underserved	①	②	③
Served	④	⑤	⑥

We introduce a multi-objective model to determine the optimal FQHC locations considering target groups with different priorities. Demand is estimated based on current access and coverage status in order to target groups preferentially.

2.2.1 Demand Estimation

Potential demand of each facility differs according to the level of need in the community, which may depend on socio-demographics, prevalence of conditions, or other characteristics. While national data is publicly available for the prevalence of health conditions (e.g., National Health and Nutrition Survey (NHANES) [29]), there is little data available for smaller regions such as counties or voting tracts for several types of conditions. In previous work, Griffin et al [26] derived local (county level) estimates using a two-stage approach, combining data from the NHANES and from the U.S. Census [30]. Figure 2 shows the demand estimation process. They started from the number of people in a county based on CENSUS data. Using a local estimation technique, the number of people in county with the condition can then be estimated. They determined the prevalence of health conditions for specified demographic populations based on NHANES and CENSUS data using logistic regression. After applying the likelihood of a FQHC visit, they estimated the number of people with a condition that would use a clinic. The average number of encounters per person is then estimated, which gives FQHC demand based on number of encounters.

In this thesis, we expand their work by applying insurance and access information from CENSUS and Medically Underserved Area (MUA) data [31], to estimate demand for the six previously defined groups. We use age, gender, race, income, and insurance status as explanatory variables for the prevalence of condition in a logistic regression. Income and insurance type were found to be correlated. In the model to predict prevalence of conditions, we used income, while in the model for estimating likelihood of FQHC visit, insurance type was used as these choices provided the best fit. Details of the logistic regressions are provided in the Appendix.

We also estimate the demand by current access status. Access information of each county level came from the U.S. Health Resources & Services Administration (HRSA) data [31]. HRSA develops a medical shortage designation criterion based on geographic area, population group, or facility. This designation is called a Health Professional Shortage Area (HPSA) or a Medically Underserved Area (MUA). HRSA also provides a publically available HPSA data which contains HPSA designation population by area. We compute the ratio of population who do not have access by county and compare this designation population to the CENSUS data. If a county does not have any HPSA area, this ratio for the county will be zero. However, if a county contains an HPSA area, population group, or facility, the ratio of the aggregated designation population to the total population will be applied to the demand set. In order to illustrate the process, the demand estimation for dental needs will be explained here. The detailed data for general and mental conditions are provided in Appendix B.

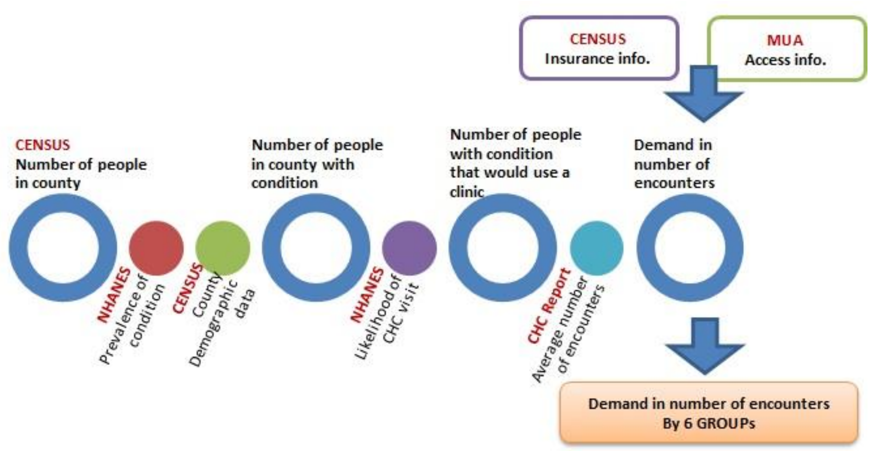


Figure 2. Demand Estimation Process

The NHANES subjects used (N=10,087) were all people who answered the pertinent demographic and examination questions. To predict the prevalence of oral health conditions, we used the question from NHANES asking whether the respondent had felt problems with teeth, mouth or dentures during the past year. As independent variables, we consider demographic information such as age, sex, race/ethnicity, income, and insurance status; all are categorical variables. The age variable was defined by three categories: “below age 19”, “between ages 19 and 64”, and “age 65 and above”.

The race/ethnicity variable race has four categories: “non-Hispanic white”, “non-Hispanic black”, “Hispanic”, and “Others”. Income is grouped into “below 100% FPL”, “100-200% of FPL”, and “above 200% FPL”. Insurance has three categories: “Private”, “Public’, and “Uninsured”. As seen in Table 3, age is not significant while sex, race/ethnicity, and income are significant. The respondents who are female, non-Hispanic black, and less than 100% FPL are more likely to have dental disease than their counterparts. Table 3 shows the estimated parameters and odds ratios, and Table 4 shows the probability that each demographic group has dental disease. Since age and insurance source are excluded, we have 24 demographic groups (2 Sex $\times$ 4 Race $\times$ 3 Poverty Levels), and the same probabilities from Table 4 will be applied to all the age and insurance groups.

Table 3. Results from logistic regression model predicting demand of dental care.

Var.	Categories	Estimated Parameters	Odds Ratio			P value
			Point	95% C.L		
Age	Age 19- (vs. Age 65+)	-0.0251	1.007	0.657	1.542	0.8636
	Age 19-64 (vs. Age 65+)	0.0569	1.093	0.945	1.263	0.5057
Sex	Male (vs. Female)	-0.0727	0.865	0.786	0.952	0.003
Race	Mexican/Hispanic (vs. White)	-0.028	1.111	0.93	1.326	0.5482
	Black (vs. White)	0.1005	1.263	1.037	1.539	0.0909
	Others (vs. White)	0.0608	1.214	0.977	1.508	0.4176
Poverty Level	FPL100%- (FPL200%+)	0.1184	1.419	1.157	1.741	0.0626
	FPL 100~200%(FPL200%+)	0.1134	1.412	1.191	1.674	0.0362

Table 4. Probability of dental disease prevalence by group.

Poverty Level	White		Black		Mexican/Hispanic		Others	
	Female	Male	Female	Male	Female	Male	Female	Male
FPL100%-	0.433	0.385	0.478	0.429	0.446	0.398	0.455	0.406
FPL 100~200%	0.432	0.384	0.476	0.427	0.444	0.396	0.453	0.405
FPL200%+	0.355	0.311	0.397	0.350	0.367	0.322	0.375	0.329

In order to predict the number of people within each county in Pennsylvania with each health condition, we multiply the prevalence estimates by county census population data for each demographic category. For example, since the prevalence of dental disease for white females below 100% FPL is 0.433, we multiply the number in Centre county in that demographic (8,079) by 0.433. Table 7 shows the population and estimated number of people with dental disease for this case. In the group, we have nine subgroups, and the total estimated demand of this group is 3,498. We repeat this process for each of the 24 demographic groups. The total sum is the overall estimate for Centre County.

Once the number of people with dental disease is estimated, the value is converted into the number of people who will likely go to a county's FQHC with that need. To estimate the likelihood of using an FQHC, we use results from a logistic regression model with the NHANES question "What kind of place do you go to most often: is it a clinic, doctor's office, emergency room, or some other place?" as the response variable. The independent variables are made up of sociodemographic information including age, sex, race/ethnicity, and insurance type.

Table 5. Results from logistic regression model predicting likelihood of FQHC visit.

Var.	Categories	Estimated Parameters	Odds Ratio			P value
			Point	95% C.L		
Age	Age 19- (vs. Age 65+)	0.019	1.234	0.847	1.798	0.8332
	Age 19-64 (vs. Age 65+)	0.173	1.441	1.036	2.004	0.0139
Sex	Male (vs. Female)	0.022	1.045	0.925	1.180	0.4800
Race	Mexican/Hispanic (vs. White)	0.646	2.490	1.947	3.185	<0.0001
	Black (vs. White)	-0.141	1.133	0.885	1.451	0.1152
	Others (vs. White)	-0.240	1.027	0.648	1.627	0.2284
Insurance	Private Ins (vs. Uninsured)	-0.479	0.422	0.298	0.599	<0.0001
	Public Ins (vs. Uninsured)	0.097	0.751	0.501	1.128	0.3827

Table 6. FQHC visit probabilities from each group.

	Age 19-				Age 19~64				Age 65+			
	White	Black	Hispanic	Others	White	Black	Hispanic	Others	White	Black	Hispanic	Others
Private Ins	0.104	0.117	0.225	0.107	0.120	0.133	0.253	0.122	0.086	0.096	0.190	0.088
Public Ins	0.172	0.190	0.340	0.175	0.194	0.215	0.375	0.199	0.143	0.159	0.294	0.147
Uninsured	0.217	0.238	0.408	0.221	0.244	0.267	0.445	0.248	0.183	0.202	0.357	0.294

As seen in Table 5, sex is an insignificant variable while age, race/ethnicity, and insurance type have a significant relationship with the likelihood of using an FQHC. The respondents who are 19-64 years old, Hispanic, and public/uninsured are more likely use FQHCs than other groups. Table 5 shows the estimated parameters and corresponding odds ratios, and Table 6 presents the probability that each demographic group will use an FQHC.

To estimate demand in number of patient encounters, we use the average number of annual dental encounters per dental user in Pennsylvania [32]. Table 7 shows the results of dental demand estimation from the subgroup of non-Hispanic white, Female, and Below 100% in Centre county.

Table 7. Estimated demand (non-Hispanic white, Female, below 100%FPL, Centre County)

InsGrp	Age	Population (A)	Prevalence (B)	People with dental disease (C=A*B)	Likelihood of using FQHC (D)	Estimated FQHC dental user (E=C*D)	Average number of dental encounters per dental user (F)	Estimated Demand (G=E*F)
Private	19-	649	0.433	281	0.104	29	2.5	73
	19~65	3,726	0.433	1,613	0.12	194	2.5	484
	65+	0	0.433	0	0.086	0	2.5	0
Public	19-	1,048	0.433	454	0.172	78	2.5	195
	19~65	1,455	0.433	630	0.194	122	2.5	306
	65+	297	0.433	129	0.143	18	2.5	46
Uninsured	19-	0	0.433	0	0.217	0	2.5	0
	19~65	904	0.433	391	0.244	95	2.5	239
	65+	0	0.433	0	0.183	0	2.5	0
Total		8,079		3,498		537		1,342

Finally, we want to estimate the demand by current access status. To obtain access information at the county level, we use HRSA data [31]. For example, the underserved ratio in Centre County is 0.015, and the estimated demand of non-Hispanic white females below 100% FPL from Table 7 is 1,342. Therefore, demand is divided to that with access (1,342 ×0.985) and without access (1,342 $\times$0.015). The applied ratios of underserved population of each county in Pennsylvania are distributed between 0 to 0.65, with a mean value of 0.115.

2.2.2 Distance

Distance to an FQHC influences the likelihood that an individual will visit it. To account for this, we determine distances between counties from census latitude and longitude data, measured from the center of each county. HRSA has guidelines that access is desired to be within 40 minutes of travel [33], which they define as between 20-30 miles of travel. We therefore made the likelihood of visiting a FQHC a decreasing function of distance, with the maximum distance defined by the guidelines.

We use four distance levels, indexed by l, with the likelihood of visiting a FQHC of l distance away as P_l which are $P1$ = 1.0, $P2$ = 0.75, $P3$ = 0.5, and $P4$ = 0.25. People in category l = 1 are not willing to travel outside of their location, l=2 up to 10 miles, l = 3 up to 20 miles, and l = 4 up 30 miles. For distances greater than 30 miles, the probability was set to 0. For example, if the distance between i and z is 15 miles, that corresponds to level 3 and 50% of location i's population is willing to travel to location z for service. Patients from a county can be served by more than one FQHC location. However, the total number of a county's patients served by all FQHCs is constrained by the total demand from that county. Figure 3 shows an example of Lebanon County in Pennsylvania. Lebanon County itself becomes level 1 since there is no county less than or equal to 10 miles from the center of Lebanon. Dauphin County becomes level 3, and the three counties of Berks, Lancaster, and Schuylkill are level 4 since they are located between 20 to 30 miles from Lebanon. According to our assumption of distance level and willingness of travel, only 25% of the population of Lebanon County would be served by FQHCs in all these counties in spite of the long travel distance, since they could travel to the level 4 county. Similarly, 50% of the population would be served by FQHCs located in Dauphin or Lebanon County, but not travel to the Berks, Lancaster, and Schuylkill Counties. On the other hand, the maximum demand from Lebanon County which can be served by FQHC in Dauphin County will be 50% of Lebanon County's demand.

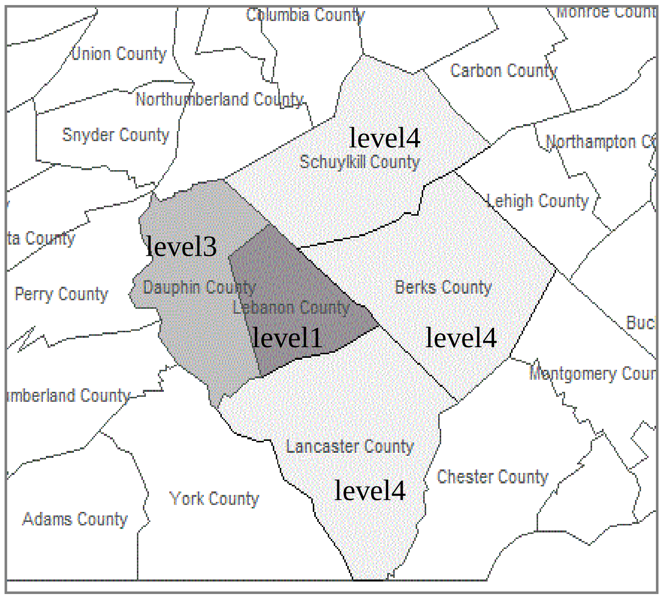


Figure 3. Example of distance levels

2.2.3 Model

Before the impact of investment in FQHC expansion can be compared to the alternative of relaxing Medicaid eligibility, we must first determine the best way to invest in FQHCs. In this section we present a multi-objective model to determine the location of FQHCs and which services should be offered for a particular budget.

The following are the notation for the indices and parameters used in the model.

Indices

i : FQHC location

z : Population location

j : Service type (General, OB/GYN, Dental, and Mental)

k : Capacity (small, medium, large)

l : Distance level (0, ~10mile, ~20mile, ~30mile)

g_1: Insurance group (Private, Government, None)

g_2: Access (access, no access)

Parameter

FL: Annual fixed cost per location

FS_k : Annual fixed cost per capacity level

VS_j : Annual variable cost per service

RB_{g1}: Reimbursement rate

CAP_{jk}: Number of patients of service type j that can be served at level k

P_l : Maximum portion of z's population that can be served at distance level l

$n_{zjg_1g_2}$: Demand for service j in county z of insurance and access group

$m_{izjg_1g_2}$: Maximum demand of county z that can be served by FQHC located in county i

(=P_l $n_{zjg_1g_2}$, if the distance between *i* and *z* corresponds to level *l*, 0 otherwise)

I_{izl} : 1 if distance level between i and z is greater than l, 0 else.

w_j : Weight associated with serving a customer of service type j

We categorize demand by insurance and access group, which makes it possible to give different priorities for each group. We set the first priority to maximize insurance coverage of

Equation (1), which is the sum of total weighted number of encounters for the uninsured population ($g_1 = 3$). The second priority is to maximize access of Equation (2), which is from the underserved population ($g_2 = 2$). Finally, we maximize utilization of FQHCs by providing the most weighted services of Equation (3). Note that this last priority is the same objective used in Griffin et al. [26]. Estimation of weight for service type (w_j) could be found in Appendix C.

Objective:

$$1^{st} \text{ objective (Max Coverage) : } \quad \max \sum_{\substack{izjg_2 \\ g_1=3}} w_j \; y_{izjg_1g_2} \tag{1}$$

$$2^{nd} \text{ objective (Max Access) : } \quad \max \sum_{\substack{izjg_2 \\ g_2=2}} w_j y_{izjg_1g_2} \tag{2}$$

$$3^{rd} \text{ objective (Max Utilization) : } \quad \max \sum_{izjg_1g_2} w_j y_{izjg_1g_2} \tag{3}$$

To define decision variable $y_{izjg_1g_2}$, we assume that the proportion of each group in FQHC encounters will follow the same rate of estimated demand at the population location. This variable is defined as the ratio of each group in the estimated demand ($n_{zjg_1g_2}$) at the location to the total number of encounters (y_{izj}).

$$y_{izjg_1g_2} = y_{izj} \times \frac{n_{zjg_1g_2}}{\sum_{g_1g_2} n_{zjg_1g_2}} \qquad for\ i, z, j, g_1,\ g_2 \tag{4}$$

The other constraints follow the work of Griffin et al. [26]. Equation (5) is the budget constraint and Equation (6) ensures that patients can only be served if there is capacity available for them at that service level. Equation (7) states that there can only be as many locations offering service type *j* as there are open locations, and, combined with Equation (8), implicitly requires that patients of type *j* can be served at facility *i* only if that center is open and offering service *j*. Equation 8 ensures that only the proportion of patients that are eligible based on the distance calculation can be served. Equation (9) enforces the maximum total percentage of location *i*'s population served by locations more than each distance level away.

$$\sum_{\mathrm{i}} \mathrm{FL}\ \mathrm{c_i} + \sum_{ijk} FS_k\ s_{ijk} + \sum_{\mathrm{izjg_1g_2}} \mathrm{VS_j}\ RB_{g1}\ \mathrm{y_{izjg_1g_2}} \leq B \tag{5}$$

$$\sum_{\mathrm{z}} \mathrm{y_{izj}} \leq \sum_{k} CAP_{jk}\ s_{ijk} \qquad for\ i,\ j \tag{6}$$

$$\sum_{k} s_{ijk} \leq c_i \qquad for\ i,\ j \tag{7}$$

$$\sum_{i} I_{izl} y_{\mathrm{izj}} \leq P_l \sum_{g_1,g_2} n_{zjg_1g_2} \qquad for\ l,\ z,\ j \tag{8}$$

$$\mathrm{y_{izj}} \leq \sum_{\mathrm{g_1,g_2}} m_{izj\mathrm{g_1g_2}} \qquad for\ i,\ z, j \tag{9}$$

2.2.4 Results

We solved the model using data for the state of Pennsylvania where locations were based at the county level. Pennsylvania has 67 counties, and the full data for the model including variable and fixed costs, prevalence estimates, and demand estimates is provided in the Appendix. The model was solved using SAS/OR. To see the effect of our multi-objective model, we compared it to the single objective version given in [26]. The number of variables and number of constraints are approximately 52 thousand, and it takes 5 minutes to obtain the solution for a single objective problem, and approximately 15 minutes for the multi objective version.

2.2.4.1 Comparison between Single and Multi-objective Problem

Table 8 presents the results for the percent of demand that can be served by FQHCs when a $50M budget is used.

Table 8. Satisfied demand from optimal solutions with budget of $50M.

		Single Objective	Multi Objective
Total	Total	27.2%	24.8%
Access Group	Served	28.7%	21.7%
	Underserved	6.9%	67.1%
Insurance Group	Private Insurance	29.7%	21.4%
	Public Insurance	25.0%	29.7%
	No Insurance	20.7%	31.1%

For the single objective problem, 27% of total estimated demand is served by optimally located FQHCs. However, only 6.9% of the underserved and 20.7% of the uninsured groups receives FQHC services.

For the multi-objective case, the percent of total number of encounters decreases from 27% to 25%. This lower value occurs since we focus on specific vulnerable populations. For the underserved group, the percent of satisfied demand increases from 6.9% to 67.1%. Similarly, for the uninsured group, the percentage goes up from 20.7% to 31.1%. Note that although there is a slight decrease in total number of encounters, there is a tremendous increase in the outcome of utilization for needy populations, which was our goal.

Figure 4 is a map of Pennsylvania; darker areas correspond to those counties with higher underserved populations. Markers (x) show the FQHC locations from the solution to the single objective model, and the markers (•) are from multi objective model. Figure 5 shows the related results for coverage. In both figures, there is better targeting from the multi-objective model.

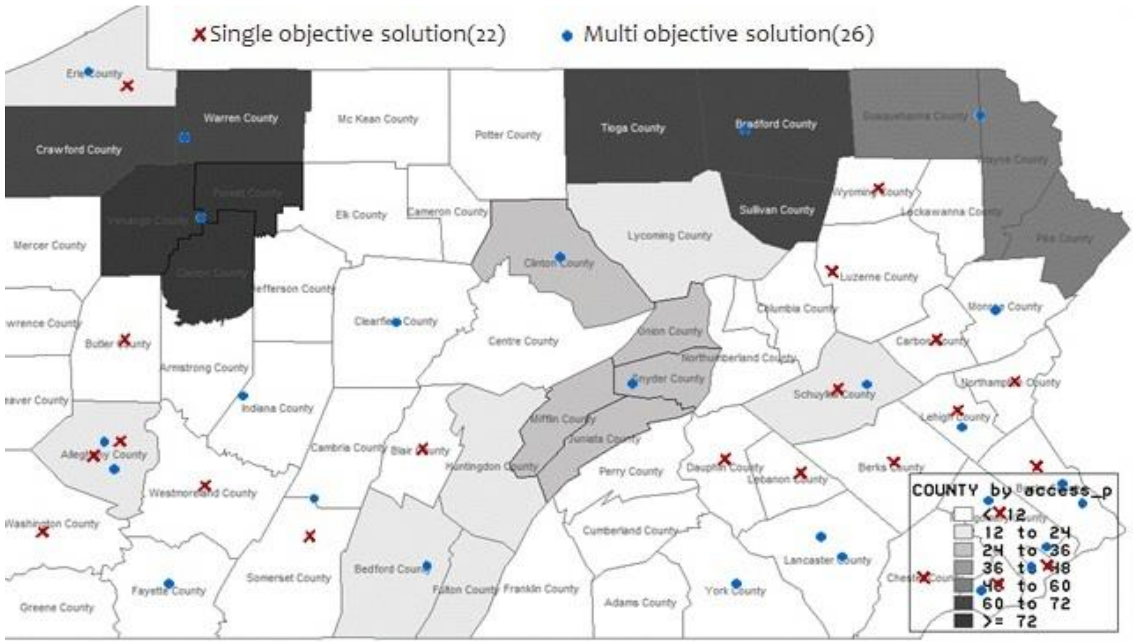


Figure 4. FQHC optimal locations comparing current access status.

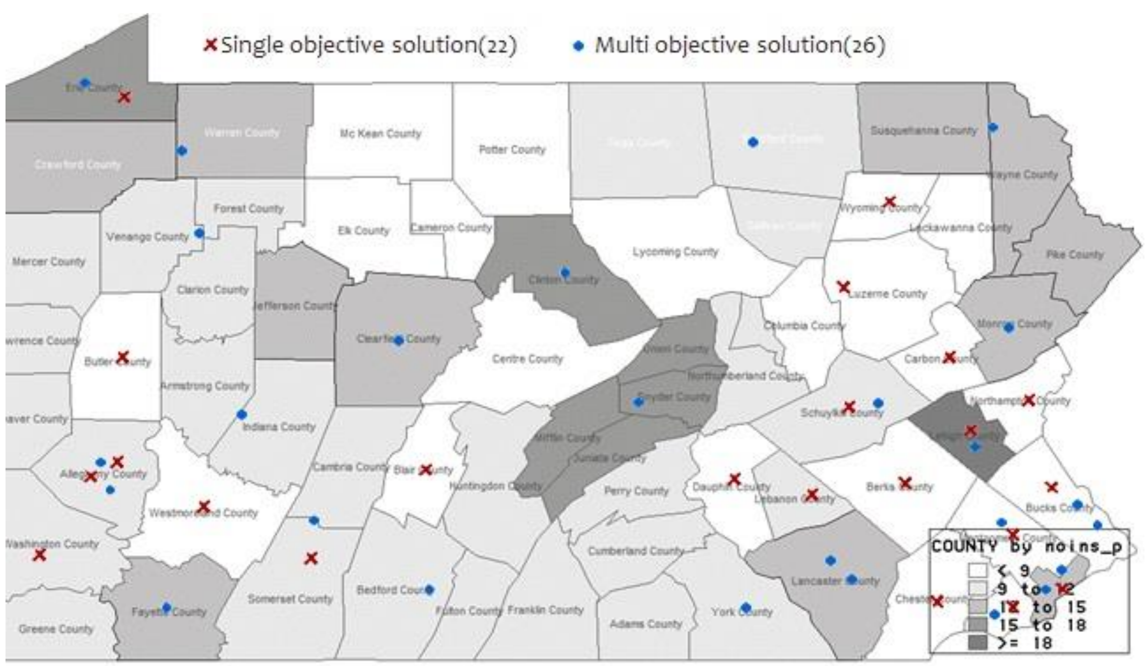


Figure 5.FQHC optimal locations comparing current coverage status.

2.2.4.2 Comparison between Different Budgets

The solution from the optimization model suggests satisfied demand by the four service types and so we need to aggregate them to estimate total improvement. To do this, a transformation function is developed based on importance of service type. Table 9 shows satisfied demand percentage by service type for various budgets.

Table 9. Satisfied Demand % by service type.

Budget	Satisfied Demand (%)				Satisfied Demand (#)			
	Primary ($\mathbf{P_1}$)	OB/GYN ($\mathbf{P_2}$)	Dental ($\mathbf{P_3}$)	Mental ($\mathbf{P_4}$)	Primary ($\mathbf{N_1}$)	OB/GYN ($\mathbf{N_2}$)	Dental ($\mathbf{N_3}$)	Mental ($\mathbf{N_4}$)
20M	18%	55%	0%	0%	695,995	16,681	188,018	116,592
40M	36%	67%	0%	0%	699,478	16,764	188,959	117,175
60M	52%	82%	0%	0%	702,962	16,848	189,900	117,759
80M	66%	89%	0%	0%	706,445	16,931	190,841	118,343
100M	78%	100%	0%	0%	709,928	17,015	191,782	118,926
120M	89%	100%	0%	0%	713,412	17,098	192,723	119,510
140M	99%	100%	0%	0%	716,895	17,182	193,664	120,093
160M	100%	100%	26%	36%	720,378	17,265	194,605	120,677
180M	100%	100%	56%	50%	723,861	17,349	195,546	121,260
200M	100%	100%	84%	67%	727,345	17,432	196,487	121,844

Service type weights were developed in [24], which we use here. The detailed process to obtain the weights is provided in Appendix C. Table 10 shows the weight and adjusted weight that sums to one.

Table 10. Adjusted weight for service type.

	Primary($\boldsymbol{w_1}$)	OB/GYN($\boldsymbol{w_2}$)	Dental($\boldsymbol{w_3}$)	Mental($\boldsymbol{w_4}$)	Total
Weight	0.88	1.20	0.07	0.05	2.20
Adjusted Weight	0.40	0.55	0.03	0.02	1.00

Among the four service types, primary care is a basic service, and as seen in Table 11, the satisfied primary care demand is larger than the others. Starting with the satisfied demand of primary care services (N_1), there are eight possible cases.

Table 11. Possible eight cases.

NO	Primary	OB/GYN	Dental	Mental	Weight	Portion
1	1	1	1	1	w_1+w_2+w_3+w_4=100%	$P_1 \times P_2 \times P_3 \times P_4$
2	1	1	1	0	w_1+w_2+w_3=98%	$P_1 \times P_2 \times P_3 \times (1\text{-}P_4)$
3	1	1	0	1	w_1+w_2+w_4=97%	$P_1 \times P_2 \times (1\text{-}P_3) \times P_4$
4	1	0	1	1	w_1+w_3+w_4=45%	$P_1 \times (1\text{-}P_2) \times P_3 \times P_4$
5	1	1	0	0	w_1+w_2=95%	$P_1 \times P_2 \times (1\text{-}P_3) \times (1\text{-}P_4)$
6	1	0	1	0	w_1+ w_3=43%	$P_1 \times (1\text{-}P_2) \times P_3 \times (1\text{-}P_4)$
7	1	0	0	1	w_1+ w_4=42%	$P_1 \times (1\text{-}P_2) \times (1\text{-}P_3) \times P_4$
8	1	0	0	0	w_1=40%	$P_1 \times (1\text{-}P_2) \times (1\text{-}P_3) \times (1\text{-}P_4)$

The weights in Table 11 are a measure of the quality levels each combination of services compared to the case where all services are provided. It is calculated by adding the related weights from Table 10 (w_j). As an example, the sixth case has a 43% quality level compared with the case all the services are served. Our goal is to determine the proportion of N1 to include in each case. Under the assumption that receiving a specific service is independent of the provision of other services, the portion of each case is calculated by multiplying the percentages (P_j) for the service of "1" value or ($1\text{-}P_j$) for "0" value. For example, the portion of sixth case will be $P_1 \times (1\text{-}P_2) \times P_3 \times (1\text{-}P_4)$, since the case represents that population who can get primary and dental service but cannot get OB/GYN or mental service. The aggregated percentage is obtained by summing the weighted portions as follows:

$$f(y) = (w_1 + w_2 + w_3 + w_4)P_1P_2P_3P_4$$

$$+(w_1 + w_2 + w_3)P_1P_2P_3(1 - P_4)$$

$$+(w_1 + w_2 + w_4)P_1P_2(1 - P_3)P_4$$

$$+(w_1 + w_3 + w_4)P_1(1 - P_2)P_3P_4$$

$$+(w_1 + w_2)P_1P_2(1 - P_3)(1 - P_4)$$

$$+(w_1 + w_3)P_1(1 - P_2)P_3(1 - P_4)$$

$$+(w_1 + w_4)P_1(1 - P_2)(1 - P_3)P_4$$

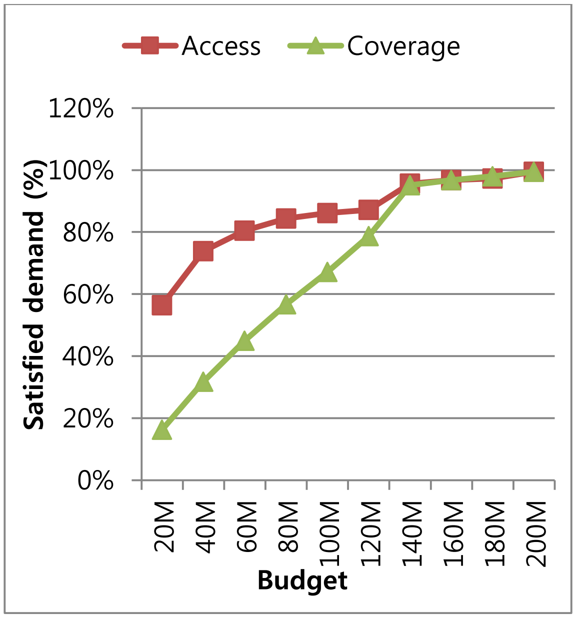
$$+(w_1)P_1(1 - P_2)(1 - P_3)(1 - P_4)$$

Finally, if we simplify the equation above, we can obtain the following functional form:

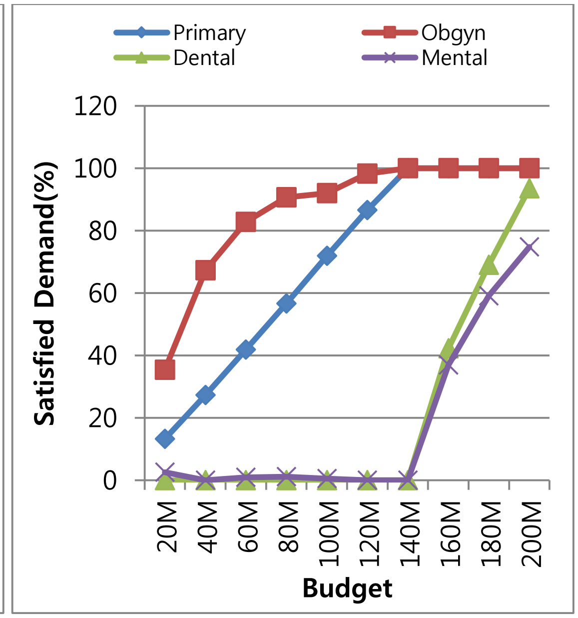
$$f(\boldsymbol{y}) = w_1P_1 + w_2P_1P_2 + w_3P_1P_3 + w_4P_1P_4$$

$$where \qquad P_j = \frac{\sum_{iz} y_{izj}}{\sum_{zg_1g_2} n_{zjg_1g_2}} \qquad for\ all\ j$$

Figure 6 shows how the percentage of satisfied demand will change according to budget increase from \$20M to \$200M by different population group (Figure 6A), and different service type (Figure 6B).



(A)



(B)

Figure 6. Satisfied demand by increasing budget.

As the budget increases, the percent of satisfied demand increases asymptotically to 100%. Table 12 shows all the counties' statistics of uninsured/underserved population percentages. While the uninsured percentage has a higher mean than underserved, it has a lower standard deviation. The uninsured percentage is distributed in the range of 10%-29%, and the underserved percentage is in the range of 0%-65% for all counties. This implies that the access disparity between regions is larger than the coverage disparity.

Table 12. Statistics of needy population percentages over all regions.

	Mean*	StdDev	Min	Max
Uninsured %	17.2%	0.04	10%	29%
Underserved %	11.5%	0.19	0%	65%

* mean of means for all the regions percentage

2.3 Balanced Investment in FQHC and Medicaid

To improve the provision of public health, it is important to determine a balanced investment across the portfolio of potential policies since they are not independent of one another. We compare the effect of investment in FQHC expansion and Medicaid expansion, considering the appropriate tradeoffs. FQHCs require a fixed cost to build and operate, and may also serve people living in the area that are not among the neediest. On the other hand, Medicaid has no fixed costs but may not be sufficient to increase access. Additionally, if we increase new enrollees in Medicaid, demand will shift from uninsured to public insurance patients and there will be a corresponding decrease in the variable costs of FQHCs since the reimbursement cost of uninsured patients are higher than others.

2.3.1 Utility Function

To properly compare the impact of FQHCs and Medicaid expansion in the same units, a utility function is developed. Phillips *et al*. [34] illustrated that patients receive care in an average month according to four possible cases of health insurance and having a usual source of care (having both insurance and source of care, having only insurance, having only a usual source of care, lack of both insurance and source of care) based on the Medical Expenditure Panel Survey (MEPS) [35]. They assert that access to a usual source of care and coverage by insurance have an additive effect on care and health outcomes. We use these results to set a service quality score for each case, and transform these scores into utilities. Table 13 shows the differences for how patients receive care in physician’s offices, hospital outpatient departments, hospitals, and their homes. Assuming that all the visit types have the same effect of increasing service quality, the number of total visits represents the quality level that the population receives. In order to determine the quality score, the number of total visits is adjusted by comparing the first group's 321 total visits. For example, the score 50 for second group means that the population which has health insurance but no usual source of care obtains a 50% quality level when compared to a population that has both.

Table 13. Difference between groups from the Medical Expenditure Panel Survey.

	Health insurance and a usual source of care Group①	Health insurance but no usual source of care Group②	Usual source of care but no health insurance Group③	No health insurance and no usual source **Group④**
Physician's office	258 visits	119 visits	149 visits	62 visits
Hospital outpatient clinic	25	11	15	10
Home health care	16	10	14	5
Emergency department	13	8	3	2
Hospital	9	8	3	2
Total	321	156	184	81
Quality Score	100	50	55	25

*Out of 1000 people in an average month

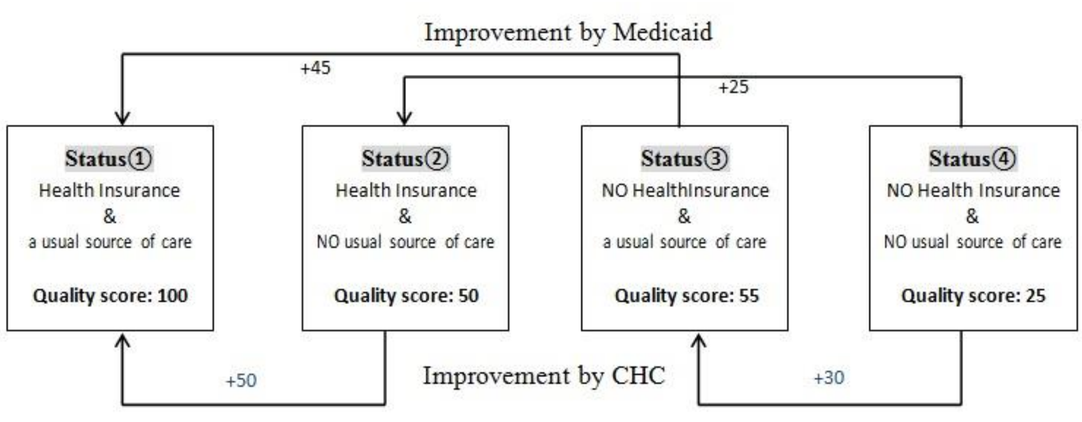


Figure 7. Service quality scores for four possible statuses.

Figure 7 shows the resulting service quality scores for the four possible statuses. In particular, the potential improvements obtained by either locating a FQHC or expanding Medicaid coverage are shown. For example, if a person is in the fourth status (lowest quality score of 25), there are two possible improvements. If FQHC service becomes available, the individual receives a usual source of care and they will change to the third status (55 quality score). Therefore, this movement is worth 30 points of improvement. If the individual becomes eligible for Medicaid service, they move to the second status, and this change will be worth 25 points of improvement. There are similarly two more improvements from the third and second statuses.

Table 14. Improvement type and weight α.

From			To Status	Improvement by	Improvement weight α
Status	g_1	g_2			
④No Insurance & No access	3	2	②Insurance & No access	Medicaid	0.5
④No Insurance & **No access**	3	2	③No Insurance & Access	FQHC	0.6
③No Insurance & Access	3	1	①Insurance & Access	Medicaid	0.9
②Insurance & **No access**	1,2	2	①Insurance & Access	FQHC	1.0

Table 14 shows how the four types of improvement can be matched with our population group (g_1, g_2) along with the corresponding adjusted improvement weight α. We set this weight by scaling the improvement values to make 1.0 the largest improvement (from status2 to status1).

According to Table 14, when we serve the population that has insurance but no access with a newly located FQHC, the health care quality shows the largest improvement, so we set that weight to 1.0. If we serve the population that has access but no insurance with Medicaid, the improvement would be 0.9. For the population lacking both, there could be 0.6 improvement by an FQHC, and

0.5 by Medicaid. The following equation represents the utility function including both the Medicaid and FQHC parts.

$$U(x,y) = \sum_{(g_1=3),g_2} \alpha^{M}{}_{g_1 g_2} x_{g_1 g_2} + f_j \left\{ \sum_{izg_1g_2} \alpha^{C}{}_{g_1 g_2}\ y_{izjg_1g_2} \right\} \tag{10}$$

This utility can be applied to the FQHC location model as follows: i) x_{g1g2} is the number of new Medicaid enrollees by population group, ii) *f(y)* is a transformation function that aggregates the number of people who can get covered by a FQHC, and iii) weight $\alpha^{M}{}_{g1g2}$ is used for Medicaid utility and $\alpha^{C}{}_{g1g2}$ for FQHC utility. Table 15 indicates the weight α used in this model. Since a potential Medicaid beneficiary should be currently in the uninsured population, it is not necessary to define α^M for the insured group (*g1*=1, 2). In addition, to indicate the minimum improvement, a value of 0.05 is assumed for α^C for the group that has a usual source of care (*g2*=1). As previously discussed, the transformation function *f(y)* will be nonlinear, and solutions for *x* and *y* must be integer. The problem is therefore a mixed integer nonlinear program.

Table 15. Weight α by coverage and access group.

Coverage	Access	For FQHC($\boldsymbol{\alpha^{C}{}_{g_1 g_2}}$)	For Medicaid($\boldsymbol{\alpha^{M}{}_{g_1 g_2}}$)
Insured(g_1=1,2)	Served(g_2=1)	0.05	-
Insured(g_1=1,2)	Underserved(g_2=2)	1.0	-
Uninsured(g_1=3)	Served(g_2=1)	0.05	0.9
Uninsured(g_1=3)	Underserved(g_2=2)	0.6	0.5

2.3.2 Demand Movement

Since FQHCs and Medicaid share the same demand, there could be a relationship between investments in these programs. If we invest in Medicaid, then new enrollees will be added, and this demand should be moved from the uninsured group to the public insured group. Consequently, it will decrease the variable cost of FQHCs since the reimbursement rate of uninsured patients is higher than others. To account for this properly, it is necessary to adjust demand $n_{zjg_1g_2}$ of the FQHC optimization model using the number of new Medicaid enrollees.

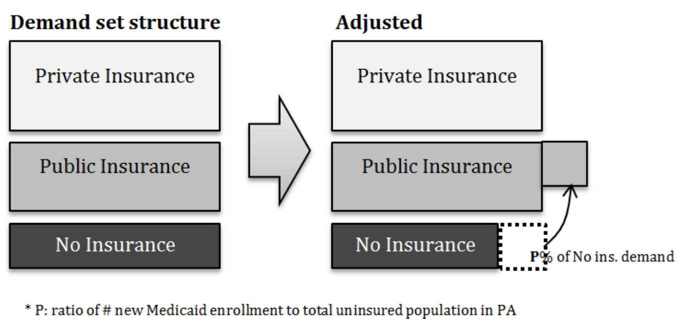


Figure 8. Demand adjustment from Medicaid investment.

Figure 8 illustrates the adjustment. In the optimization model, demand $n_{zjg_1g_2}$ is defined by county z, service j, insurance group g1, and access group g2. The demand set in Figure 8 could be one for specific service, county, and access group. First, the ratio of new Medicaid enrollment to the total uninsured population in Pennsylvania should be calculated, which is called P. Demand for the uninsured group will decrease by the same ratio P, and the same amount will move to the government insured group. The amount of demand moved (A_{zjg_2}) is therefore:

$$A_{zjg_2} = n_{zjg_2(g_1=3)} \times \frac{x}{\mathrm{U}} \qquad for\ z, j,\ g_2$$

2.3.3 Process of Integrated Problem

Since the demand for the uninsured population will move to the public insured population, the portion *y* of the public insured group will be increased while the portion of the uninsured group will be decreased by A_{zjg_2} .

$$(g_1 = 1): \quad y_{izjg_1g_2} = y_{izj} \times \frac{n_{zjg_1g_2}}{\sum_{g_1g_2} n_{zjg_1g_2}} \quad for\ i, z, j,\ g_2 \tag{11}$$

$$(g_1 = 2): \quad y_{izjg_1g_2} = y_{izj} \times \frac{n_{zjg_1g_2} + A_{zjg_2}}{\sum_{g_1g_2} n_{zjg_1g_2}} \quad for\ i, z, j,\ g_2 \tag{12}$$

$$(g_1 = 3): \quad y_{izjg_1g_2} = y_{izj} \times \frac{n_{zjg_1g_2} - A_{zjg_2}}{\sum_{g_1g_2} n_{zjg_1g_2}} \quad for\ i, z, j,\ g_2 \tag{13}$$

Since *x* and *y* are both decision variables, these equations become nonlinear, and the model turns into a mixed integer nonlinear program. We linearize Equations (11)–(13) by fixing the portion of budget allocated to FQHC and Medicaid expansion. Eleven different investment options under the same total budget are set and each FQHC optimization problem is solved. Figure 9 illustrates the procedure.

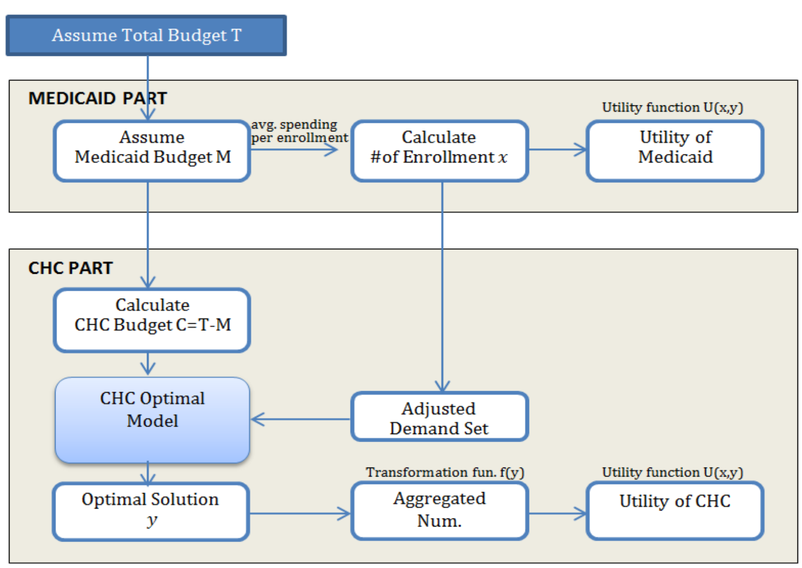


Figure 9. Integrated problem solving process.

2.3.4 Results

We set the level of total budget to \$300M, and make eleven different levels of investment for Medicaid from 0% to 100% for the state of Pennsylvania. We determine the number of possible Medicaid enrollees and corresponding utility from the amount of Medicaid investment and the average Medicaid cost per enrollment. The average Medicaid cost was \$5,300 per new enrollee in 2009, with 34% of the costs provided by the state government. In addition, the number of people who are able to be served by FQHCs along with the corresponding utility is determined by the FQHC optimization model. The results are shown in Table 16.

Table 16. Results from 11 problem sets with 300M budget.

No.	Total budget T	Medicaid			FQHC			Total Utility
		Budget M	Enrollment	Utility	Budget C	Served population	Utility	
1	300M	0M	0	0	300M	1,456,641	169,694	158,631
2	300M	30M	5,660	4,913	270M	1,456,639	169,657	163,590
3	300M	60M	11,321	9,826	240M	1,456,629	169,647	168,569
4	300M	90M	16,981	14,740	210M	1,452,978	168,890	172,840
5	300M	120M	22,642	19,653	180M	1,431,563	166,543	175,669
6	300M	150M	28,302	24,566	150M	1,403,302	163,944	178,251
7	300M	180M	33,962	29,479	120M	1,174,824	149,177	169,770
8	300M	210M	39,623	34,392	90M	808,630	127,080	154,706
9	300M	240M	45,283	39,306	60M	438,399	89,868	124,918
10	300M	270M	50,943	44,219	30M	187,084	35,391	77,603
11	300M	300M	56,604	49,132	0M	0	0	49,132

Total utility from the first case is much higher than the eleventh, which means that FQHCs are more cost effective than Medicaid if all of the resources are invested into a single policy. However, if both Medicaid and FQHC receive an investment of $150M, the highest total utility is reached.

Figure 10 shows the utility for each of the eleven investment cases. Medicaid utility increases linearly, while FQHC utility decreases nonlinearly due to economies of scale. The basic results are quite similar for different starting budget amounts.

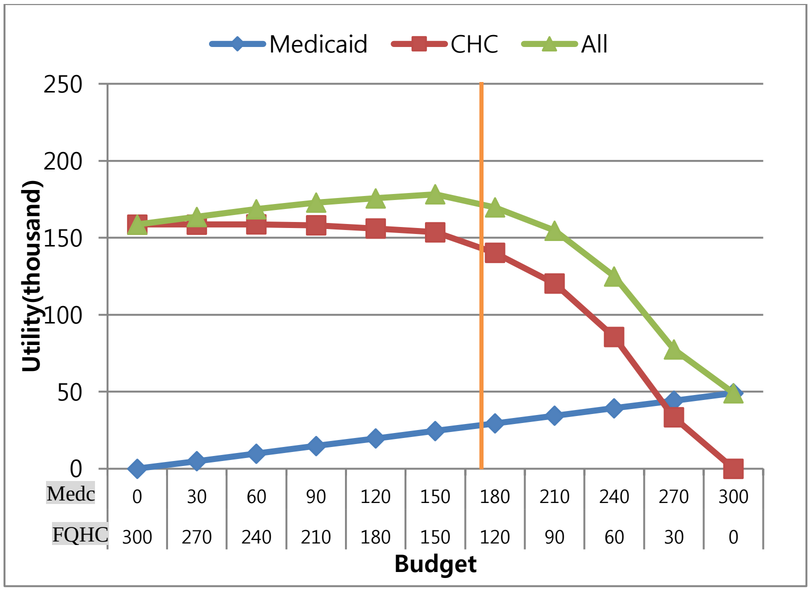


Figure 10. Balanced investment in FQHCs and Medicaid.

As and additional example, we used the perspective that we only consider state government spending on Medicaid (i.e., the federal match does not impact the state budget, which would mean that Medicaid would have a lower average cost in the optimization model). In this case, the average cost of Medicaid per enrollment would decrease to 34% of $5,300. Table 17 shows the results.

Table 17. Results with 300M budget and reduced average cost of Medicaid.

No.	Total budget T	Medicaid			FQHC			Total Utility
		Budget M	Enrollment	Utility	Budget C	Served population	Utility	
1	300M	0M	0	0	300M	1,456,641	169,694	158,631
2	300M	30M	16,648	14,451	270M	1,456,639	169,657	173,127
3	300M	60M	33,296	28,901	240M	1,456,629	169,647	187,644
4	300M	90M	49,945	43,352	210M	1,452,978	168,890	201,452
5	300M	120M	66,593	57,802	180M	1,431,563	166,543	213,819
6	300M	150M	83,241	72,253	150M	1,403,302	163,944	225,938
7	300M	180M	99,889	86,704	120M	1,174,824	149,177	226,994
8	300M	210M	116,537	101,154	90M	808,630	127,080	221,468
9	300M	240M	133,185	115,605	60M	438,399	89,868	201,217
10	300M	270M	149,834	130,055	30M	187,084	35,391	163,440
11	300M	300M	166,482	144,506	0M	0	0	144,506

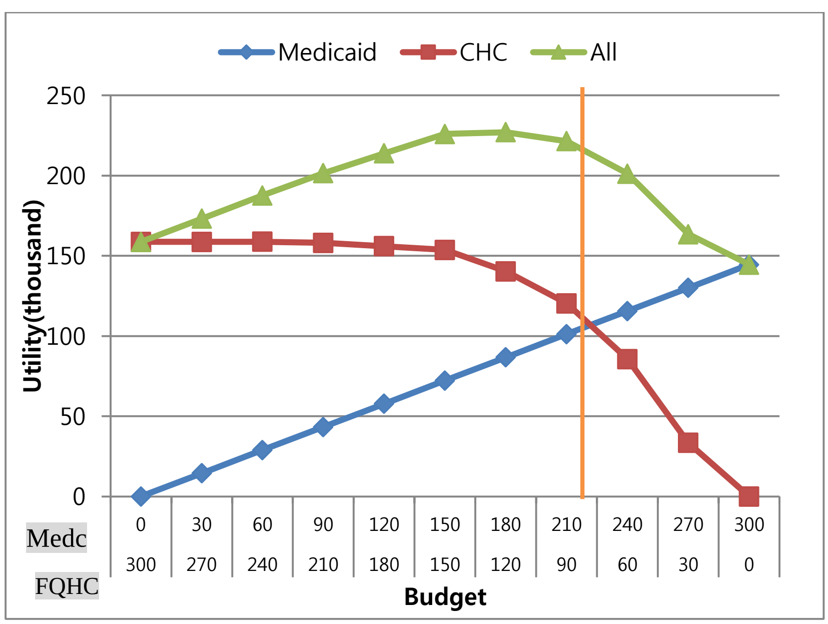


Figure 11. Balanced investment in FQHCs and Medicaid with reduced average cost of Medicaid.

As seen in the Figure 11, the first and the eleventh instances of the problem are comparable since the Medicaid utility would be satisfied with less budget than the previous example. The optimal option is seventh problem which means more investment for Medicaid ($180M) and less for FQHCs ($120M). The important issue is that the model can be applied from both the state and federal perspective. However, this could lead to different results.

2.4 Chapter Summary

Both Medicaid and FQHC expansion can improve health outcomes for the provision of care to populations that are either uninsured or without any source of primary care. We present a multi-criteria optimization model for balanced investment in FQHCs and Medicaid that also helps to identify the optimal FQHC locations and services to provide.

A benefit of the optimization model used in this work is that it considers the entire FQHC organizational network in the solutions including geographic information, local estimates of need, and current health care access and coverage status. We recommend that the current coverage status be considered as factor, since FQHCs play a more important role in primary care for uninsured patients. Considering both access and coverage information can help policy analysts make better decisions to reduce health care disparities.

According to Shi and Stevens [28] , Medicaid remains important for high quality primary care, even with the presence FQHCs. To improve public health care effectively, we should consider both policies, though it is important to find a balanced investment among them. This analysis showed that for the state of Pennsylvania, FQHCs are a more cost effective alternative for increasing both access and coverage for smaller budgets, but that Medicaid becomes a beneficial alternative as budgets increase.

It is important to mention that the data used in this analysis was publically available, and so this study is replicable for any state. It is also important to mention that there are significant state differences including reimbursement rates, eligibility criteria, and demand for services. The conclusions drawn for Pennsylvania are therefore not necessarily applicable to other states in the US.

There are several limitations to this study. First, we suggest only the number of new enrollees for Medicaid as a solution, so eligibility requirements related with this number must be decided by policy makers. It is common for persons who are eligible for Medicaid to not enroll for a variety reasons. This can be an important consideration for Medicaid expansion.

Second, we assume there is unlimited physician capacity. Both Medicaid and FQHC expansion would require an increase in medical personnel capacity. For FQHCs, the issue is recruiting physicians, with some in rural settings. For Medicaid, the issue is how many physicians would participate in the Medicaid program, whether they would be willing to accept new Medicaid patients, and if so how many. Note that we do consider a supply model for the specific case of oral health in Chapter 4. The consideration of a supply model would be an important extension to the work presented here. Finally, we do not explicitly model other safety net providers such as hospital sponsored outpatient clinics, and assume that the services they provide would be independent of FQHC or Medicaid expansion.

CHAPTER 3

THE IMPACT OF FLUORIDE & MEDICAID UTILIZATION ON CHILDREN'S ORAL HEALTH OUTCOMES

In this Chapter, we will study the association of fluoride and the comprehensiveness of state Medicaid policy on oral health outcomes of children. The objective is to determine how effective these interventions are on reducing health disparities.

3.1 Literature Review

Oral health is an important component of the overall health of individuals [36]. The Surgeon General has declared that ''oral health is essential to the general health and well-being of all Americans'' [37]. Further associations between poor oral health status and other conditions such as diabetes and cardiovascular disease have been found. Among children, poor oral health leads to poor performance in school and poor social relationships, and these conditions have been shown to continue to have an effect in adulthood [38].

According to a CDC Report [39], tooth decay affects more than one-fourth of U.S. children aged 2–5 years and half of those aged 12–15 years. About half of all children and two-thirds of adolescents aged 12–19 years from lower-income families have decay. Disparities in oral health outcomes also exist among children. For example, 40% of Mexican-American children aged 6–8 years have untreated decay as compared with 25% of non-Hispanic whites. Among all adolescents aged 12–19 years, 20% currently have untreated decay. These oral health problems are costly. Each year, Americans make roughly 500 million visits to dentists, and in 2010 an estimated $108 billion was spent on dental services in the United States.

Several previous studies looked at the impact of different factors on oral health outcomes. Fisher-Owens et al. [35] and Patrick et al. [40, 41] described a multilevel conceptual model with the individual, family, and community levels of influence on oral health outcomes. Hay and et al. showed that number of dental visits had a negative effect on the number of decayed teeth, demonstrating the beneficial effect of dental care [42]. Griffin and et al. examined the impact of two financing strategies- increasing Medicaid dental reimbursements and providing school sealant programs- and found that both strategies can be effective in increasing sealant prevalence [43]. Decker and et al. also showed that higher Medicaid payment levels to dentists were associated with higher rates of receipt of dental care among children and adolescents [44]. Several studies [45-48] have shown that community water fluoridation has a positive effect on dental health status, and a meta-analysis [11] was performed on the 21 studies used in the evidence review on community water fluoridation, the suitability of the study designs, and quality of the evidence used to determine the magnitude of its effectiveness.

There have been several studies about oral health disparities. Nash and Ismail found that dental insurance is often considered one of the primary factors to maintaining good oral health [49, 50]. Several empirical studies have documented the lack of access to dental insurance as a factor for widespread dental caries in young children [51-55].

Oral health improvements have not been equal across subgroups of the U.S. population defined by socioeconomic status, disability status, race or ethnicity, and other factors. It is therefore necessary to analyze how these interventions work for different subgroups and find a way to reduce these gaps. In this study, we examine the association of children’s oral health status by insurance type using data from the National Survey of Children’s Health (NSCH).

3.2 Inequality of Children's Dental Health Status

This NCHS survey provides data on the physical and emotional health of children 0 to 17 years of age [56]. The data has a panel structure composed of 51 states (each state has 1500 to 2000 responses) over two time periods (2003 and 2007). Respondents self-report their oral health status as one of five categories: excellent, very good, good, fair, and poor.

Table 18 shows the responses for the self-reported oral health question. The majority of the respondents had reported that their oral health status is excellent or very good. The weighted mean is 2.01 (1.99-2.02) for year 2003 and 1.93 (1.91-1.95) for year 2007, which means that the oral health status has significantly improved over time.

Table 18. Self-reported oral health score from NSCH 2003 and 2007.

year	Total Responses	How would you describe the condition of teeth?					Weighted Mean (95% C.I.)
		Excellent(1)	Very good(2)	Good(3)	Fair(4)	Poor(5)	
2003	95,601	44254	25478	18742	5597	1530	2.01(1.99-2.02)
		46.3%	26.7%	19.5%	5.9%	1.6%	
2007	86,655	44438	21622	15619	4014	962	1.93(1.91-1.95)
		51.3%	25.0%	18.0%	4.6%	1.1%	

We hypothesize that type of insurance impacts the oral health status in children. Table 19 shows health insurance coverage of the total population and children who are 0-18 years old. Note that 10% of children (approximately 8 million) remain uninsured, including 5 million who are eligible for Medicaid and SCHIP but are not enrolled [57].

Table 19. Insurance coverage statics.

	Private Insurance	Medicaid& SCHIP	Other Public	Uninsured
Total Population	54%	16%	13%	17%
Children	55%	34%	1%	10%

*USA 2008~2009 from Kaiser State Health Facts [8].

A t-test shows the average self-reported dental health scores are statistically different between insurance types and also between years. As seen in Table 20 and Figure 12, there is a significant improvement between the years regardless of insurance source. In 2007, children covered by Medicaid had poorer oral health (2.25) than children with private insurance (1.72), although they had better oral health than children without insurance (2.35). The scores from 2003 have similar results.

Table 20. Weighted average self-reported dental health score by insurance source.

Year	Private Insurance (95%C.I)	Medicaid (95%C.I)	No Insurance (95%C.I)
2003	1.82(1.81-1.83)	2.31(2.29-2.32)	2.45(2.43-2.48)
2007	1.72(1.71-1.73)	2.25(2.23-2.26)	2.35(2.32-2.37)

*The smaller score implies better self-reported oral health.

As seen in the Table 19, one-third of children are insured through Medicaid and the State Children’s Health Insurance Program (SCHIP). Insurance provides them with significantly better oral health status than for the uninsured, but still worse oral health status as compared to privately insured children.

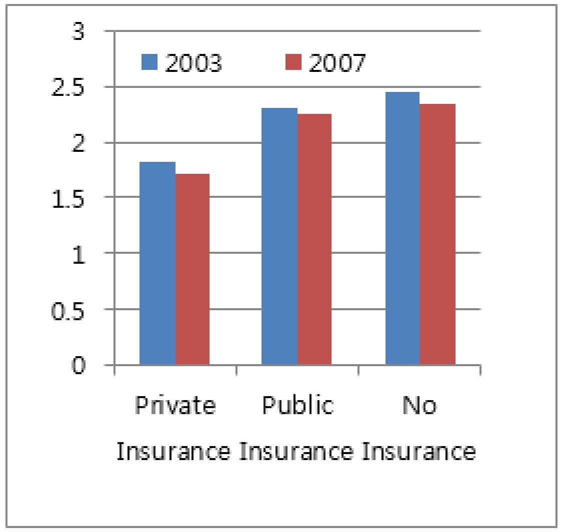


Figure 12. Average self-reported oral health by insurance type and year.

Medicaid expansion could help to reduce this disparity since the score for Medicaid children is significantly higher than their uninsured counterparts. There are approximately 5 million uninsured children who are eligible for Medicaid [57]. States have continued to strengthen children's coverage, often utilizing new tools and incentives to expand coverage and enroll eligible children. Kaiser [58, 59] suggests strategies a state can take to increase their Medicaid and SCHIP participation rates, and thus reach more "eligible but uninsured" children.

Second, we could identify factors that affect the oral health of Medicaid children and try to reduce this difference with those privately insured. To determine the feasibility, we fit a regression model with interactions of interventions and dummy variables for insurance type. If there is a significant effect for the interaction with Medicaid children, then the intervention is associated with a reduction in children's oral health disparities.

Two important state interventions are community water fluoridation (CWF) and the delivery of preventive dental services through the Early Periodic Screening, Diagnosis, and Treatment (EPSDT) Program. As mentioned previously, several studies have shown that CWF has a positive effect on dental status. We therefore need to control for this in order to determine to the actual effect of insurance type on oral health outcomes.

3.3 States' Preventive Interventions

Fluoride has considerable benefits in the prevention of tooth decay. Due to the presence of fluoride in beverages, food, dental products, and dietary supplements in non-fluoridated areas, the differences in percentage of children with untreated caries between fluoridated and non-fluoridated communities are not as great as has been observed in the past. However, numerous studies clearly establish that there a causal relationship between CWF and the prevention of dental caries still exists. The U.S. Public Health Service periodically reports water fluoridation statistics [60], including the percentage of population receiving fluoridated water in each state. Since the reports are for 2002, 2004, 2006, and 2008, the average value is calculated for year 2003 and 2007 in order to match the EPSDT data.

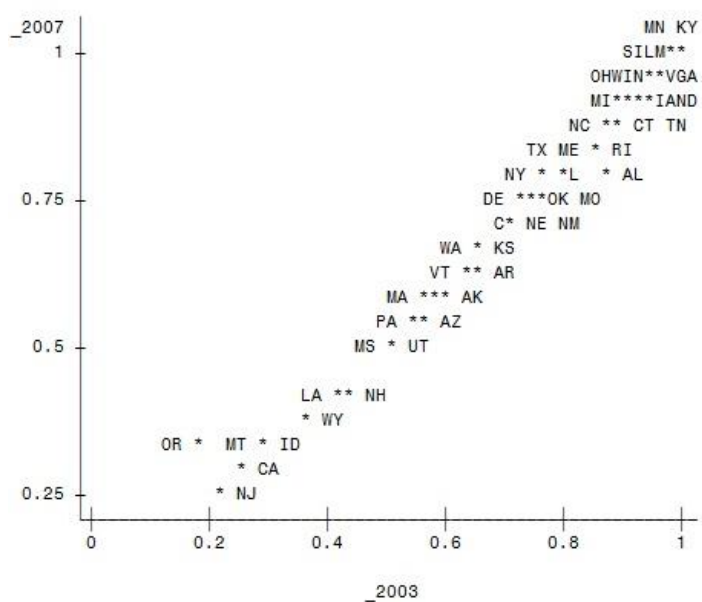


Figure 13. Proportion of population on public water supply systems receiving fluoridated water.

In Figure 13, we see a strong linear relationship between the years 2003 and 2007 for percent of population with fluoridated water, which means that state CWF has not changed much over the 4-year period. For the year 2003, the states of Kentucky and DC have 100% of their population receiving fluoridated water, while only 0.19 of the population in Oregon received fluoridated water (the smallest percentage in the study). For the year 2007, Kentucky and DC remain at 1.0, and New Jersey has 0.23, which is a minimum. The average percentage was 0.721 for year 2003 and 0.724 for 2007. Table 21 divides states into three groups according to the average percentages over two years.

Table 21. Grouping of states by ratio of population receiving fluoridated water.

Group	State
67~100 percentile	DC,KY, IL, MN, ND, GA, IN, SD, VA, SC, TN, MD, IA, WV, MI, WI, OH
34~66 percentile	CT,NC, RI, AL, MO, ME, TX, FL, NM, CO, DE, OK, NY, NV, NE, KS, AR
0~33 percentile	WA, AK, VT, MA, AZ, UT, PA, MS, HI, NH, LA, WY, MT, ID, CA, OR, NJ

The EPSDT benefit provides comprehensive and preventive health care services for children under age 21 who are enrolled in Medicaid. EPSDT is key to ensuring that children and adolescents receive appropriate preventive, dental, mental health, and developmental, and specialty services. For Medicaid children, the utilization of dental care has a major effect on oral health outcomes.

The annual EPSDT report [61] provides basic information on participation in the Medicaid child health program. The information is used to assess the effectiveness of State EPSDT programs in terms of the number of children who are provided child health screening services. From this information, we collect the number of total eligibles receiving preventive dental services, which is the unduplicated number of children receiving at least one preventive dental service. This total is divided by the total number of eligibles in order to determine the preventive dental service utilization.

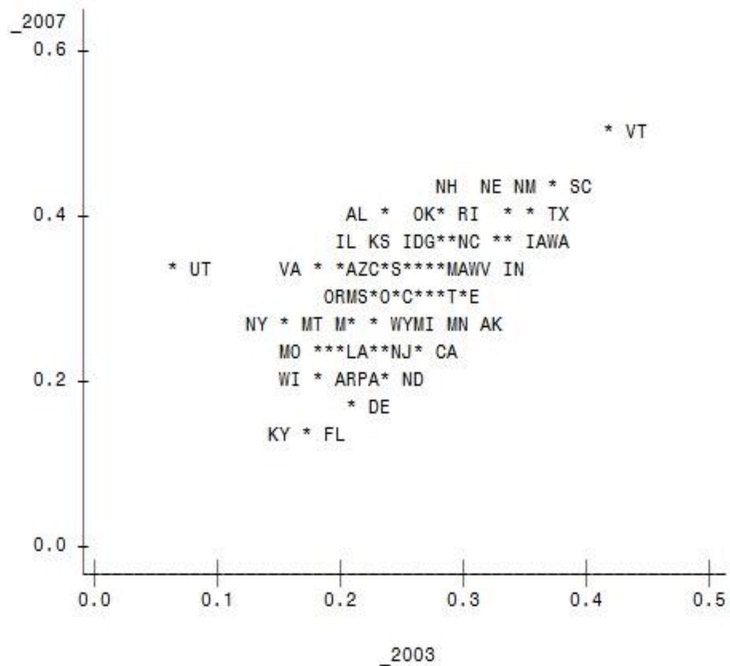


Figure 14. Proportion of eligible children receiving preventive dental services with state EPSDT.

Figure 14 shows how the preventive care utilization is distributed by time and states. Average utilization improved from 0.25 (year 2003) to 0.31 (year 2007). For the year 2003, the maximum utilization is from the state of Vermont (0.42 of eligible), while states with minimum utilization were Hawaii and Utah. For the year 2007, Vermont showed the maximum utilization of 0.52 and Kentucky showed the lowest utilization of 0.13. The relationship between utilization and time is linear over the two years, but not as strong as for fluoridation. This implies there are greater changes in these outcomes for states. Table 22 divides states into three groups according to the average preventive utilization for two years.

Table 22. Grouping of states by EPSDT utilization.

Group	State
67~100 percentile	VT, SC, WA, NE, TX, NM, IA, IN, NH, MA, NC, RI, WV, OK, AL, GA, AK
34~66 percentile	ME,ID, TN, CO, MN, OH, CT, KS, MI, SD, IL, WY, AZ, VA, MD, MS, NJ
0~33 percentile	CA, LA, PA, OR, DC, ND, MT, NY, AR, MO, UT, DE, WI, NV, FL, KY, HI

3.4 Model and Results

We used individual NCHS survey results data (N=182,257) to fit the model. Self-reported oral and general health is defined into two categories: "Excellent" and "Very Good" are classified as "1", and the others are combined to "0". Since two variables about preventive interventions were collected at the state level, all the data in a same state will have same value of proportion of population receiving fluoridated water (Fluoridation) and the proportion of eligible children receiving preventive dental services with state EPSDT (Utilization). Demographic information, on the other hand, such as age, sex, and race/ethnicity are at the individual level. The model includes three continuous variables (Fluoridation, Utilization, and age), four categorical variables (insurance type, self-reported general health, sex, race/ethnicity), and the two-way interactions between Fluoridation, Utilization, and insurance type (Medicaid, Private, Uninsured). Note that self-reported general health was included in the model since previous research has shown that it is related to self-reported oral health; we therefore wanted to control for the effect.

Table 23 and Table 24 show the summary statistics of the categorical variables and continuous variables. For categorical variables, the group with "Good/Excellent" general health, private insurance, female, and white non-Hispanic will be used as the baseline group for comparison.

Table 23. Summary statistics of the categorical variables.

Variable	Category	2007				2003			
		Frequency	Weighted Frequency	Percent	Std Err of Percent	Frequency	Weighted Frequency	Percent	Std Err of Percent
SROH	Good/Excellent	75919	58332027	84.1	0.36	83051	57295586	83.8	0.23
	Fair/poor	10736	11018135	15.9	0.36	12550	11063310	16.2	0.23
SRGH	Good/Excellent	66060	49066627	70.8	0.42	69732	46792111	68.5	0.28
	Fair/poor	20595	20283536	29.2	0.42	25869	21566785	31.5	0.28
Insurance	Private	61649	43252978	62.4	0.43	67500	43791179	64.1	0.29
	Medicaid	18270	19482156	28.1	0.41	20399	18263737	26.7	0.28
	Uninsured	6736	6615028	9.5	0.28	7702	6303979	9.2	0.18
Sex	Female	41641	33796680	48.7	0.43	46455	33434201	48.9	0.29
	Male	45014	35553482	51.3	0.43	49145	34923583	51.1	0.29
Race	White	63980	45164886	72.3	0.41	71510	45995151	74.7	0.29
	Black	8922	10353379	16.6	0.32	9559	10186702	16.5	0.25
	Multi	4449	3302446	5.3	0.22	3997	2223296	3.6	0.11
	Others	4206	3660715	5.9	0.25	4175	3193162	5.2	0.19

Table 24. Summary statistics of continuous variables.

Variable	2007				2003			
	Mean	Std Error of Mean	Range	N	Mean	Std Error of Mean	Range	N
Fluoridation	0.698	0.002	0.81	95601	0.708	0.003	0.77	86655
Utilization	0.252	0.000	0.311	95601	0.294	0.001	0.388	86655
Age	9.132	0.027	16	95601	9.093	0.043	16	86655

To explain the differential effect of Fluoridation and Utilization among individuals covered by different insurance types, the interactions between Fluoridation and the dummy variables for insurance type (Medicaid × Fluoridation, Uninsured × Fluoridation) , and Utilization and insurance type (Medicaid × Utilization, Private × Utilization) were included. The interactions of Private × Fluoridation, and Uninsured × Utilization will be used as the reference categories for comparison. All of the analysis used sample weights and standard errors accounting for the complex design of the NCHS survey, and year and state fixed effect are included in the model to control for any of their effects.

Table 25 shows statistics for the overall model fit and Table 26 shows the maximum likelihood estimates and odds ratios from the logistic regression model predicting children's oral health score. Chi-square values from three different tests show that we should reject the null hypothesis ($\beta = 0$).

Table 25. Overall model fit statistics.

Number of Observations	Testing Global Null Hypothesis: BETA=0			
	Test	Chi-Square	DF	Pr > ChiSq
182257	Likelihood Ratio	13891950.0	26	<.0001
	Score	14725317.4	26	<.0001
	Wald	3530.0	26	<.0001

Table 26. Estimated parameters, odds ratios and p-values.

Analysis of Maximum Likelihood Estimates							Odds Ratio Estimates		
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Point Estimate	95% Wald Confidence Limits	
Intercept		1	0.217	0.0093	541.9	<.0001	-	-	-
SRGH	Fair/poor (vs. Good/excellent)	1	-0.7285	0.0179	1657.8	<.0001	0.233	0.217	0.25
Insurance	Medicaid (vs. Private)	1	-0.3665	0.1248	8.6	0.0033	0.417	0.301	0.579
	Uninsured (vs. Private)	1	-0.1409	0.1648	0.7	0.3927	0.523	0.32	0.854
Fluoridation		1	0.1242	0.0844	2.2	0.1412	1.132	0.96	1.336
- Medicaid×Fluoridation		1	0.3895	0.1537	6.4	0.0113	1.476	1.092	1.995
- Uninsured×Fluoridation		1	0.399	0.2331	2.9	0.0869	1.49	0.944	2.353
Utilization		1	-1.6623	0.6063	7.5	0.0061	0.19	0.058	0.623
- Medicaid×Utilization		1	1.4412	0.6893	4.4	0.0365	4.226	1.094	16.317
- Private× Utilization		1	1.7724	0.6373	7.7	0.0054	5.885	1.688	20.52
Age		1	-0.0361	0.0026	196.4	0.0012	0.965	0.96	0.969
Sex	Male (vs. Female)	1	-0.059	0.0120	22.0	<.0001	0.888	0.844	0.934
Race	Black (vs. White)	1	-0.1773	0.0333	28.4	<.0001	0.701	0.655	0.751
	Multi (vs. White)	1	0.1729	0.0539	10.3	<.0001	0.996	0.868	1.142
	Others (vs. White)	1	-0.1729	0.0533	10.5	0.0013	0.705	0.616	0.806
Year	2003 (vs.2007)	1	-0.1559	0.0297	27.6	<0.0001	0.856	0.807	0.907

Compared with children covered by private insurance, children covered by Medicaid were less likely to have good oral health, while the effect for uninsured children was insignificant. The reason that the effect of uninsured children is not significant is due to the interaction of Utilization and insurance type; the interactions (Medicaid and Private with Utilization) have significant positive effects as compared to the uninsured group. The model results explain the difference between uninsured and private insurance using the interaction with Utilization rather than the main effect. Even though the main effect of Fluoridation is not significant and Utilization has a negative effect, the interactions with the Medicaid dummy variable for both interventions have positive effects. This implies means that the higher percentages of both variables would improve Medicaid children's oral health status. In addition, demographic variables are significant in this model. For example, older children, males, and being other than non-Hispanic white lowered the chance of having good oral health.

3.5 Chapter Summary

We found that disparities exist in children's oral health based on demographics and insurance type. Water fluoridation has a significant effect on dental status, particularly for Medicaid and uninsured children; the effect is much greater than for children who have a private insurance. This implies that fluoridation helps to achieve equity in children's oral health. According to Healthy people 2020 [1], increasing the proportion of the U.S. population served by community water systems with optimally fluoridated water is an oral health objective. The target is 79.6%, while the current average percentage is 72.4%. In addition, there are several states which have low level of fluoridation. Therefore, fluoridation should remain as a public oral health priority.

The preventive dental care utilization for EPSDT turns out to be significant for Medicaid children's oral health status. This intervention could therefore help to reduce disparities for Medicaid children. A CMS report [62] identified several key barriers to children receiving adequate dental care including limited availability of dental providers, low reimbursement rates, administrative burdens for providers, lack of clear information, inadequate transportation, cultural and language competency, and need for consumer education about the benefits of dental care. These barriers must be addressed to support good oral health outcomes in Medicaid children.

CHAPTER 4

ESTIMATING THE IMPACT OF MEDICAID POLICY ON DENTAL UTILIZATION IN CHILDREN: A SUPPLY AND DEMAND PERSPECTIVE

In chapter 3, we saw that there are disparities in children's oral health outcomes due to insurance type. In particular, Medicaid expansion to cover additional uninsured persons could lead to better outcomes. However, these results would only be realized if supply were available to satisfy the new demand. An alternative approach would be to increase Medicaid reimbursement fees so that more dentists and hygienists accept Medicaid patients. In this chapter, we will develop dental supply and demand estimation models for Medicaid policies. We develop a non-linear programming model, to determine an optimal balanced investment between expanding Medicaid enrollment and increasing the Medicaid reimbursement rate for dental procedures.

A key motivation for the work in the Chapter is the 2013 Oral Health Initiative of the Center for Medicaid and Medicare Services (CMS). The Initiative in to increase access to quality dental care for Medicaid and CHIP enrolled children by at least 10% by 2015 [87]. The outcome of the work in this Chapter will assist states in to how to best meet this goal.

4.1 Literature Review

Oral health was cited as the greatest unmet health need among U.S. children [63]. In addition, disparities are a significant problem in the provision of dental care services [64-68]. For example, non-Hispanic Whites are much less likely to have fair/poor oral health and much more likely to receive preventive care than non-Hispanic Blacks or Hispanics [65]. Further, number of decayed teeth, number of missing teeth, and prevalence of oral health pain have been shown to decrease with income [69]. Even with Medicaid coverage, low income and minority children receive preventive services at a much lower level than their counterparts [70-72], and only four in ten Medicaid enrolled children received some type of preventive dental service in 2010 [73]. Further, the costs of neglected oral disease in childhood can be significant [66].

Medicaid removes most financial barriers for dental care receipt [44, 74]. However, Medicaid programs typically have lower reimbursement rates than the private market [75, 76]. Many studies have found that dentist participation increased with sufficiently high reimbursement rates [44, 75, 77-81]. Low reimbursement rates have also been cited by dentists as a key reason for their lack of participation in state Medicaid programs [82, 83]. However, fee levels alone do not necessarily lead to increased participation by providers; community factors can also play an important role [83, 84]. Expansion of Medicaid through changing eligibility requirements or introducing programs such as State Children's Health Insurance Program (CHIP) have also been shown to effectively increase the percentage of at-risk children that receive preventive dental services [74, 85]. Recent expansion of Medicaid and CHIP has led to a significant increase in enrollees; over one-third of US children were enrolled in Medicaid or CHIP in 2010 [86]. Expansion will likely continue under the Affordable Care Act.

In 2013, the Center for Medicaid and CHIP services (CMCS) as part of the CMS Oral Health Initiative has made access to quality dental care for Medicaid and CHIP enrolled children a priority [87]. Specifically, they desire a 10% increase in the number of Medicaid-enrolled children that receive preventive dental care by 2015. If states are to meet this goal, they will need to implement policies to increase utilization of dental services among this population. Two approaches that can be used are increasing Medicaid reimbursement rates for preventive services and increasing the number of Medicaid/CHIP eligibles.

Mayer et al. [80] used claims data to examine the impact in North Carolina of increasing the nominal Medicaid reimbursement rate by 23% (from 1988-1991) and doubling enrollment through eligibility expansions (from 1985-1991). They found that both changes had an impact on increasing access to dental services among Medicaid eligibles. As with most previous studies, the approach is a retrospective one. At present, no studies exist that provide guidance for states as to how to best design policies to meet the goal.

In this research, we develop a method to estimate the change in children's dental utilization as a result of two aforementioned policies: (1) expanding the number of Medicaid/CHIP eligibles and (2) increasing Medicaid reimbursement levels for procedures. Expanding Medicaid eligibility induces demand of dental care while increasing Medicaid payment levels induces the supply of dental care. We therefore develop supply and demand models for dental services. We then develop an optimization model to determine the best investment strategy across the two policies for a given budget. To the best of our knowledge, this is the first study to include both factors in the analysis in a prescriptive manner.

In the next section we present separate models of dental supply and estimate the parameters from CMS data provided for seven states and national data from the U.S. Health Resources Services Agency (HRSA). In Section 4.3 we present an example for the state of Washington of supply and demand inducement using the developed models. In Section 4.4 we present an optimization model that considers both policies simultaneously and apply it to all seven states. Conclusions are given in Section 4.5.

4.2 Supply and Demand Modeling

In this Section we present supply and demand models for dental services to US children. As mentioned previously, we consider the two state policies of changing the reimbursement rate for a service or the eligibility criteria for Medicaid/CHIP. It should be mentioned that states can influence supply by other means including changing dental practice acts or offering location incentive programs for dentists. Further, states can impact the demand for dental services by community water fluoridation and school sealant programs. However, we will not consider these alternative policies in this work.

Supply of services in a county depends on the dental workforce of that area, the reimbursement rate of the state, and the features of the area. Demand for services depends on the number of Medicaid eligibles in an area, population demographics, and features of the county. Our unit of measure for demand is number of Medicaid/CHIP eligibles, and for supply is potential number of Medicaid/CHIP eligibles that can be served by the participating dental population. Note that the number served in a county will be the minimum of supply of services and demand for services.

4.2.1 Data

Data on the number of Medicaid children who received dental care during a year by state is publicly available from CMS. However, county level data is managed by each state Medicaid agency. We received county-level data from seven states: Alabama (61 counties), Georgia (123 counties), Iowa (99 counties), Louisiana (64 counties), Minnesota (85 counties), Texas (183 counties) and Washington (38 counties) for four years (2007-2010).

The Area Resource File (ARF) data from the U.S. Health Resources Services Agency (HRSA) was used for workforce and demographic data by county over the 4-year period [88]. This includes the number of active dentists, age and gender distribution of dentists, number of eligible Medicaid children, county features of population, median income, number of children in poverty, economic dependent typology, and dental health professional shortage area designation.

The Medicaid/CHIP dental reimbursement level was also used as an explanatory variable. Medicaid Statistical Information System (MSIS) data [89] contains information about state expenditures for children's Medicaid/CHIP dental programs and the number of Medicaid/CHIP dental claims for children during a given year. We divided the expenditures by the number of claims and used it as an average Medicaid dental reimbursement level. Note that all counties in a state have the same reimbursement rate as states set the level.

General features of the county including median income, percent unemployed, rural/urban classification, and dental Health Professional Shortage Area (HPSA) are also important factors. The economic and rural/urban typologies are from the Economic Research Service of the U.S. Department of Agriculture [90]. The economic typology classifies all U.S. counties according to six non-overlapping categories of economic dependence (farming, mining, manufacturing, government, service, and non-specialized), while the rural/urban continuum code classifies counties by population size, degree of urbanization, and adjacency to a metro area. Dental shortage areas (HPSAs) are designated by HRSA if the geographic area has a shortage of dental professionals [91] for the year of interest. Table 27 shows a complete list of all variables and their sources.

Table 27. List of variables.

Variable		Explanation	Source
Continuous	Number of children who get Medicaid dental care		State Medicaid Agencies
	% of children who get Medicaid dental care		State Medicaid Agencies
	Number of dentists		ARF
	Ratio of dentists to population	Number of Dentists/ Population*1000	ARF
	% of male dentists	# Male Dentists/# Dentists	ARF
	% of dentists<age 35		ARF
	% of dentists >age 65		ARF
	Ratio of hygienists to population	# Hygienists/population	ARF
	# of eligible children	# Medicaid Eligible <age 19	ARF
	% of male children		ARF
	% of white children		ARF
	Median age of population		ARF
	% Male		ARF
	% White		ARF
	% <19 without health insurance		ARF
	Median income		ARF
	Population density per sq. mile	Population/land area of county	ARF
	Unemployment rate		ARF
	State average Medicaid fee	Total Medicaid dental expenditure / # claims	MSIS
Binary	Dental HPSA	Dental Health Professional Shortage Area	ARF (HRSA)
	Farming-dependent county	Typology classifies all U.S. counties according to six non-overlapping categories of economic dependence	ARF (Dep. of Agriculture)
	Mining-dependent county		
	Manufacturing-dependent county		
	Government-dependent county		
	Services-dependent county		
	Non-specialized-dependent county		
	Housing stress	Typology classifies all U.S. counties according to seven overlapping categories of policy	ARF (Dep. of Agriculture)
	Low-education		
	Low-employment		
	Persistent poverty		
	Population loss		
	Nonmetro recreation		
	Retirement destination		
	Metropolitan counties(1-3)	By population size	ARF (Dep. of Agriculture)
	Non-metropolitan counties(4-9)	By degree of urbanization and adjacency to a metro area or non-metro areas.	

We divided the data into two groups of counties using the dental HPSA designation as shown in Table 28. HPSA designated counties are categorized into group 1, and we can expect that their dental supply will be less than the demand. The other counties are set as group 2, and their demand will be less than or equal to the supply. Furthermore, we can assume that the number of served children in the data would be determined at the supply level for group 1 and the demand level for group 2. Although we do not have information about the demand level for group 1, we can expect that it will be greater than or equal to supply level. Similarly, the unknown supply level of group 2 would be greater than or equal to the demand level.

Table 28. Grouping of Counties by dental HPSA.

Counties	Supply Estimation Model(SM)	Demand Estimation Model(DM)
GRP1 : HPSA designated counties (Supply<Demand)	Supply= Num. of Served	Demand= Num. of Served + α
GRP2 : (Supply>=Demand)	Supply= Num. of Served +β	Demand= Num. of Served

4.2.2 Model Description

We develop a two-stage model to estimate the number of served children. Figure 15 shows the scope of the estimation model. As the first stage, we will build two different estimation models for supply and demand. We will identify significant independent variables to explain the supply and/or demand for each model. Once the demand and supply level is estimated, the number of children that receive Medicaid dental care can be determined at the estimated supply and demand minimum.

We can expect that the number of dentists should be related to the dental supply. However, we may not see the relationship in counties with a demand shortage. To resolve this problem, we fit the supply model with selected data from counties with supply shortages (group 1). Similarly, we use the data from counties with demand shortages to fit the demand estimation model (group 2). If we use a single model without separating supply and demand, the effects may be confounded, making it difficult to estimate the appropriate parameters. Note that the reimbursement level of the second category and the number of enrollees of the fifth category can be controlled by state policy.

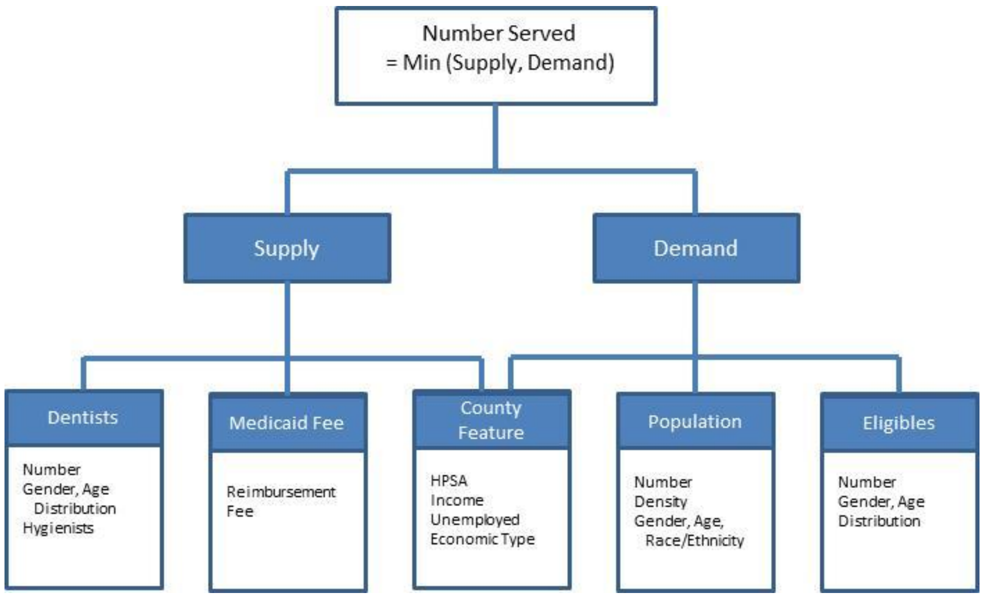


Figure 15. Scope of the estimation model.

4.2.3 Supply Estimation and Inducement

In this section, we present the regression model to estimate the dental supply for Medicaid children using 2007-2009 data. Data from 2010 was saved for model validation presented in the Appendix G. The ratio of dentists to population (per thousand) represents dentist availability. To determine the available dental supply for Medicaid/CHIP children, Dentist Productivity for Medicaid Children (DPMC) is computed in Equation (14). The number of Medicaid children receiving dental service during a given year is divided by the number of dentists, representing the number of Medicaid children that a dentist could see during a year on average.

$$\text{Dentist Productivity for Medicaid Children (DPMC)} =$$

$$\frac{\text{Number of Medicaid children who get dental service during a year}}{\text{Number of Dentists}} \tag{14}$$

We use regression to fit a supply model with DPMC as the dependent variable. We log transformed DPMC to improve the fit. Year and state fixed effects were included in the model to control for any trends and attributes that may affect the DPMC. To fit the supply model, we only used data from group 1 counties. The corresponding model for supply is defined by Equations (15) and (16). Notation is provided in Table 29.

$$\log(\text{DPMC}) = \beta_0 + \sum_{i=1}^{23} \beta_i x_i \tag{15}$$

$$\text{Supply} = \text{Number of Dentists} \times \exp(\beta_0 + \sum_{i=1}^{23} \beta_i x_i) \tag{16}$$

Table 29 shows summary of regression results (N=1182) including parameter estimates and *p*-values of significant effects. The adjusted R-squared value was 0.91. The diagnostic plots are provided in the Appendix I. Note that the plots show that the standard regression assumptions were satisfied.

Counties with higher Medicaid reimbursement fees are more likely to have higher dentist productivity for Medicaid children, which means that financial support could lead to increased dental professional participation in the program. According to the definition, the dentist to population ratio has a negative effect with DPMC. However, we found that the interactions of Medicaid reimbursement fees and the log of dentist ratio has a positive effect with DPMC, which means that the effect of Medicaid reimbursement fees is higher in the counties having more dentists.

Table 29. Regression results for supply model.

i	Variable ($\mathbf{x_i}$)		Parameter Estimate ($\boldsymbol{\beta_i}$)	Standard Error	t Value	Pr > |t|
0	Intercept		9.517	0.162	58.67	<.0001
1	Main	Medicaid Reimbursement Fee	0.005	0.002	2.34	0.0195
2		Log (Dentist ratio)	-1.175	0.037	-31.82	<.0001
3		% of dentists >age 65	-0.129	0.049	-2.62	0.009
4		Hygienists to Population	-0.00009	0.000	-1.01	0.3137
5		Unemployment rate	0.023	0.005	4.64	<.0001
6		Number of FQHCs	0.102	0.021	4.97	<.0001
7		Median Income	-2.521	0.376	-6.7	<.0001
8		Economic type: Farming	0.078	0.025	3.14	0.0017
9		Economic type: Government	-0.795	0.184	-4.33	<.0001
10	Interactions	Medicaid Fee ×Log (Dentist ratio)	0.002	0.000	6.7	<.0001
11		Log (Dentist ratio) × Hygienists	0.021	0.010	2.03	0.0431
12		Log (Dentist ratio) ×Number of FQHCs	-0.022	0.005	-4.39	<.0001
13		Log (Dentist ratio) ×Income	0.247	0.102	2.42	0.0155
14		Log (Dentist ratio) × Government	0.088	0.038	2.3	0.0214
15		Medicaid Fee × Government	0.007	0.003	2.54	0.0112
16	Year	Year2008	0.016	0.027	0.6	0.5509
17		Year2009	0.050	0.036	1.38	0.1693
18	State	State AL	-0.600	0.038	-15.93	<.0001
19		State GA	-0.291	0.050	-5.86	<.0001
20		State IA	-0.469	0.034	-13.78	<.0001
21		State LA	-0.358	0.041	-8.75	<.0001
22		State MN	-0.665	0.035	-19.08	<.0001
23		State TX	-0.127	0.041	-3.13	0.0018

Dentists over the age 65 are less likely to serve Medicaid children. The rate of hygienists to population has no significant effect while the interaction with dentist ratio shows a positive significant effect. This implies that hygienists are required with dentists to affect supply (i.e., together they make a Leontief input-output model). The effect increases as both the number of dentists and hygienists increase. The unemployment rate is positively related with DPMC so that counties with higher unemployment rate are more likely have a higher supply for Medicaid children, *ceteris paribus*. The number of Federally Qualified Health Centers (FQHCs) has a positive effect while the interaction of FQHCs with dentist ratio shows a negative effect. This implies that the increase in DPMC from FQHCs decreases as the number of dentists increases. Similarly, the main effect of median income is negatively related with DPMC while the interaction with dentist ratio shows a positive relationship. Counties with higher income are more likely have less DPMC, and this decreasing rate is slightly diminished if the counties have more dentists. In a related way, dentists tend to locate in counties with higher median income. Among the six non-overlapping economic dependent typologies, only farming and government dependent counties have significant effects. Farming dependent counties have higher supply and government dependent counties have lower supply than other counties. In addition to, the negative relation of government dependent counties becomes weaker as the number of dentists and/or Medicaid/CHIP fees increase, since the interactions between these factors and government dependent economic factors are positively related. There are no significant year effects, but all the state effects are significant (Washington being the baseline).

We excluded group 2 counties from the regression model since we assumed they had supply shortages. To see if this assumption holds, we used a *t*-test to compare the actual mean value of the DPMC from the group 2 data to the estimated DPMC of group 2 using the supply estimation model with the estimated parameters. We found a difference in the means at the 95% level.

We can use the developed supply model to estimate the induced supply that would result from a state increasing the dental Medicaid/CHIP reimbursement level. For the supply estimation model, the reimbursement level was one of the significant control variables. In Equation (15), it is related with the first term of main effects and the tenth and fifteenth term of the interactions with the dentist ratio and government dependent economic county. We can expand the supply estimation model as follows:

$$\log(\text{DPMC}) = \beta_0 + \beta_1(\mathbf{x_1} + \mathbf{Y}) + \beta_2 x_2 + \cdots \beta_9 x_9$$

$$+\beta_{10}(\mathbf{x_1} + \mathbf{Y})x_2 + \cdots + \beta_{15}(\mathbf{x_1} + \mathbf{Y})x_9 \quad + \textstyle\sum_{i=16}^{23} \beta_i\, x_i \tag{17}$$

where x_1 = Medicaid reimbursement level , $x_2 = \log(\text{Dentist ratio})$, $\beta_1 = 0.005$, $\beta_{10} = 0.002$, $\beta_{15} = 0.007$ and other β_i, x_i values are found in Table 29. If we increase the reimbursement level, the response variable would increase (+0.005/ unit), but also the increasing rate will grow by the dentist ratio (+0.002/unit). Consequently, counties with a higher dentist ratio could receive larger effects for increasing reimbursement levels. If we increase the reimbursement level by Y, the estimated log transformed DPMC will be (after rearranging terms):

$$\log(\text{DPMC}) = \text{Y}(\beta_1 + \beta_{10}x_2 + \beta_{15}x_9) + \textstyle\sum_{i=0}^{23} \beta_i\, x_i \tag{18}$$

Since the response variable was a log transformed DPMC, the equation should be an exponential function of additional reimbursement level (Y) shown in Equation (19).

$$\begin{aligned} \text{Supply} &= \text{DPMC} \times \text{Num of Dentists} \\ &= \exp\left\{\text{Y}(\beta_1 + \beta_{10}x_2 + \beta_{15}x_9) + \textstyle\sum_{i=0}^{23} \beta_i\, x_i\right\} \times \text{Num of Dentists} \\ &= \alpha \exp(\gamma \mathbf{Y}) \end{aligned} \tag{19}$$

where α and γ are calculated by:

$$\alpha = \exp\left(\textstyle\sum_{i=0}^{23} \beta_i\, x_i\right) \times \text{Num of Dentist} \tag{20}$$

$$\gamma = \beta_1 + \beta_{10}x_2 + \beta_{15}x_9 \tag{21}$$

For counties with sufficient supply, an increase in supply would not change the number served. For the counties with a supply shortage, the new number served will be determined at the demand level, and a supply increase is effective in increasing number served.

The total cost for the investment is calculated by multiplying the new level of number served by the new reimbursement fee $(Y + f)$ and average dental visits per beneficiary V, as shown in Equation (22). If we increase the Medicaid fee, we pay not only for the incremental number of served children, but the increase also applies to current utilizers since this is a state decision. Therefore, as the existing number of beneficiaries grows, the average cost per improvement would increase. Additional investments are calculated using Equation (23) and the average cost for increasing the number served is calculated using Equation (24).

$$\text{Total Cost} = \sum\nolimits_{i=\text{county}} (z_i + s_i)\,(Y + f)\,V \tag{22}$$

$$\text{Additional Cost} = \sum\nolimits_{i=\text{county}} z_i\,(Y + f)\,V + s_i\,YV \tag{23}$$

$$\text{Average Cost} = \frac{\sum_{i=\text{county}} z_i\,(Y+f)V + s_i Y\,V}{\sum_{i=\text{county}} z_i} \tag{24}$$

where Y = Additional Medicaid reimbursement fee, f = Current Medicaid reimbursement fee, z_i = Increment of # served in county i, s_i = Number of Served in county i before inducing supply, V = average dental visits per beneficiary (based on MSIS data [89]).

4.2.4 Demand Estimation and Inducement

We similarly built a regression model to estimate dental demand for Medicaid/CHIP eligible children. Utilization of dental services is calculated by dividing the number of children that received at least one Medicaid/CHIP dental service by the number of eligible children.

$$\text{Utilization} = \frac{\#\text{ Children who served at least one Medicaid dental service}}{\#\text{ Elgibles}} \tag{25}$$

The number of eligible children can be changed by the state policies of Medicaid/CHIP eligibility for dental services. The demand model is given by (notation in Table 30):

$$\text{Utilization} = \beta_0 + \sum_{i=1}^{22} \beta_i x_i \tag{26}$$

$$\text{Demand} = \text{Number of Eligible} \times \left(\beta_0 + \sum_{i=1}^{22} \beta_i x_i \right) \tag{27}$$

Utilization is the dependent variable and the variable categories provided in Figure 15 were used for the independent variables. In addition, year and state fixed effects were included to control for any trends and attributes that may affect utilization. To fit the demand model, we only used data from group 2 counties where the supply is greater than the demand. Table 30 shows regression summary results and parameter estimates and *p*-values. Data from 950 counties are used for the demand estimation model and the adjusted R-square value was 0.50. The diagnostic plots are provided in the Appendix J. Note that the plots show that the standard regression assumptions were satisfied.

Not surprisingly, counties with a higher percentage of eligible children are more likely to have higher utilization of services. Metropolitan county types are all significant and counties with larger population have larger positive. The main effect of the government dependent economic variable has a negative effect while the interaction with the percent of eligible children shows a positive effect. The government dependent economic counties are more likely to have a higher percentage of eligible children than other counties. Counties of service dependent economic and retirement destination are more likely have a higher utilization. The main effects of the percent of uninsured children and low employment are insignificant, although some of their interactions are significant. The interaction between percent eligible children and percent uninsured children has a negative effect meaning that the increasing effect of eligible children decreases when there are more uninsured children in a county. In addition, if counties have government dependent economic structure or are designated as low employment area, the utilization decreases in the percent of uninsured children.

Table 30. Regression results for demand model.

i	Variable (x_i)		Para. Estimate (β_i)	Standard Error	t Value	Pr > |t|
0	Intercept		0.536	0.054	9.96	<.0001
1	Main	% of Eligible Children	0.323	0.116	2.79	0.0054
2		% Male	-0.337	0.092	-3.66	0.0003
3		Metropolitan type: Population >1M	0.027	0.005	4.9	<.0001
4		Metropolitan type:0.25M< Pop.<1M	0.016	0.007	2.2	0.028
5		Metropolitan type: Pop. <0.25M	0.018	0.005	3.39	0.0007
6		Economic type: Government	-0.068	0.021	-3.26	0.0012
7		Economic type: Service	0.023	0.008	2.99	0.0029
8		Policy type: Retirement Destination	0.016	0.004	3.55	0.0004
9		Policy type: Low Employment	0.032	0.021	1.52	0.1277
10		% Uninsured Children	0.001	0.001	0.93	0.3544
11	Interactions	% of Eligible × Government	0.715	0.146	4.91	<.0001
12		% Uninsured × % Eligible	-0.012	0.006	-1.93	0.0544
13		% Uninsured × Government	-0.003	0.001	-2.81	0.0051
14		% Uninsured × Low Employment	-0.003	0.001	-2.61	0.0093
15	Year	Year 08	0.014	0.004	3.6	0.0003
16		Year 09	0.046	0.004	11.31	<.0001
17	State	State AL	-0.057	0.022	-2.62	0.0089
18		State GA	-0.035	0.019	-1.78	0.0748
19		State IA	0.063	0.021	3.07	0.0022
20		State LA	-0.105	0.022	-4.84	<.0001
21		State MN	-0.079	0.020	-3.99	<.0001
22		State TX	-0.052	0.020	-2.62	0.0089

We tested the assumption that for group 1 counties demand would be greater than or equal to the number served since it is limited by supply. To test this assumption, we used a *t*-test to compare the actual mean value of utilization from the group 1 county data to the estimated utilization of group 1 counties using the demand estimation model with the estimated parameters. The means were significantly different at the 95% level.

The demand model can be used to estimate the demand induced by expanding Medicaid/CHIP eligibility. For this model, the ratio of eligible children to population was the first significant control variable x_1, and has significant interaction effects with sixth and tenth variables. The ratio was calculated by dividing the number of eligible children by the total population of children. If we increase the number of Medicaid eligibles by E, then the new ratio of eligible children will be $x_1 + \frac{E}{t}$, where t represents the population of children, and the estimated utilization will be determined by (after arranging terms):

$$\text{Utilization} = E\left(\frac{\beta_1+\beta_{11}x_6+\beta_{12}x_{10}}{t}\right) + \sum_{i=0}^{22} \beta_i x_i \qquad (28)$$

Since demand is defined as the utilization multiplied by the number of eligibles, the demand equation should be quadratic in the additional number of eligible children (E) as shown in Equation (29).

$$\begin{aligned} \text{Demand} &= \text{Utilization} \times \text{Num of Eligible} \\ &= (E + x_1 t)\left\{E\left(\frac{\beta_1+\beta_{11}x_6+\beta_{12}x_{10}}{t}\right) + \sum_{i=0}^{22} \beta_i x_i\right\} \\ &= \rho \mathbf{E}^2 + \sigma \mathbf{E} + \tau \qquad (29) \end{aligned}$$

where constants $\rho, \sigma,$ and τ are defined by:

$$\rho = \frac{\beta_1+\beta_{11}x_6+\beta_{12}x_{10}}{t} \qquad (30)$$

$$\sigma = \sum_{i=0}^{22} \beta_i \, x_i + (\beta_1 + \beta_{11} x_6 + \beta_{12} x_{10}) \, x_1 \tag{31}$$

$$\tau \;=\; x_1 t \sum_{i=0}^{22} \beta_i \, x_i \tag{32}$$

Increasing the number of eligible children does not always lead to an increase in the number of children served, since the number served is determined as the minimum of supply and demand. For the counties with enough demand, a policy inducing demand would not make any difference. The policy of inducing demand would only be helpful for counties with a demand shortage. The total cost for this type of investment is composed of the enrollment cost for incremental enrollment and the reimbursement cost for incremental beneficiaries as shown in Equation (33). The average cost for increasing the number served is calculated in Equation (34).

$$\text{Total Cost} \;=\; C\,E + \sum_{i=\text{county}} z_i \;f\; V \tag{33}$$

$$\text{Average Cost} \;=\; \frac{C\,E + \sum_{i=\text{county}} z_i \, fV}{\sum_{i=\text{county}} z_i} \tag{34}$$

where C= Average Medicaid enrollment cost per child, z_i =Increment of # served in county i, f = Current reimbursement fee, V=Average dental visits per beneficiary. According to Kaiser [92], the average cost for a child enrollee is in the range $1500 to $2500. We therefore assume that the enrollment cost is at least $1500. Also the average dental visits per beneficiary (V) is determined from the MSIS data [89].

4.3 Medicaid/CHIP Policy

In this section we apply the supply and demand models from Section 4.2 to the seven states to see the impact of raising Medicaid/CHIP reimbursement levels and of expanding the number of Medicaid/CHIP eligibles. An integrated model for both policies is presented in Section 4.4.

4.3.1 Supply Inducement Results

We first illustrate with a simple example for 10 counties in the state of Washington. Full results are given in the Appendix K. Table 31 shows the result of supply inducement by increasing the Medicaid reimbursement fee by $10. Column (A), (B) and (C) are supply, demand, and the number of children served in each county before taking any intervention. As previously discussed, the number of beneficiaries (C) is determined at the minimum of supply and demand. Column (D)-(I) explain changes from the intervention of increasing the reimbursement fee by $10. If we increase the reimbursement fee, DPMC will be increased by (D), and supply is also increased by (E) according to the Equation (19). The new number of beneficiaries (G) is the minimum of the new supply (F) and demand (B), and the difference between column (C) and column (G) will be the incremental beneficiary (H). The cost for the intervention (I) is calculated by Equation (22).

Table 31. Example of supply inducement effect (State of Washington).

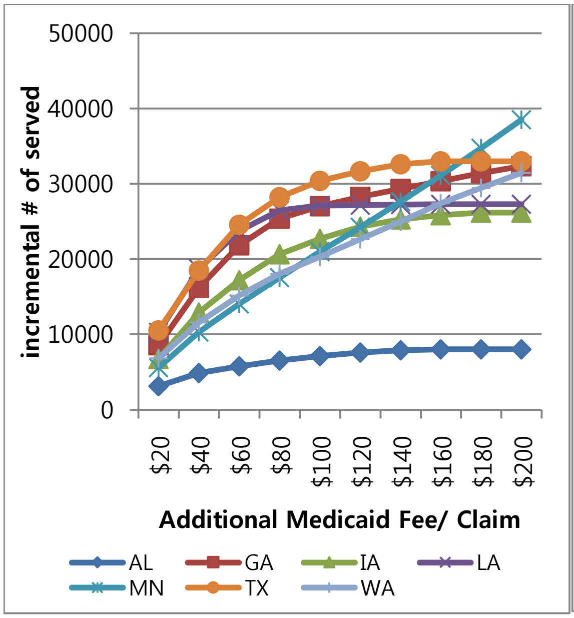
County	No intervention			Intervention : Increase Reimbursement fee (+$10)					
	Supply (A)	Demand (B)	Beneficiary (C)	Incremental DPMC (D)	Incmt. Supply (E)	New supply (F)	New beneficiary (G)	Incmt. Beneficiary (H)	Cost (I)
1	1320	3412	1320	5.2	73	1392	1392	73	114,795
2	1637	1523	1523	9.9	60	1697	1523	-	106,620
3	11638	14053	11638	3.4	428	12066	12066	428	946,630
4	5326	7125	5326	4.4	223	5549	5549	223	441,612
5	4595	3906	3906	3.4	224	4818	3906	-	273,451
6	29092	28421	28421	2.7	841	29933	28421	-	1,989,439
7	359	239	239	9.3	19	378	239	-	16,703
8	7997	8340	7997	5.8	265	8262	8262	265	641,281
9	2920	3222	2920	5.6	128	3048	3048	128	243,846
10	492	535	492	10.9	22	513	513	22	41,108
State Total (Average cost/Incremental beneficiary)								3,565	21,442,098 (6,014)

In this example, the first county's supply is less than demand before the fee is increased, so the intervention has an effect that 73 additional children get served. However, in the second county that already has enough supply, the intervention has no effect and incremental benefits will be zero. Since increasing the reimbursement fee is a decision at the state level, an additional cost has risen for all counties. As an aggregated result, Washington could serve 3,565 additional beneficiaries with a $21M budget by taking a policy of increasing the reimbursement fee by $10. The average cost for one incremental beneficiary is $6,014.

To apply the approach to all seven states, we used ten different increment levels of Medicaid reimbursement from $20 to $200. Figure 16A shows the increment of the number served as the Medicaid reimbursement fee increases. From Equation (19), the supply should increase exponentially in reimbursement level. However, the increment of number served increases at a decreasing rate (Figure 16A). This is because only part of the supply can be transformed to served children due to the counties' demand status. Figure 16A shows unmet demands for each state in the study. All of the lines with a terminating point stop at the maximum demand for the state. For example, Alabama unmet demand for the state is less than 10,000. Meanwhile, Minnesota and Washington do not have a terminating point, which means they still have available demand even after increasing the reimbursement level by $200. Georgia, Texas, Iowa, and Louisiana show similar results, which have 2,500-3,500 of unmet demand.

Figure 16B represents the average cost to improve one additional beneficiary. Georgia and Texas show a higher average cost in 16B, even though they have a larger increment for the beneficiary than other states in the interval between $20-$160. This is because Georgia and Texas have a larger number of existing dental beneficiaries (s_i), which leads to a higher cost for the existing number served (s_i Y) than in other states, and they should spend more of the state budget on increasing the reimbursement fee. As shown in 16B, Alabama, Georgia, and Texas need more investment to increase the number served, whereas Iowa and Minnesota have better cost effectiveness than other states.

<Figure16A. Effect of Supply Inducement> <Figure16B. Average cost of Supply Inducement>



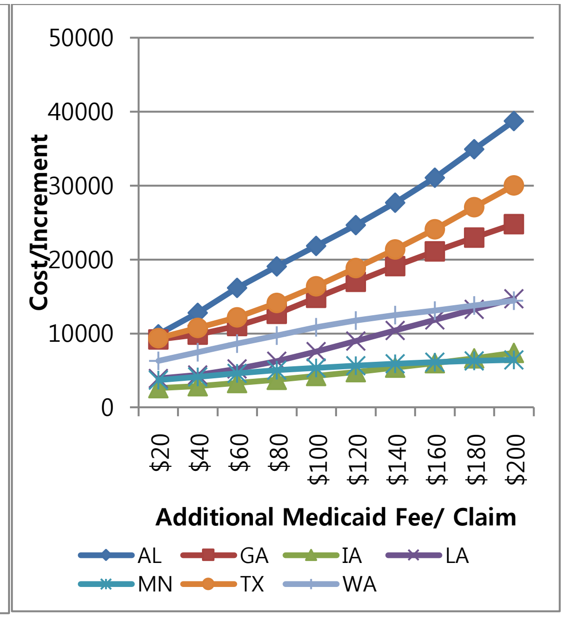


Figure 16. Results for supply inducement.

4.3.2 Demand Inducement Results

Table 32 shows the results for the same 10 counties in Washington from Section 3.1 when Medicaid/CHIP enrollment is increased by 10,000 children. Full results are given in the Appendix L. Column (A), (B) and (C) are supply, demand, and the number of children served in each county before taking any intervention. Column (D)-(J) explain changes from the intervention of increasing enrollment. Column (D) is the distributed incremental enrollment in each county and is weighted by the number of uninsured children in the county. If we increase enrollment by (D), utilization (E) and demand (F) are also increased according to the Equations (26) and (27). Comparing the supply (A) and new demand (G), the new number of beneficiaries (H) is determined. The cost for the intervention (J) is calculated by Equation (33).

Table 32. Example of demand inducement effect (State of Washington).

County	No intervention			Intervention : Increase enrollment(+10,000)						
	Supply (A)	Demand (B)	Beneficiary (C)	Incmt. Enroll (D)	Incmt. util (E)	Incmt. demand (F)	New demand (G)	New beneficiary (H)	Incmt. Benef. (I)	Cost (J)
1	1320	3412	1320	69.7	0.000015	43	3455	1320	-	104,550
2	1637	1523	1523	38.0	0.000020	21	1544	1544	21	62,062
3	11638	14053	11638	358.6	0.000002	203	14256	11638	-	537,900
4	5326	7125	5326	208.3	0.000005	122	7247	5326	-	312,450
5	4595	3906	3906	144.6	0.000007	77	3984	3984	77	235,283
6	29092	28421	28421	857.7	0.000001	471	28891	28891	471	1,398,612
7	359	239	239	8.7	0.000118	5	243	243	5	14,156
8	7997	8340	7997	203.4	0.000004	114	8454	7997	-	305,100
9	2920	3222	2920	116.4	0.000009	65	3287	2920	-	174,600
10	492	535	492	21.6	0.000057	11	546	492	-	32,400
State Total (Average cost/incremental beneficiary)									3,256	15,774,589 (4,845)

The counties that have enough supply (2, 5, 6, 7) can supply additional beneficiaries by taking this intervention. New Medicaid enrollment leads to an expense even when enrollment does not lead to a dental service, and it increases the average cost. As an aggregated result, Washington produces 3,256 new beneficiaries with a $15M budget when is increased Medicaid enrollment by 10,000 individuals. The average cost for one incremental beneficiary is $4,845.

We examined the effect of ten different levels of eligible children increments from 100K to 1M on new Medicaid dental beneficiaries. Figure 17A shows the increment of number served as Medicaid/CHIP eligibility is expanded. Similar to Figure 16A, demand is only realized when supply is available, and the rate increases in a decreasing rate of additional enrollment. Figure 17B shows the change in the average cost from one additional beneficiary. Georgia and Texas show increased cost effectiveness when compared to other states for inducing demand, whereas Iowa and

Minnesota do not have enough additional available supply, and hence show relatively poorer cost effectiveness.

<Figure17A. Effect of demand Inducement> <Figure17B. Avg. cost of Demand Inducement>

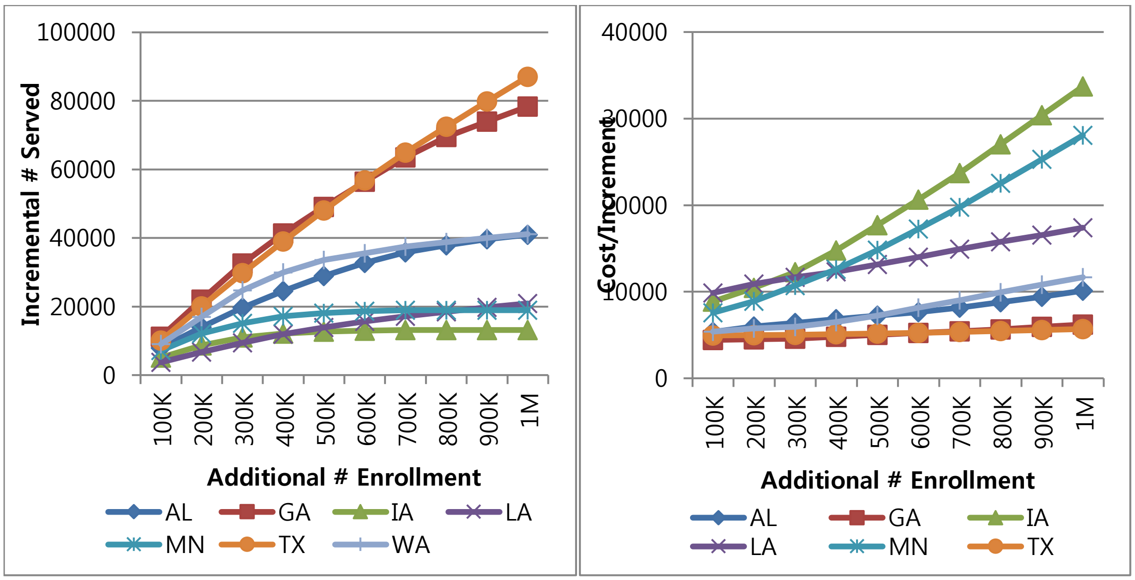


Figure 17. Results for demand inducement.

4.4 Integrated Model to Maximize the Number of Children Served

In Section 4.3, we investigated how two interventions affect children's dental outcomes. The model we have developed has some restrictions. First, it is difficult to decide which intervention is more effective since the total budget is not a controlling variable but an outcome related with several other variables. Second, we need an approach to consider the tradeoffs between two interventions if offered simultaneously. To resolve this limitation, we develop an optimization model to maximize the impact of a budget increase. In this section, data from 2010 is used as it is the most recent data available.

4.4.1 Optimization Model

The objective is to maximize the incremental number of Medicaid children who receive dental services, as specified by the CMS Oral Health Initiative [87] subject to allowable budget. The index, decision variables, parameters, and optimization model are as follows:

Index

i County

Decision Variables

E Incremental number of Medicaid enrollment of state

e_i Incremental number of Medicaid enrollment in county i

Y Additional Medicaid Reimbursement fee

z_i Incremental number of served children in county i

Parameters

f Current Medicaid Reimbursement fee

C Medicaid enrollment cost per enrollment

V Average dental visits per beneficiary

B Budget

s_i Number of Existing Served Children

w_i Counties' weight for uninsured children ($\sum_i w_i = 1$)

Model

$$\max \sum_i z_i \tag{35}$$

$$\sum_i \{C\,\mathbf{e_i} + \mathbf{z_i}\,(\mathbf{Y} + f)V + s_i\mathbf{Y}V\} \leq B \tag{36}$$

$$\mathbf{e}_i = E\,w_i \qquad \text{for all i} \tag{37}$$

$$\mathbf{z_i} + s_i \leq \alpha_i \exp(\mathbf{Y}\gamma_i) \qquad \text{for all i} \tag{38}$$

$$\mathbf{z_i} + s_i \leq \rho_i \mathbf{e_i}^2 + \sigma_i \mathbf{e_i} + \tau_i \qquad \text{for all i} \tag{39}$$

$$\sum_i w_i = 1 \tag{40}$$

In the model, equation (36) is the budget constraint. The total cost is composed of the enrollment cost for new enrollees, the new reimbursement fee for dental visits from new beneficiaries, and the incremental reimbursement cost for dental visits from existing beneficiaries. Since both z_i and Y are decision variables, this constraint is nonlinear. Equation (37) ensures that new enrollees come from uninsured children. In this constraint, w_i is the counties' weight for uninsured children Equation (40) ensures that the sum of the weights is 1 across all counties. Equations (38) and (39) ensure that the new number of served children $(z_i + s_i)$ is determined at the minimum of estimated supply and demand. The term $\alpha_i \exp(Y\gamma_i)$ is the estimated supply and $\rho_i {e_i}^2 + \sigma_i e_i + \tau_i$ is the estimated demand. Note that all of the nonlinear constraints are convex functions of the decision variables.

4.4.2 Results

We solved the non-linear program using data from the seven states with the NLP solver in SAS/OR. Thirty-five instances of the model are considered by applying five different levels of the total budget from \$10M to \$100M to the problems of seven states that are mutually independent. Table 33 shows the solution summary. The number of variables, constraints, and nonlinear constraints are also listed in the table. It takes approximately 25 min (approximately 10,000 iterations) to solve the largest problem, which was Texas. For states with fewer counties such as Alabama, Iowa, and Minnesota, we can calculate the optimal solutions in less than five minutes.

The solution summary shows that the optimal policy of two different interventions: the additional reimbursement level (Y), and additional enrollment (E). The optimal investment in Alabama is found by both increasing the reimbursement level and expanding enrollment. Alabama has balanced demand and supply, so policies of inducing supply and demand are both effective for all budget levels. Georgia and Texas show similar patterns of optimal solution by investing all budgets to induce demand. The optimal solution of Iowa's problem with a budget of \$10M or \$30M is entirely focused on inducing supply. As the budget increases above \$30M, the investment to induce demand also becomes effective. Therefore, Iowa does not have enough dental supply and the investment should focus on inducing supply until a balance of supply and demand is found. Louisiana and Minnesota show similar patterns, while Washington shows the opposite result to Iowa. The optimal investment for Washington is with a budget of \$10M to induce demand, since Washington has more counties with a demand shortage. After resolving this shortage problem, we would also invest in a policy to induce supply. The average number of improvements based on optimal investments from the model is also listed. Washington could make additional improvements with the same budget when compared to other states, while Georgia and Texas show worse improvement.

Table 33. Integrated solution summary.

State	Budget	Problem Summary						Solution Summary			
								Interventions		Objective	
		Num. of Variables	Num. of Constraints	Nonlinear Con.	Optimality Error	Infeasibility	Iterations	SUPPLY Add. Med.Fee (Y)	DEMAND Add. Enrollment (E)	Avg. # Served	Avg. # Improvement (z)
AL	10M	552	612	184	0.00	0.00	25	1	5640	3538	35
	30M				0.00	0.00	72	5	14066	3599	96
	50M				0.00	0.00	52	9	22402	3660	156
	70M				0.00	0.00	130	13	31005	3719	216
	100M				0.00	0.00	158	18	43742	3809	306
GA	10M	1110	1232	370	0.02	0.02	10000	0	6117	4371	19
	30M				0.89	0.02	10000	0	18292	4408	55
	50M				0.14	0.02	10000	0	99743	4443	91
	70M				26.54	0.02	10000	0	42323	4479	126
	100M				0.85	0.02	10000	0	61421	4532	180
IA	10M	894	992	298	0.00	0.00	52	11	0	1123	39
	30M				0.00	0.00	67	33	0	1193	109
	50M				0.00	0.00	132	51	2514	1245	161
	70M				0.00	0.00	140	64	15975	1284	200
	100M				0.00	0.00	159	89	23580	1337	253
LA	10M	498	552	166	3.10	0.03	10000	5	289	4667	51
	30M				0.03	0.03	10000	15	0	4760	144
	50M				0.03	0.03	10000	25	238	4841	225
	70M				3.37	0.03	10000	34	104	4915	299
	100M				29.34	0.03	10000	46	13946	5017	401
MN	10M	768	852	256	0.00	0.00	55	10	0	1586	34
	30M				0.00	0.00	176	29	0	1644	92
	50M				0.00	0.00	271	47	2	1689	137
	70M				0.00	0.00	121	35	58394	1722	171
	100M				0.00	0.00	149	48	82201	1788	236
TX	10M	1650	1832	550	0.13	0.07	10000	0	19373	3675	11
	30M				0.07	0.07	10000	0	59436	3697	32
	50M				0.07	0.07	10000	0	99276	3719	55
	70M				0.07	0.07	10000	0	138742	3742	77
	100M				0.08	0.08	10000	0	199756	3775	110
WA	10M	345	382	115	0.03	0.03	10000	0	20187	7703	55
	30M				0.31	0.03	10000	2	54006	7808	159
	50M				0.03	0.03	10000	6	76633	7907	259
	70M				0.03	0.03	10000	9	99055	8007	359
	100M				0.03	0.03	10000	15	132322	8155	506

Figure 18 shows the examples of Iowa and Washington. The vertical axis represents county average improvement. For Washington, investing all resources in expanding enrollment is better than investing in increasing reimbursement fees. For Iowa, supply inducement by increasing reimbursement fees is better than demand inducement. The optimal solutions show the best improvement for all the cases.

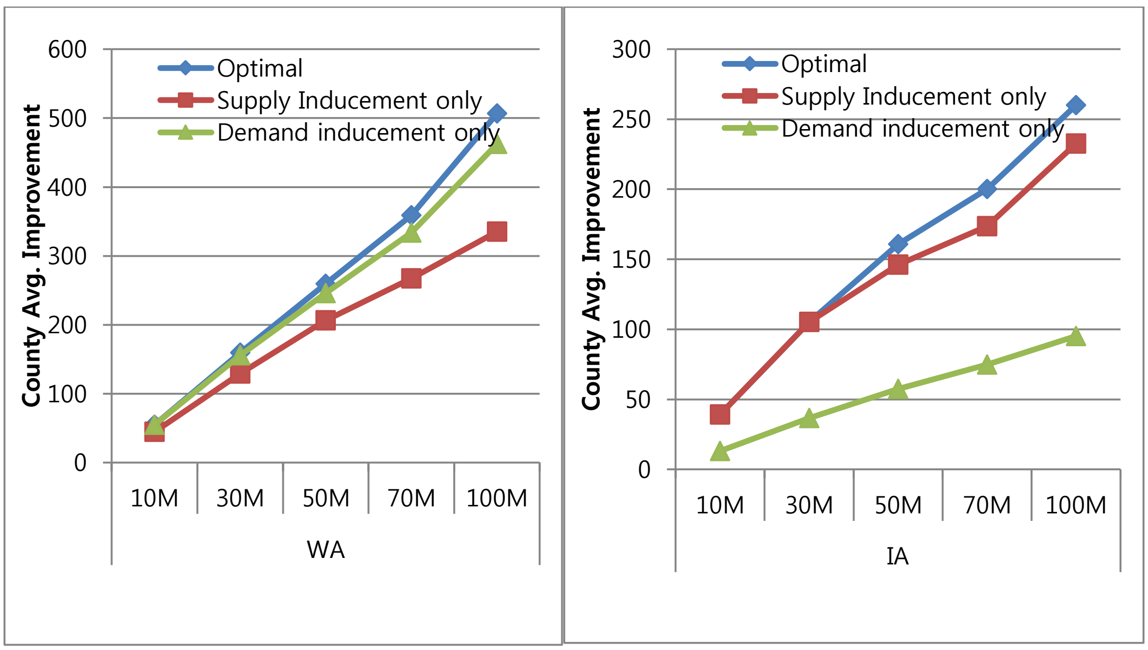


Figure 18. Comparison of optimal solutions for Washington and Iowa.

4.5 Chapter Summary

In this research, we developed a supply and demand model based on a regression model using CMS to explain Medicaid/CHIP eligible children's utilization of dental services. Using these models, we assessed the interventions of expanding Medicaid eligibility to induce demand and increasing Medicaid reimbursement levels to induce supply. In order to find a balanced investment between the two interventions considering dental supply and demand level in each state, an optimization model was developed. We solved several instances for seven states with data from 2010 and found the best policies for each.

One of benefits of the model that we developed is to make more detailed analysis possible, since it not only explains dental supply and demand separately, but also estimates dental outcomes at the county level. If we do not separate supply and demand or conduct aggregated state level analysis, a major effect could be lost and incorrect conclusions can be drawn. In addition, the methodology we suggested to assess interventions is helpful to understand what happens in different counties when we apply a health policy at the state level.

It is important to note that there were several state differences in the results. Results from one state are not necessarily applicable to others. This emphasizes the importance of prescriptive decision support models as opposed to a reliance on a few retrospective studies. In addition, results from this study should not be directly applied to states not in the study.

There are, however, several limitations to this study. First, the mean parameter values are used, and the estimation error is not considered in any of the models. If the approach were modified to include estimation errors, then confidence intervals could be developed for the results. Second, we assume that counties are managed independently, that is, they do not share dental supply or demand. This assumption is violated if patients from one county seek dental care in another county. Data was not available to develop a model to estimate between county movement.

In spite of these limitations, the methodology we suggest in this research is useful to support decision making for each state. It may also be easily extended to other states with county-level Medicaid/CHIP data. Further, the research is novel in that it is the first attempt to model supply and demand explicitly from actual data in order to accurately assess the impact of state policies.

CHAPTER 5

CONCLUSIONS AND FUTURE RESEARCH

In this dissertation we have shown how mathematical models and cost effective analysis can be used to solve various public health care issues. In addition, we have provided strategies to address the key research challenges of i) specifying an appropriate quantitative objective, ii) developing a framework to compare access and insurance on the same scale, and iii) building an integrated supply and demand model that considers complex interactions. Unlike previous research, we not only found key reasons that explain disparities, but more importantly suggested feasible and efficient interventions and strategies that can be used to reduce them. This analysis of the costs and outcomes of comparative interventions is essential for policy makers to make informed decisions about using health care resources efficiently. In this Chapter, we conclude by summarizing the key contributions and suggest future research topics.

Table 34. Summary of chapters.

Chapter	Target	Methodology	Interventions to reduce disparities
Chapter 2	Uninsured Underserved	Multi Criteria Optimization model Utility based Analysis	Optimal location of FQHCs Balanced investment on FQHCs and Medicaid
Chapter 3	Children	Logistic Regression	Utilization and Fluoridation
Chapter 4	Low income Children	Regression Nonlinear optimization model	Balanced investment on expanding Medicaid enrollment and Increasing reimbursement rate

We have built a multi-criteria optimization model for a balanced investment in FQHCs and Medicaid that also identifies the optimal FQHC locations and services to provide. A benefit of the optimization model used in this work is that it considers the entire FQHC organizational network in its solutions including geographical information, local estimates of need, and current health care access and coverage status. In addition, a utility approach was used to compare FQHC and Medicaid expansion in the same framework. We recommend that the current coverage status should be considered as factor, since FQHCs play a more important role in primary care for uninsured patients. We believe that this model, which considers both access and coverage information, can help policy analysts make better decisions to address health care disparities.

We analyzed NSCH data and found that there is inequality in children's oral health outcomes based on insurance type. We built a regression model to predict the health score using interventions and demographic information. Water fluoridation has a significant effect on oral health status, particularly for Medicaid and uninsured children. Preventive dental care utilization for EPSDT also turns out significant for Medicaid children's oral health status. The results show that it can also be a very critical intervention to reduce the disparities for Medicaid children.

Finally, we developed a regression model to explain children's dental health outcomes and assess two different interventions of expanding Medicaid eligibility and increasing Medicaid reimbursement levels. Moreover, we find a balanced investment between these two interventions considering dental supply and demand level in each state by introducing a NLP optimization model. We solved examples for seven states with 2010 data from CMS, and found the optimal solutions. One of benefits of the model is to make more detailed analysis possible, since it not only explains dental supply and demand separately, but also estimates dental outcomes at the county level. If we do not separate the supply and demand or conduct aggregated state level analysis, a major effect could be lost and an incorrect conclusion could be generated. Also the methodology we suggested to assess interventions is helpful to understand what happens in different counties when we apply a health policy at the state level.

There are several opportunities for future research. For the optimization model described in Chapter 2, we assumed there is sufficient health workforce capacity. However, both Medicaid and FQHC expansion would require additional healthcare workers. This would be similar to the work performed in Chapter 4; determining how to properly consider workforce capacity would be an important extension. Performing this is a more complicated health care setting is difficulty since supply and demand are for multiple conditions which may have co-morbidities.

Further, one limitation in Chapter 2 is that we estimated the likelihood of visit by travel distance based on a decreasing function of distance, with the maximum distance defined by the guidelines. However, we can expect the visits by travel distance could also depend on socio-demographic factors. If we could collect appropriate data and find significant relationships, the model in chapter 2 would provide better demand estimates.

Further, we do not explicitly model other safety net providers such as hospital sponsored outpatient clinics. We also assumed that the services they provide are independent of FQHC or Medicaid expansion. We were not able to find data that would allow us to add this level of complexity including other safety net providers in the model is another potentially fruitful, though challenging, avenue.

In Chapter 2, we modeled the state of Pennsylvania. It would not be appropriate to conclude that the results would be similar for all other states. Therefore, it is important in the future to obtain data from other states and apply the methodology. Similarly, more data from other states could improve the results for the model described in Chapter 4.

We have focused on cost-effectiveness analysis throughout this dissertation. However, more cost-effective care does not necessarily mean better health care. Using the health care expenditures as a measure of an intervention helps with the analysis, but there could be other measures that better represent individual health outcomes. Developing such measures could be very helpful. Furthermore, we limited target group to low income and residents in rural areas in chapter 2, and low income children in chapter 3 and 4. We can expand the problems to other vulnerable populations such women, racial and ethnic minorities, and older adults.

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APPENDIX A. NHANES QUESTIONNAIRE

NHANES QUESTION (General Care)

MCQ.010 Has a doctor or other health professional **ever** told {you/SP} that {you have/s/he/SP has} asthma (**az**-ma)?

CAPI INSTRUCTION:
IF SP AGE >= 12, DISPLAY SP NAME AND "S/HE":
IF SP AGE < 12, DISPLAY "YOU" AND SP NAME.

HELP SCREEN:
Asthma: Asthma is a condition that affects your airways.that carry air in and out of your lungs. It causes symptoms like wheezing (a whistling sound when you breathe), coughing, chest tightness, and trouble breathing,

INTERVIEWER: DO NOT ACCEPT SELF-DIAGNOSED OR DIAGNOSED BY A PERSON WHO IS NOT A DOCTOR OR OTHER HEALTH PROFESSIONAL.

YES	1	
NO	2	(MCQ.053)
REFUSED	7	(MCQ.053)
DON'T KNOW	9	(MCQ.053)

MCQ.220 {Have you/Has SP} **ever** been told by a doctor or other health professional that {you/s/he} had cancer or a malignancy (ma-**lig**-nan-see) of any kind?

HELP SCREEN:
Cancer: An abnormal uncontrolled growth of tissue that has potential to spread to distant sites of the body, also known as a malignant tumor.

Malignancy: A tumor or growth that is cancerous. (see Cancer)

YES	1	
NO	2	(MCQ.245)
REFUSED	7	(MCQ.245)
DON'T KNOW	9	(MCQ.245)

MCQ.080 Has a doctor or other health professional **ever** told {you/SP} that {you were/s/he/SP was} overweight?

YES	1
NO	2
REFUSED	7
DON'T KNOW	9

DIQ.010 {Other than during pregnancy, {have you/has SP}/{Have you/Has SP}} **ever** been told by a doctor or other health professional that {you have/{he/she/SP} has} diabetes or sugar diabetes?

CAPI INSTRUCTION:
IF SP AGE < 15, DISPLAY "HAS SP" FOR THE FIRST DISPLAY AND "SP HAS" FOR THE SECOND DISPLAY.
IF SP IS FEMALE AND AGE >= 20, DISPLAY "OTHER THAN DURING PREGNANCY, {HAVE YOU/HAS SP}".

YES	1	
NO	2	(BOX 4)
BORDERLINE OR PREDIABETES	3	(BOX 4)
REFUSED	7	(BOX 4)
DON'T KNOW	9	(BOX 4)

KIQ.022 {Have you/Has SP} **ever** been told by a doctor or other health professional that {you/s/he} had weak or failing kidneys? Do not include kidney stones, bladder (**bladd**-er) infections, or incontinence (in-**kon**-ti-nens).

YES	1	
NO	2	(KIQ.026)
REFUSED	7	(KIQ.026)
DON'T KNOW	9	(KIQ.026)

BPQ.020 {Have you/Has SP} **ever** been told by a doctor or other health professional that {you/s/he} had hypertension (hy-per-**ten**-shun), also called high blood pressure?
IF HIGH BLOOD PRESSURE **ONLY** DURING PREGNANCY, CODE NO.

INTERVIEWER INSTRUCTION: IF SP SAYS "HIGH NORMAL BLOOD PRESSURE", "BORDERLINE HYPERTENSION" OR "PREHYPERTENSION" CODE NO.

YES	1	
NO	2	(BPQ.052)
REFUSED	7	(BPQ.052)
DON'T KNOW	9	(BPQ.052)

PFQ.020 {Do you/Does SP} have an impairment or health problem that limits {your/his/her} ability to {crawl, walk or play} {walk, run or play} {walk or run}?

CAPI INSTRUCTION:
IF CHILD'S AGE = 1-4, DISPLAY "CRAWL, WALK OR PLAY". IF CHILD'S AGE = 5-15, DISPLAY "WALK, RUN OR PLAY". IF SP'S AGE = 16-19, DISPLAY "WALK OR RUN".

YES	1	
NO	2	(BOX 1BB)
REFUSED	7	(BOX 1BB)
DON'T KNOW	9	(BOX 1BB)

AUQ.191 In the **past 12 months**, {have you/has SP} been bothered by ringing, roaring, or buzzing in {your/his/her} ears or head **that lasts for 5 minutes or more**?

YES	1	
NO	2	(AUQ.211)
REFUSED	7	(AUQ.211)
DON'T KNOW	9	(AUQ.211)

HSQ.510 Did {you/SP} have a stomach or intestinal illness with vomiting or diarrhea that started during those 30 days?

YES	1
NO	2
REFUSED	7
DON'T KNOW	9

HSQ.520 Did {you/SP} have flu, pneumonia, or ear infections that started during those 30 days?

YES	1
NO	2
REFUSED	7
DON'T KNOW	9

HCQ.030 Was the test result in our letter the first time you were told (you had/SP has) hepatitis C?

1. Yes (HCQ.070)
2. No
7. Refused (HCQ.070)
9. Don't know (HCQ.070)

NHANES QUESTION (Oral Care)

OHQ.620 How often during the last year {have you/has SP} had painful aching anywhere in {your/his/her} mouth? Would you say . . .

HAND CARD OHQ1

Very often,	1
Fairly often,	2
Occasionally,	3
Hardly ever, or	4
Never?	5
REFUSED	7
DON'T KNOW	9

OHQ.630 How often during the last year {have you/has SP} felt that life in general was less satisfying because of problems with {your/his/her} teeth, mouth or dentures?

HAND CARD OHQ1

VERY OFTEN,	1
FAIRLY OFTEN,	2
OCCASIONALLY,	3
HARDLY EVER, OR	4
NEVER?	5
REFUSED	7
DON'T KNOW	9

OHQ.640 How often during the last year {have you/has SP} had difficulty doing {your/his/her} usual jobs or attending school because of problems with {your/his/her} teeth, mouth or dentures?

HAND CARD OHQ1

VERY OFTEN,	1
FAIRLY OFTEN,	2
OCCASIONALLY,	3
HARDLY EVER, OR	4
NEVER?	5
REFUSED	7
DON'T KNOW	9

OHQ.650 How often during the last year {has your/has SP's} sense of taste been affected by problems with {your/his/her} teeth, mouth or dentures?

HAND CARD OHQ1

VERY OFTEN,	1
FAIRLY OFTEN,	2
OCCASIONALLY,	3
HARDLY EVER, OR	4
NEVER?	5
REFUSED	7
DON'T KNOW	9

OHQ.660 How often during the last year {have you/has SP} avoided particular foods because of problems with {your/his/her} teeth, mouth or dentures?

HAND CARD OHQ1

VERY OFTEN,	1
FAIRLY OFTEN,	2
OCCASIONALLY,	3
HARDLY EVER, OR	4
NEVER?	5
REFUSED	7
DON'T KNOW	9

OHQ.670 How often during the last year {have you/has SP} found it uncomfortable to eat any food because of problems with {your/his/her} teeth, mouth or dentures?

HAND CARD OHQ1

VERY OFTEN,	1
FAIRLY OFTEN,	2
OCCASIONALLY,	3
HARDLY EVER, OR	4
NEVER?	5
REFUSED	7
DON'T KNOW	9

NHANES QUESTION (Mental Care)

HSQ.480 Now thinking about {your/SP's} mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was {your/his/her} mental health not good?

CAPI INSTRUCTION:
HARD EDIT VALUES: 0-30.

|___|___|
ENTER # OF DAYS

REFUSED	77
DON'T KNOW	99

ALQ.150 Was there ever a time or times in {your/SP's} life when {you/he/she} **drank 5 or more drinks** of any kind of alcoholic beverage **almost every day**?

YES	1
NO	2
REFUSED	7
DON'T KNOW	9

DUQ.240 Have you **ever** used cocaine, crack cocaine, heroin, or methamphetamine?
(Target 12-69)
INSTRUCTIONS TO SP:
Please select . . .

Yes	1	
No	2	(DUQ.370)
REFUSED	7	(DUQ.370)
DON'T KNOW	9	(DUQ.370)

DUQ.250_ The following questions are about cocaine, including all the different forms of cocaine such as powder, 'crack', 'free base', and coca paste.

DUQ.250 Have you **ever**, even once, used cocaine, in any form?
(Target 12-69)
INSTRUCTIONS TO SP:
Please select . . .

Yes	1	
No	2	(DUQ.290)
REFUSED	7	(DUQ.290)
DON'T KNOW	9	(DUQ.290)

DUQ.270 G/Q/U How long has it been since you **last** used cocaine, in any form?

INSTRUCTIONS TO SP:
Please enter the number of days, weeks, months, or years, then select unit of time.

CAPI INSTRUCTIONS:
If SP Ref/DK then store 7/9 in DUQ.270G and DUQ.270U, 7/9-fill in DUQ.270Q
If a value is entered in Quantity and Unit store Quantity in DUQ.270Q, Unit in DUQ.270U and 1 in DUQ.270G
HARD EDIT: Response must be equal to or less than current age minus DUQ.260.
Error message: "Your response to time of last use is earlier than your response to age of first use. Please press the "Back" button, press "Clear," and try again."

|___|___|___|
ENTER NUMBER OF DAYS, WEEKS, MONTHS, OR YEARS

REFUSED 777
DON'T KNOW 999

ENTER UNIT

Days 1
Weeks 2
Months.. 3
Years 4
REFUSED 7
DON'T KNOW 9

DUQ.272 During your **life**, altogether how many times have you used cocaine, in any form?

INSTRUCTIONS TO SP:
Please select one of the following choices.

Once 1
2-5 times... 2
6-19 times... 3
20-49 times... 4
50-99 times... 5
100 times or more................................. 6
REFUSED 77
DON'T KNOW 99

APPENDIX B. DETAILED DATA FOR DEMAND ESTIMATION

Table1. Questions used for demand estimation of general care

Disease	NHANES Variable	Question
Arthritis	MCQ160A	Doctor ever said you had arthritis
Asthma	MCQ010	Ever been told you have asthma
Back of neck problem	PFQ020	Have back or neck problem
Blood Pressure	BPQ020	Ever told you had high blood pressure
BMI	MCQ080	Doctor ever said you were overweight
Cancer	MCQ220	Ever told you had cancer or malignancy
Cardiovascular	CDQ001	Ever had pain or discomfort in chest
Diabete	DIQ010	Doctor told you have diabetes
emphysema	MCQ160G	Ever told you had emphysema
Flu/Pneumonia/Ear Infection	HSQ520	Ever have flu, pneumonia, ear infection?
Hearing	AUQ191	Ears ringing, roaring, buzzing past year
Hepatitis C	HCQ030	Ever told had hepatitis C?
Kidney	KIQ022	Ever told you had weak/failing kidneys
Stomach/Intestinal	HSQ510	Ever have stomach or intestinal illness?
Stroke	MCQ160F	Ever told you had a stroke
Thyroid	MCQ160M	Ever told you had a thyroid problem

Table 2. Results from logistic regression model predicting demand of general care

Var.	Categories	Estimated Parameters	Odds Ratio			P value
			Point	95% C.L		
Age	**Age 19- (vs. Age 65+)**	**-1.5275**	**0.038**	**0.031**	**0.047**	**<.0001**
	Age 19-64 (vs. Age 65+)	**-0.2199**	**0.14**	**0.115**	**0.171**	**<.0001**
Sex	**Male (vs. Female)**	**-0.0709**	**0.868**	**0.767**	**0.982**	**0.0245**
Race	**Mexican/Hispanic (vs. White)**	**-0.2812**	**0.541**	**0.442**	**0.664**	**<.0001**
	Black (vs. White)	0.0307	0.739	0.615	0.889	0.7009
	Others (vs. White)	-0.0821	0.660	0.480	0.908	0.4573
Poverty Level	FPL100%- (FPL200%+)	-0.0624	0.845	0.652	1.096	0.4403
	FPL 100~200%(FPL200%+)	-0.0434	0.861	0.718	1.033	0.4673

Table 3. Probability of demographic group as general disease prevalence

Poverty Level	White		Black		Mexican/Hispanic		Others	
	Female	Male	Female	Male	Female	Male	Female	Male
Age 19-	0.468	0.433	0.386	0.354	0.311	0.282	0.364	0.332
Age 19-64	0.767	0.741	0.702	0.672	0.628	0.595	0.682	0.651
Age 65+	0.958	0.953	0.943	0.935	0.922	0.911	0.938	0.929

Table4. Questions used for demand estimation of mental health care

Disease	NHANES Variable	Question
Mental	HSQ480	No. of days mental health was not good
Drug	DUQ240	Used cocaine/heroin/methamphetamine
	DUQ290	Used heroin
	Q330	Used methamphetamine
Alcohol	ALQ150	Have 5 or more drinks every day?

Table 5. Results from logistic regression model predicting demand of mental care

Var.	Categories	Estimated Parameters	Odds Ratio			P value
			Point	95% C.L		
Age	Age 19- (vs. Age 65+)	-0.0208	1.535	1.082	2.178	0.8316
	Age 19-64 (vs. Age 65+)	**0.4702**	**2.508**	**2.028**	**3.102**	**<.0001**
Sex	Male (vs. Female)	-0.0256	0.95	0.813	1.111	0.5205
Race	Mexican/Hispanic (vs. White)	-0.1607	0.589	0.467	0.744	0.1345
	Black (vs. White)	0.0392	0.72	0.618	0.839	0.4072
	Others (vs. White)	**-0.2465**	**0.541**	**0.411**	**0.711**	**0.0273**
Poverty Level	**FPL100%- (FPL200%+)**	**0.2755**	**1.917**	**1.552**	**2.369**	**0.0002**
	FPL 100~200%(FPL200%+)	0.0999	1.609	1.338	1.934	0.1451

Table 6. Probability of demographic group as mental disease prevalence

Age	Poverty Level	White		Black		Mexican/Hispanic		Others	
		Female	Male	Female	Male	Female	Male	Female	Male
19-	FPL100%-	0.180	0.173	0.137	0.131	0.115	0.110	0.106	0.101
	FPL 100~200%	0.156	0.149	0.117	0.112	0.098	0.094	0.091	0.087
	FPL200%+	0.103	0.098	0.076	0.073	0.063	0.060	0.058	0.056
19~64	FPL100%-	0.264	0.254	0.205	0.197	0.175	0.167	0.163	0.156
	FPL 100~200%	0.231	0.223	0.178	0.171	0.151	0.144	0.140	0.134
	FPL200%+	0.158	0.151	0.119	0.114	0.099	0.095	0.092	0.088
65+	FPL100%-	0.125	0.120	0.093	0.089	0.078	0.074	0.072	0.069
	FPL 100~200%	0.107	0.102	0.080	0.076	0.066	0.063	0.061	0.058
	FPL200%+	0.069	0.066	0.051	0.049	0.042	0.040	0.039	0.037

To estimate the demand for general services, we multiply the number of people likely to use a clinic estimated by demographics by the likelihood of visiting a doctor in the last year, and then multiply by the average number of annual general care encounters per general service user in 2008, which was 3.01.

To estimate the demand for dental services, we scale the dental demand by likely clinic use and then multiply by the average number of annual dental encounters per dental user in 2008, which was 2.50.

For OBGyn services, we scale the number of pregnancies by likely clinic use and then multiply by seven (half of the number of visits recommended by the American College of Obstetricians and Gynecologists, as many women receiving care at CHCs do not visit until their second or third trimester and may not visit as frequently as recommended), to obtain an estimate for number of encounters.

To estimate the demand in number of encounters for mental health and substance abuse services, we scale by likely clinic use and multiply by 5.99, which was the average number of annual mental health encounters per mental health user in Pennsylvania in 2008.

APPENDIX C. ESTIMATES OF COEFFICIENTS IN THE OBJECTIVE FUNCTION FROM GRIFFIN, ET AL.

In NHANES, we define SRGH at three levels: 1=excellent or very good, 2=good, and 3=fair or poor. In addition, for each of the conditions considered, each person (N=9461) in the survey was asked if they have been told by a physician that they have the condition. NHANES also contains full sociodemographic data including income, race/ethnicity, age, and gender. We use SAS-callable SUDAAN to perform a logistic regression with the final model. The reference group was non-Hispanic whites with income greater than 200% of the federal poverty level (FPL) since the remaining significant sociodemographic factors in the final model were race and income. The odds-ratios, corresponding weights, and prevalence values are given in Table 1 for the health conditions. All were significant at the 5% level. The impact of each condition on SRGH is simply the inverse of the odds ratio, and these define the weights of our objective function. Our objective then is to maximize the number of annual weighted patient encounters, summed over the various locations and services. This is in essence equivalent to maximizing SRGH for the community over the set of services the CHCs offer. We treat OB/Gyn first as high importance (equal to the highest weight), due to prenatal care being an important service for CHCs to provide (http://bphc.hrsa.gov/chc/programexpectations.htm).

Table 1: Association between health conditions and self- reported general health (Logistic Regression, all significant at the 5% level), weights, and prevalence

Disease	Odds Ratio	Weight	Prevalence(SE)
Intercept	15.01		
Arthritis	0.65	1.54	21.80(0.71)
Asthma or bronchitis	0.56	1.79	6.12(0.31)
Back or neck problem	0.47	2.13	8.76(0.40)
Blood pressure/Hypertension	0.557	1.75	23.19(0.84)
Body Mass Index	0.96	1.04	30.17(0.93)
Cancer	0.59	1.69	8.09(0.41)
Cardiovascular	0.42	2.38	6.93(0.42)
Depression	0.59	1.69	9.35(0.48)
Diabetes	0.34	2.94	6.68(0.33)
Emphysema	0.21	4.76	1.64(0.17)
Flu/Pneumonia/Ear infection	0.89	1.06	4.81(0.33)
Hearing	.48	2.08	1.42(0.16)
Hepatitis C	0.59	1.69	2.02(0.19)
Poor Oral Health	0.46	2.17	34.75(1.12)
Stomach/Intestinal	0.81	1.23	9.24(0.48)
Stroke	0.49	2.04	2.46(0.20)
Thyroid condition	0.79	1.27	4.94(0.29)

APPENDIX D. OPTIMIZATION MODEL FROM GRIFFIN, ET AL.

Indices

i locations index (Note: we also use z when we are comparing two locations)

j services index

k index of levels for each service

l index on distance levels (Note: we also use q when summing on a subset of distance levels)

Decision variables

y_{izjl} patients from z who are served by a center in i for service type j and within distance category l from their location (relaxed to linear)

s_{ijk} binary indicator variable of service type j at level k in location i

c_i integer variable for number of centers in location i

Parameters

w_j the weight associated with serving a customer of type j

P_l the maximum percentage of one county's population that can be served in another county if those two counties are distance level l apart

n_{ij} need (demand) for service j in i

d_{izjl} maximum demand for service type j in location i that can be served in location z.

(=$P_l n_{zj}$ if the distance between i and z corresponds to level l, 0 otherwise)

CAP_{jk} number of patients of service type j that can be served at level k

B budget

FL_i Fixed cost for location i

FS_{jk} Fixed cost for service j at level k

VS_{ij} Variable cost for service j at i after patient/insurance reimbursement

Model

$$\max \quad \sum_{izjl} w_j y_{izjl} \tag{1}$$

$$\sum_{i} FL_i c_i + \sum_{ijk} FS_{ij} s_{ijk} + \sum_{izjl} VS_{ij} y_{izjl} \leq \quad B \tag{2}$$

$$\sum_{zl} y_{izjl} \leq \sum_{k} CAP_{jk} s_{ijk} \qquad \textit{for all } i, j \tag{3}$$

$$\sum_{k} s_{ijk} \leq c_i \qquad \textit{for all } i, j \tag{4}$$

$$y_{izjl} \leq d_{izjl} \qquad \textit{for all } i, z\, j, l \tag{5}$$

$$\sum_{l \geq q, i} y_{izjl} \leq P_q n_{zj} \qquad \textit{for all } z, j, q \tag{6}$$

$$y_{izjl} \geq 0 \tag{7}$$

$$s_{ijk} \ \in \{0,1\} \tag{8}$$

$$c_i \qquad integer \tag{9}$$

The objective is to maximize the total weighted number of patients served. Constraint (2) is the budget constraint and constraint (3) that patients can only be served if there is capacity available for them at that service level. Constraint (4) states that there can only be as many locations offering service type *j* as there are open locations, and, combined with constraint (3), implicitly requires that patients of type *j* can be served at facility *I* only if that center is open and offering service *j*. Constraint (5) only allows the proportion of patients that are eligible based on the distance calculation to be served. Constraint (6) enforces the maximum total percentage of location *i*'s population served by locations more than each distance level away.

APPENDIX E. LOGISTIC REGRESSION RESULTS

The SURVEYLOGISTIC Procedure

Model Information

Data Set	WORK.T4	
Response Variable	sroh	
Number of Response Levels	2	
Weight Variable	nschwt	NSCH Final Weight
Model	Binary Logit	
Optimization Technique	Fisher's Scoring	
Variance Adjustment	Degrees of Freedom (DF)	

Variance Estimation

Method	Taylor Series
Variance Adjustment	Degrees of Freedom (DF)

Number of Observations Read	182257
Number of Observations Used	170521
Sum of Weights Read	1.3771E8
Sum of Weights Used	1.2379E8

Response Profile

Ordered Value	sroh	Total Frequency	Total Weight
1	good/excellent	129636	89371587
2	fair/poor	40885	34418919

Probability modeled is sroh='good/excellent'.

NOTE: 11736 observations were deleted due to missing values for the response or explanatory variables.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	146343709	132451811
SC	146343719	132452082
-2 Log L	146343707	132451757

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	13891950.0	26	<.0001
Score	14725317.4	26	<.0001
Wald	3530.0151	26	<.0001

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
srgh	1	1657.8370	<.0001
insurance	2	29.9100	<.0001

utilization	1	7.5162	0.0061
fluoridation	1	2.1652	0.1412
Medicaid_util	1	4.3721	0.0365
Private_util	1	7.7347	0.0054
Uninsured_util	0	.	.
Medicaid_fluoride	1	6.4203	0.0113
Uninsured_fluoride	1	2.9310	0.0869
Private_fluoride	0	.	.
race	3	121.7876	<.0001
age	1	196.3975	<.0001
sex	1	21.9843	<.0001
ts2	1	27.6231	<.0001
cs4	1	9.9709	0.0016
cs20	1	9.8888	0.0017
cs22	1	23.5926	<.0001
cs29	1	4.2120	0.0401
cs31	1	26.6304	<.0001
cs34	1	13.2243	0.0003
cs40	1	9.1020	0.0026
cs12	1	6.5079	0.0107
cs19	1	13.7236	0.0002
cs21	1	8.2904	0.0040
cs47	1	28.1699	<.0001

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	0.4307	0.1185	13.2120	0.0003
srgh	fair/poor	1	-0.7285	0.0179	1657.8370	<.0001
insurance	Medicaid	1	-0.3665	0.1248	8.6265	0.0033
insurance	No	1	-0.1409	0.1648	0.7306	0.3927
utilization		1	-1.6623	0.6063	7.5162	0.0061
fluoridation		1	0.1242	0.0844	2.1652	0.1412
Medicaid_util		1	1.4412	0.6893	4.3721	0.0365
Private_util		1	1.7724	0.6373	7.7347	0.0054
Uninsured_util		0	0	.	.	.
Medicaid_fluoride		1	0.3895	0.1537	6.4203	0.0113
Uninsured_fluoride		1	0.3990	0.2331	2.9310	0.0869
Private_fluoride		0	0	.	.	.
race	Black	1	-0.1773	0.0333	28.3765	<.0001
race	Multi	1	0.1729	0.0539	10.2864	0.0013
race	Others	1	-0.1729	0.0533	10.5345	0.0012
age		1	-0.0361	0.00257	196.3975	<.0001
sex	Female	1	0.0605	0.0129	21.9843	<.0001
ts2		1	-0.1559	0.0297	27.6231	<.0001
cs4		1	-0.2046	0.0648	9.9709	0.0016
cs20		1	0.1973	0.0627	9.8888	0.0017
cs22		1	0.2914	0.0600	23.5926	<.0001
cs29		1	-0.1120	0.0546	4.2120	0.0401
cs31		1	0.3337	0.0647	26.6304	<.0001
cs34		1	-0.2425	0.0667	13.2243	0.0003
cs40		1	0.1900	0.0630	9.1020	0.0026
cs12		1	0.1815	0.0711	6.5079	0.0107
cs19		1	0.2520	0.0680	13.7236	0.0002
cs21		1	0.1682	0.0584	8.2904	0.0040
cs47		1	0.4273	0.0805	28.1699	<.0001

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
srgh	fair/poor vs good/excellent	0.233	0.217	0.250
insurance	Medicaid vs Private	0.417	0.301	0.579
insurance	No vs Private	0.523	0.320	0.854
utilization		0.190	0.058	0.623
fluoridation		1.132	0.960	1.336
Medicaid_util		4.226	1.094	16.317
Private_util		5.885	1.688	20.520
Medicaid_fluoride		1.476	1.092	1.995
Uninsured_fluoride		1.490	0.944	2.353
race	Black vs White	0.701	0.655	0.751
race	Multi vs White	0.996	0.868	1.142
race	Others vs White	0.705	0.616	0.806
age		0.965	0.960	0.969
sex	Female vs Male	1.129	1.073	1.187
ts2		0.856	0.807	0.907
cs4		0.815	0.718	0.925
cs20		1.218	1.077	1.377
cs22		1.338	1.190	1.505
cs29		0.894	0.803	0.995
cs31		1.396	1.230	1.585
cs34		0.785	0.689	0.894
cs40		1.209	1.069	1.368
cs12		1.199	1.043	1.378
cs19		1.287	1.126	1.470
cs21		1.183	1.055	1.327
cs47		1.533	1.309	1.795

APPENDIX F : DEFINITION OF COUNTY TYPOLOGY CODES

The 2004 County Typology Codes are from Economic Research Service (ERS), U.S. Department of Agriculture, www.ers.usda.gov. The typology classifies all U.S. counties according to six non-overlapping categories of economic dependence and seven overlapping categories of policy-relevant themes.

Economic Types:

- *Farming-dependent*: Either 15 percent or more of average annual labor and proprietors' earnings derived from farming during 1998-2000 or 15 percent or more of employed residents worked in farm occupations in 2000.
- *Mining-dependent*: 15 percent or more of average annual labor and proprietors' earnings derived from mining during 1998-2000.
- *Manufacturing-dependent*: 25 percent or more of average annual labor and proprietors' earnings derived from manufacturing during 1998-2000.
- *Federal/State Government-dependent*: 15 percent or more of average annual labor and proprietors' earnings derived from Federal and State government during 1998-2000.
- *Services-dependent*: 45 percent or more of average annual labor and proprietors' earnings derived from services (SIC categories of retail trade; finance, insurance and real estate; and, services) during 1998-2000.
- *Nonspecialized-dependent*: County did not meet the dependence threshold for any one of the above industries.

Policy Types (these indicators are not mutually exclusive)**:**

- *Housing stress:* 30 percent or more of households had one or more of these housing conditions in 2000: lacked complete plumbing, lacked complete kitchen, paid 30 percent or more of income for owner costs or rent, or had more than 1 person per room.

- *Low-education*: 25 percent or more of residents 25 through 64 years old had neither a high school diploma nor GED in 2000.
- *Low-employment*: Less than 65 percent of residents 21 through 64 years old were employed in 2000.
- *Persistent poverty*: 20 percent or more of residents were poor as measured by each of the last 4 censuses: 1970, 1980, 1990 and 2000.
- *Population loss*: Number of residents declined both between the 1980 and 1990 censuses and between the 1990 and 2000 censuses.
- *Nonmetro recreation*: Classified using a combination of factors, including share of employment or share of earnings in recreation-related industries in 1999, share of seasonal or occasional use housing units in 2000, and per capita receipts from motels and hotels in 1997.
- *Retirement destination*: Number of residents 60 and older grew by 15 percent or more between 1990 and 2000 due to immigration.

The Rural/Urban Continuum Codes:

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

- NONMETROPOLITAN 9:Completely rural or less than 2,500 urban population, not adjacent to a metro area

APPENDIX G: MODEL VALIDATION

Using the estimated supply and demand from Section 2, we can set the number of served children as the minimum. To validate this two-step model presented in the paper (A), we developed a new regression model (B) that directly estimates the number served regardless of supply and demand and compared the results. Figure 1 shows the differences in the approaches to estimate the number of Medicaid/CHIP eligibles served between models A and B. Data from 2010 is used for validation. Note that this data was not included in the models developed in Section 4.2.

For model B, the log function of the number of served children who received dental Medicaid service was set as the dependent variable. To fit model B, data from 2007-2009 and all of the counties were included, unlike in model A, which only used data from the group 1 counties. All of the variable categories listed in Figure 1, significant interactions in the supply and demand estimation model, and year and state effects, are considered as possible independent variables.

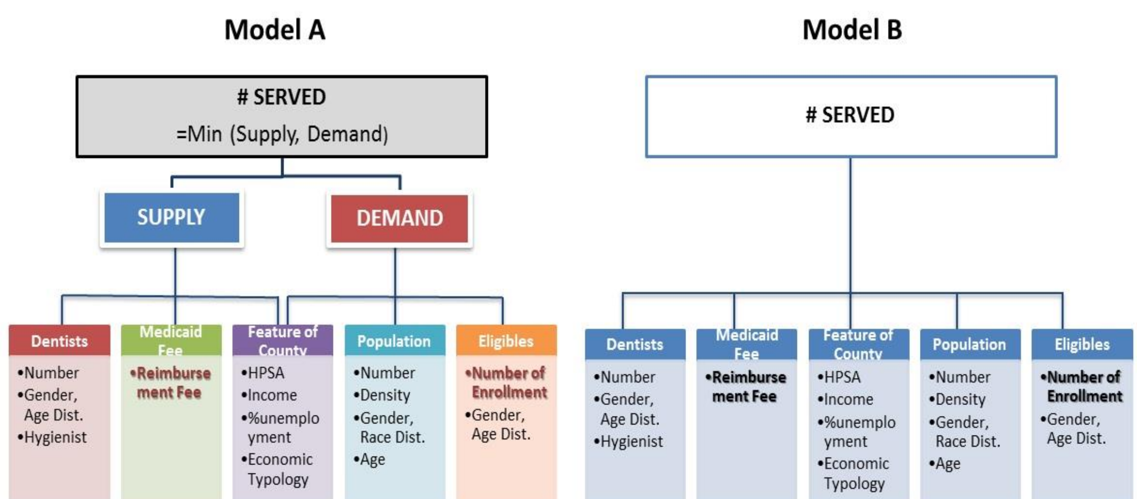


Figure 1. Estimation models A and B.

Table 1. Regression results from Model B.

Num of data	Root MSE	R-Square	Adj R-Sq	Analysis of Variance					
				Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
2304	0.66671	0.7822	0.7795	Model	28	3632.02	129.71	291.82	<.0001
				Error	2275	1011.25	0.44451		
				Total	2303	4643.27			

Table 2. Parameter Estimates of Predicting # of Served Children in Model B.

Variable		Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept		3.409	0.213	16.00	<.0001
Main	Dental HPSA	0.100	0.032	3.10	0.0020
	Log (Dentist ratio)	0.453	0.018	24.96	<.0001
	Number of Hygienist	0.004	0.000	21.32	<.0001
	% of Eligible Children	13.625	1.022	13.34	<.0001
	Median income	1.741	0.188	9.25	<.0001
	% Uninsured Children	-0.054	0.010	-5.29	<.0001
	Number of FQHC	0.438	0.044	9.96	<.0001
	Economic type: Mining	-0.140	0.065	-2.15	0.0319
	Economic type: Government	0.700	0.143	4.91	<.0001
	Policy type: Low Education	-0.094	0.041	-2.28	0.0229
	Policy type: Low Employment	-0.771	0.112	-6.87	<.0001
	Policy type: Retirement Destination	0.219	0.044	4.94	<.0001
	Metropolitan County type1	0.634	0.063	10.11	<.0001
	Metropolitan County type2	0.549	0.060	9.11	<.0001
	Metropolitan County type3	0.640	0.045	14.28	<.0001
Interaction	Log (Dentist ratio) × Hygienists	0.035	0.019	1.82	0.0686
	Log (Dentist ratio) ×Number of FQHCs	-0.095	0.011	-8.81	<.0001
	% of Eligible × Government	-3.081	0.873	-3.53	0.0004
	% Uninsured × %of Eligible	-0.100	0.055	-1.82	0.0694
	% Uninsured × Low Employment	0.037	0.008	4.85	<.0001
Year	Year08	-0.079	0.035	-2.25	0.0244
	Year09	-0.024	0.035	-0.68	0.4945
State	State AL	0.479	0.090	5.32	<.0001
	State GA	0.239	0.079	3.02	0.0026
	State IA	-0.180	0.094	-1.93	0.0543
	State LA	0.335	0.087	3.84	0.0001
	State MN	-0.396	0.085	-4.64	<.0001
	State TX	0.455	0.085	5.34	<.0001

Table 1 shows the summary of the regression results from Model B and Table 2 shows the parameter estimates and p-values. There were 2,304 observations in the regression, and the resulting adjusted R-square value was 0.78.

The number of served children in counties designated as dental HPSA is greater than in non-HPSA counties. Among the variables used for the supply estimation model, only the dentist ratio and hygienist ratio remains significant in this model. An increased number of dentists and hygienists would allow for more children to be served as the interaction of these two variables is positive. Counties with a higher percent eligible children are more likely have a higher number of served children. The median income of a county also has a positive relationship with the number of children served. Counties with a higher percent of uninsured children are more likely to have fewer children served. The number of FQHCs has a positive effect and its interaction with the number of dentists has a negative effect which means that more FQHCs could lead more beneficiaries, but the effect decreases if there are a larger number of dentists in a county. Counties of government dependent economic, retirement destination, and metropolitan are more likely have more beneficiaries while counties of mining dependent economic, low education and low employment are more likely to have fewer beneficiaries. The year effect of 2008 is significant while 2009 is not significant compared with year 2007. All the state effects are significant compared with the state of Washington. Variables including Medicaid reimbursement fees, the ratio of hygienists to dentists, and the age/gender distribution of dentists were heavily used to explain the DPMC are excluded in model B to estimate the number of served children. Those effects are weaker in model B since the supply and demand effects are combined into a single model.

For model validation, we used 2010 data. We predicted the number of served children using estimated parameters and 2010 data throughout model A and B, and compared the results. As a measure of model performance, the normalized root mean squared error (RMSE) is used, which is calculated by dividing RMSE by the range of observed values.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{obs,i} - Y_{model,i}\right)^2}{n}}$$

$$\text{Normalized RMSE} = \frac{\mathrm{RMSE}}{Y_{obs,max} - Y_{obs,min}}$$

$Y_{obs,i}$ is the observed number of served and $Y_{model,i}$ is the predicted value for county i .

Table 3 shows a comparison of the results from models A and B. We predicted 485 counties' number of served children in year 2010 using both model A and B, and calculated RMSEs and NRMSEs. The RMSE from model A is 4.82% of the range of observed value, while the RMSE from model B is 9.61% which means the prediction performance of model A is better than model B.

Table3. RMSE and normalized MSE from Model A and B.

Observations from year 2010	Estimation Model	RMSE	NRMSE
485 counties Max : 46,553 Min: 148	Model A	1989.23	4.28%
	Model B	4457.40	9.61%

Figure 2 shows the comparison of the estimated results graphically. The vertical axis is the actual number served from the data, and the longitudinal axis is the predicted number served. The results are indicated as marker (o) for model A, and marker (*) for model B. The line shows that the estimated value would be the same with actual value in the data. As can be seen from the figure, the results from model A are very close to the line (bias = -534), while the results from model B tend to underestimate the actual value (bias = -1712). This is particularly true as the number served increases.

Through validation with 2010 data, we have shown that the two-step modeling we suggested (model A) can provide a more convincing estimation result than a single model that does not consider supply and demand separately (model B).

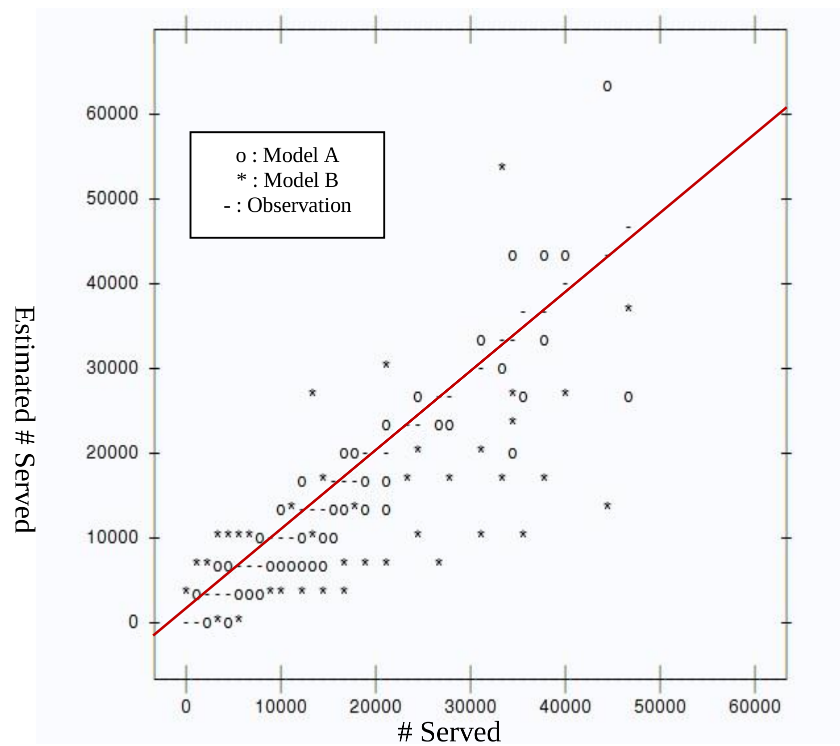
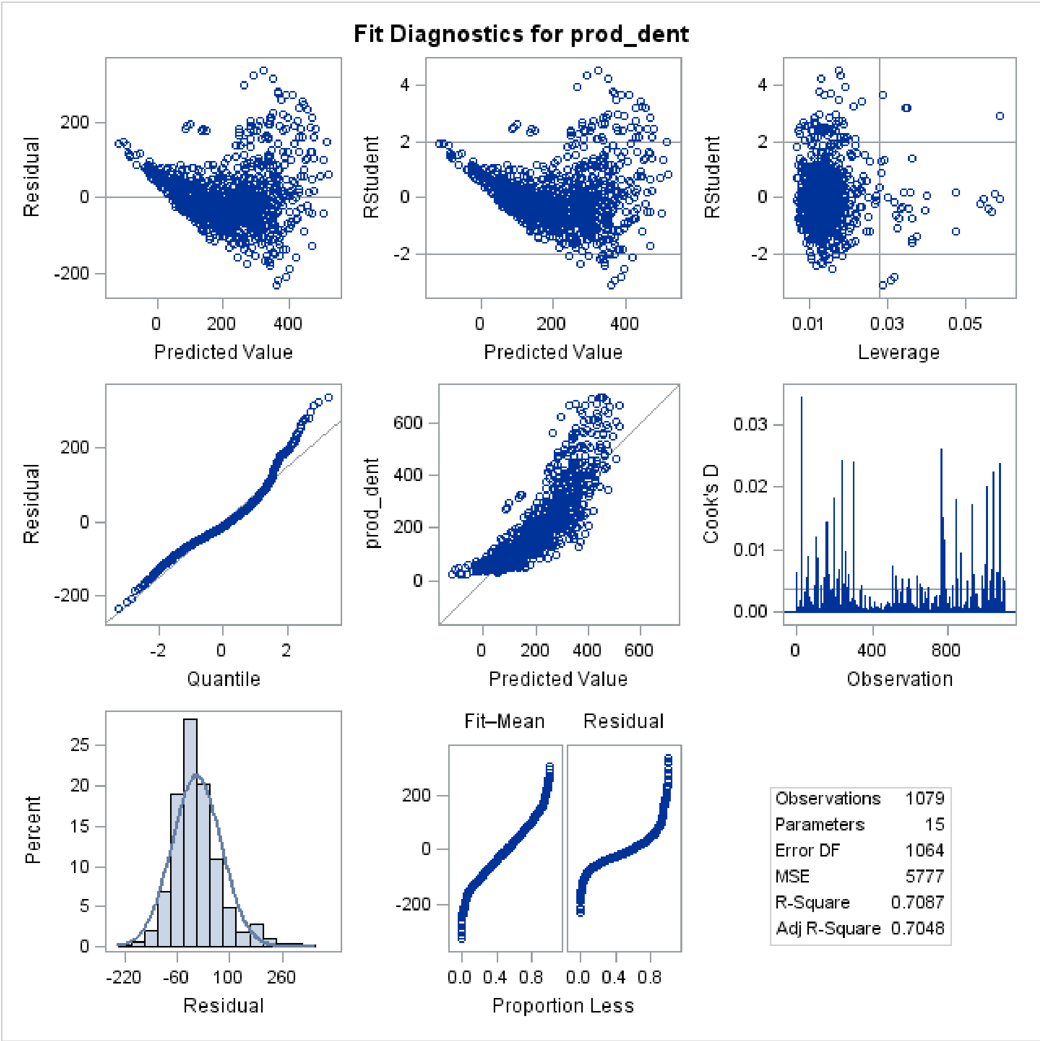


Figure 2. Comparison of estimated results from models A and B.

APPENDIX H: THE DIAGNOSTIC PLOTS FOR SUPPLY ESTIMATION MODEL (Y=DPMC)

Model: Supply Estimation Model

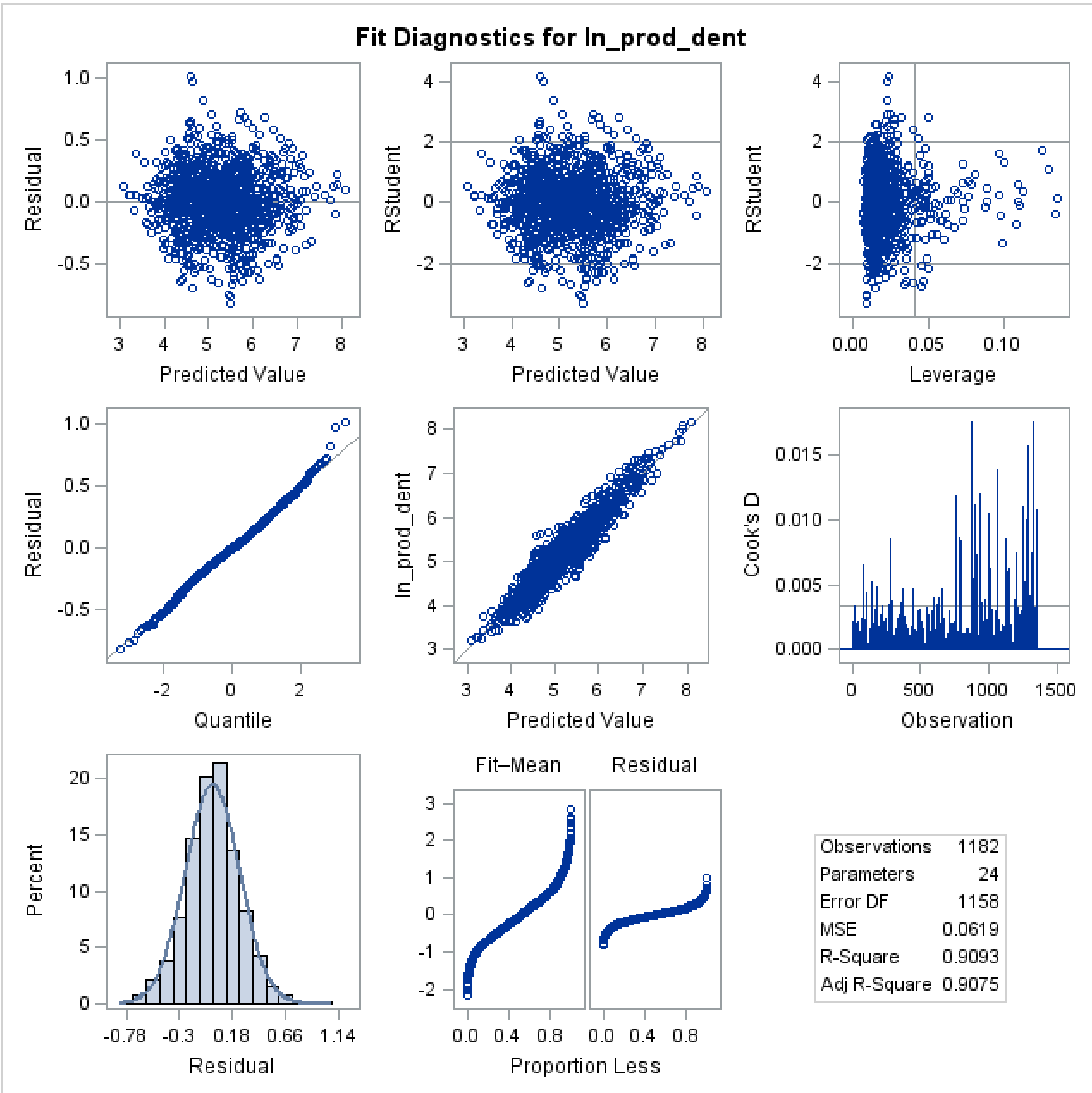
Dependent Variable: DPMC

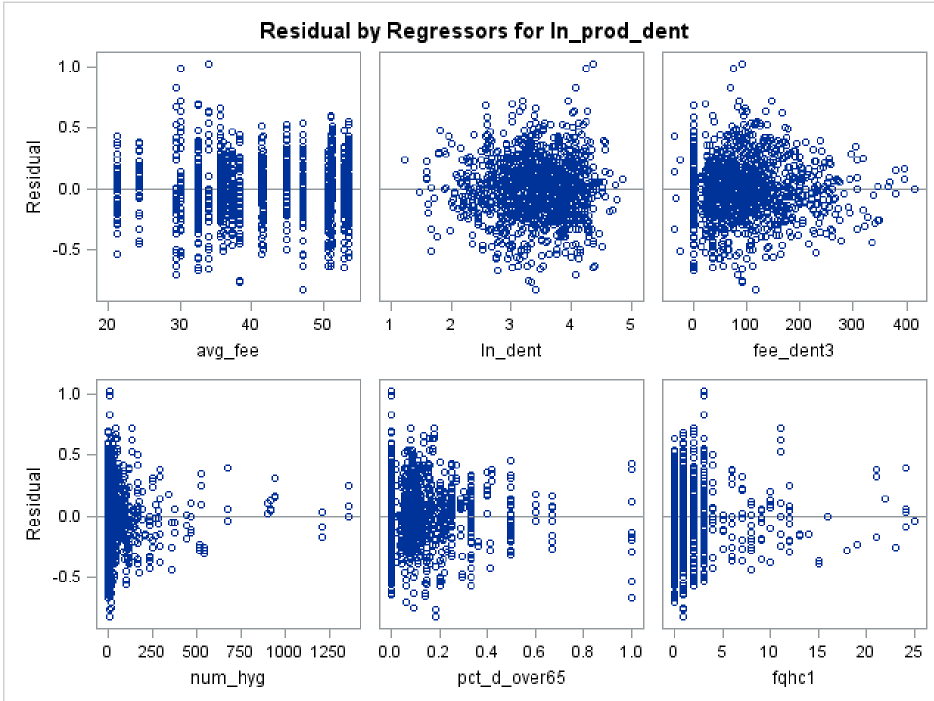


APPENDIX I: THE DIAGNOSTIC PLOTS FOR SUPPLY ESTIMATION MODEL(Y=LOG(DPMC))

Model: Supply Estimation Model

Dependent Variable: log(DPMC)




Residual by Regressors for ln_prod_dent
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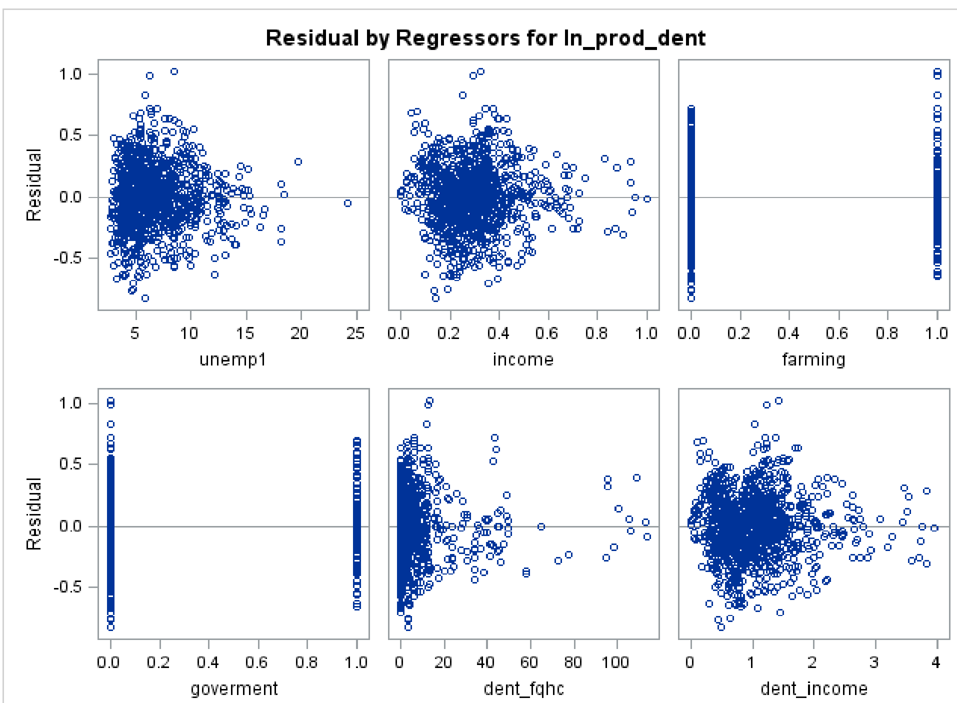
pct_d_over65
fqhc1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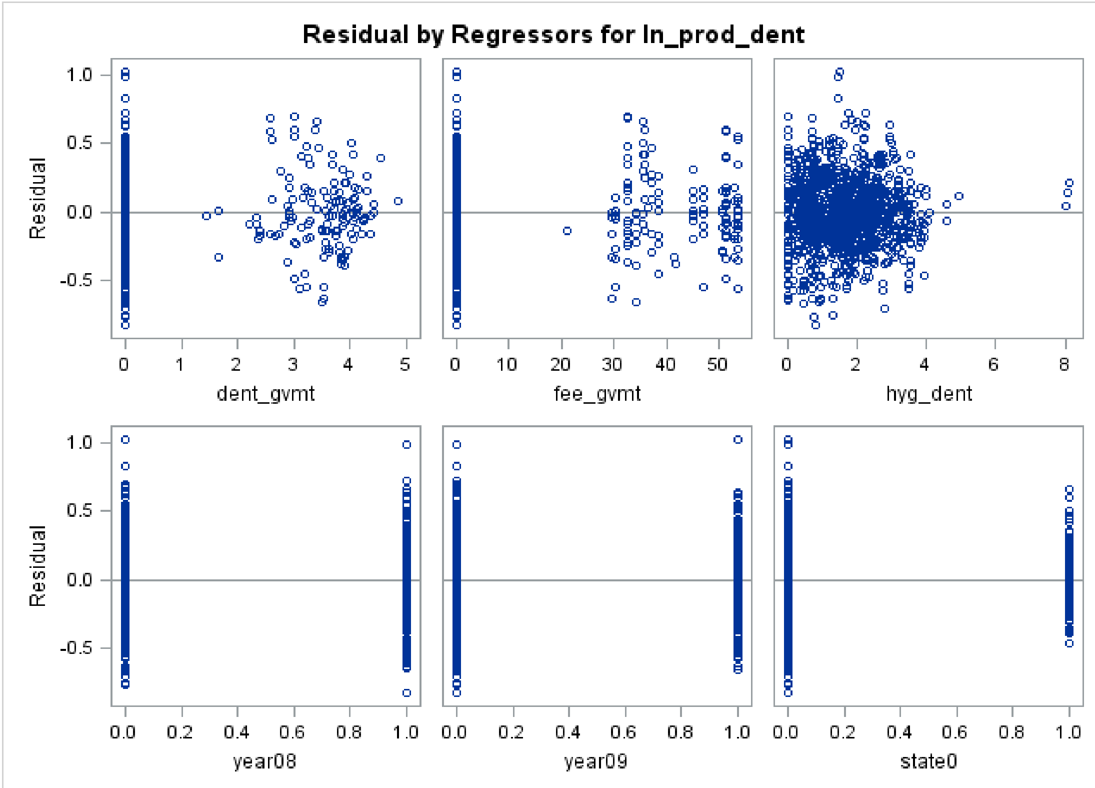
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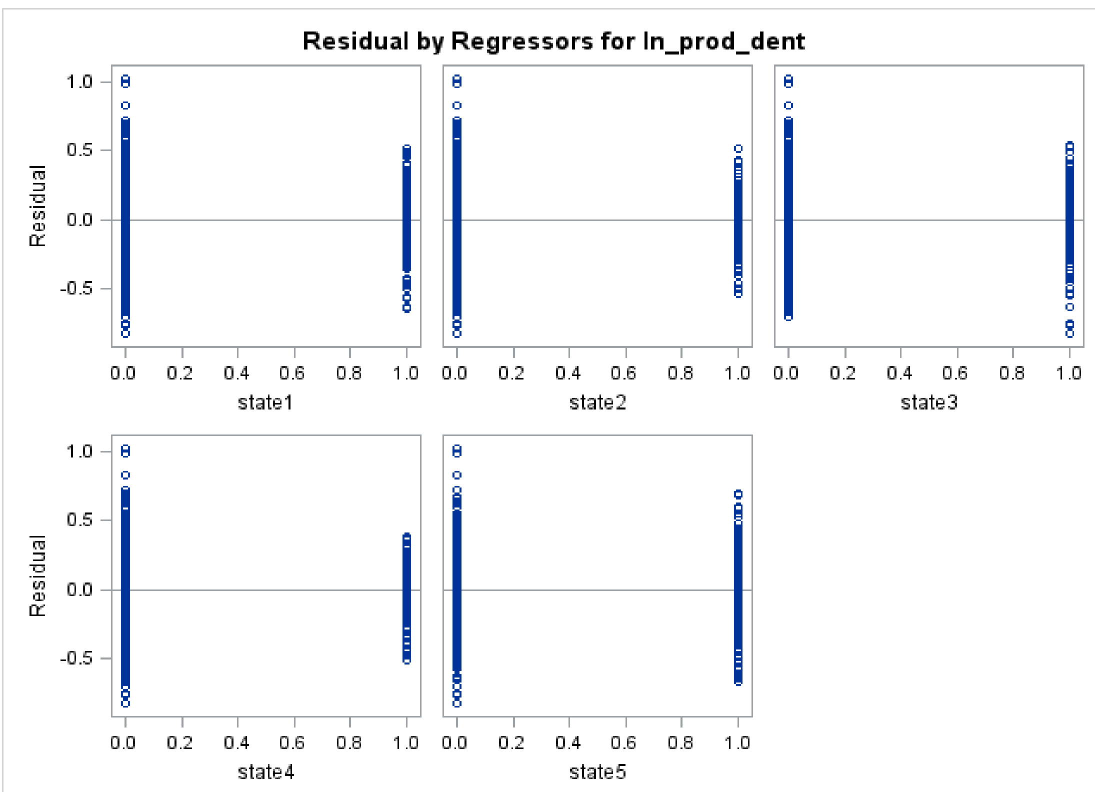
hyg_dent
year08
year09
state0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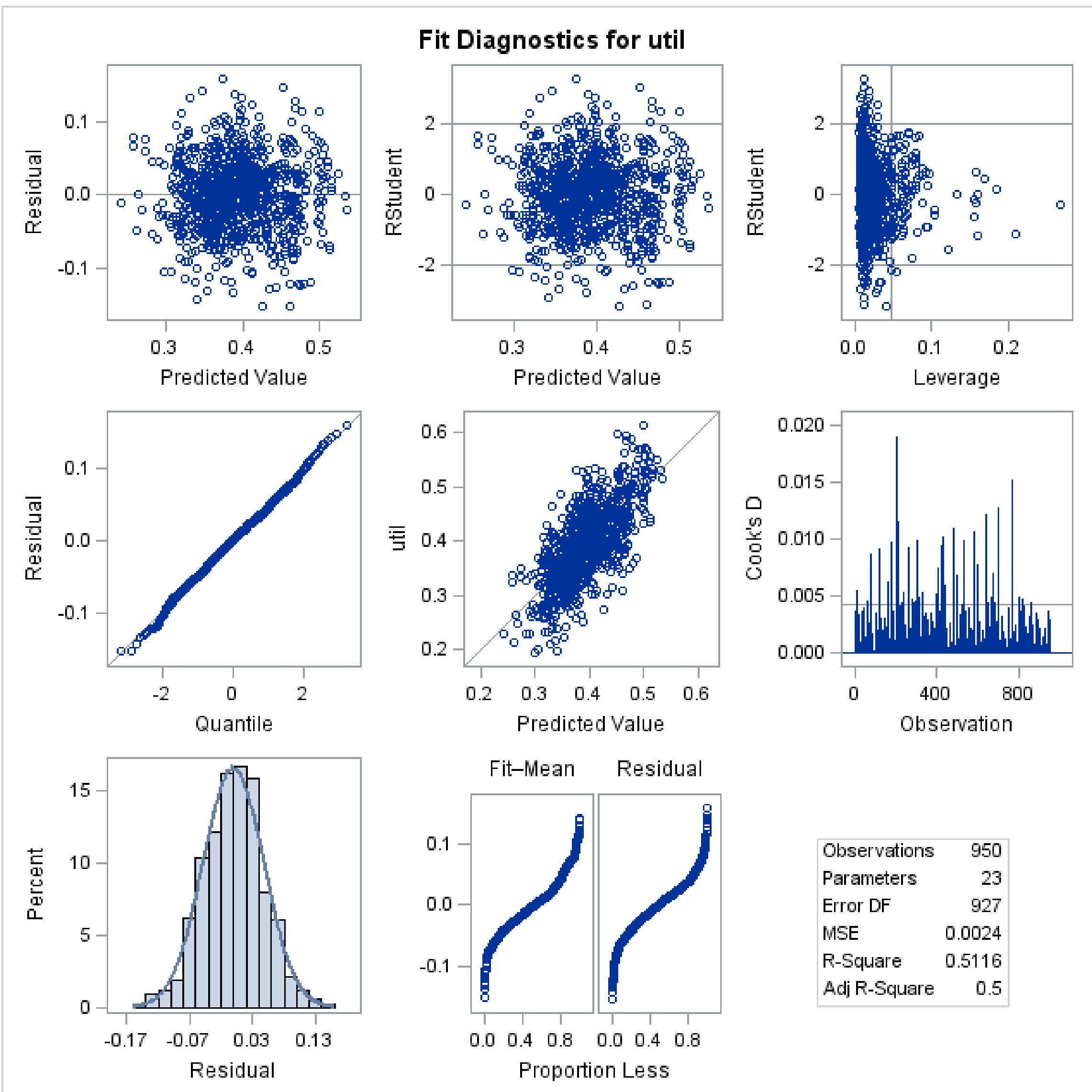
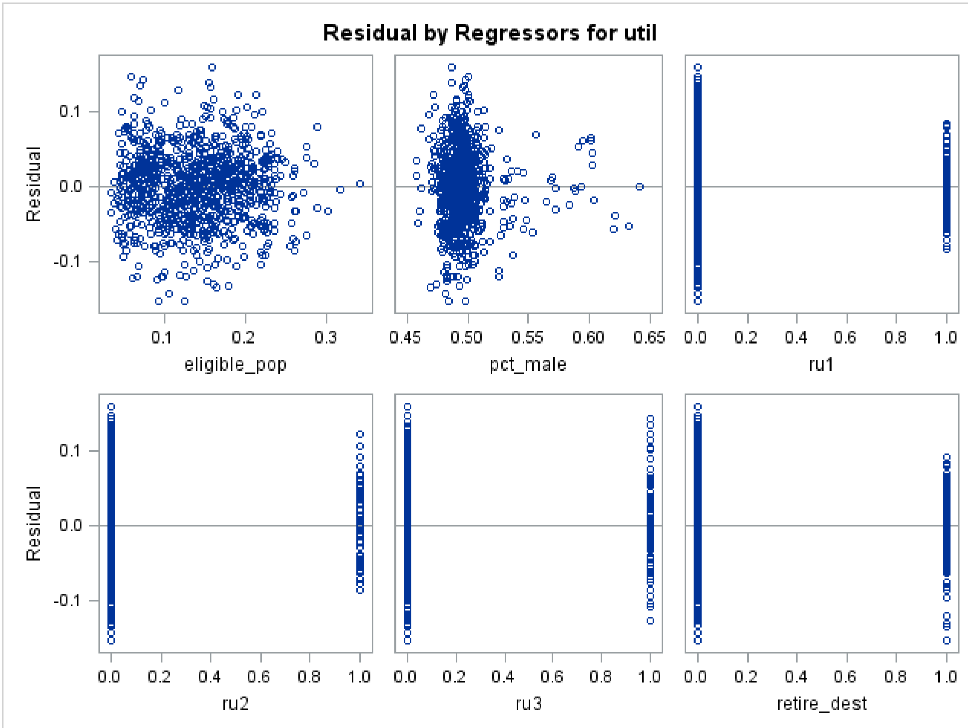
Residual
state1
state2
state3
state4
state5

APPENDIX J: THE DIAGNOSTIC PLOTS FOR DEMAND ESTIMATION MODEL

Model: Demand Estimation Model

Dependent Variable: utilization

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pct_male
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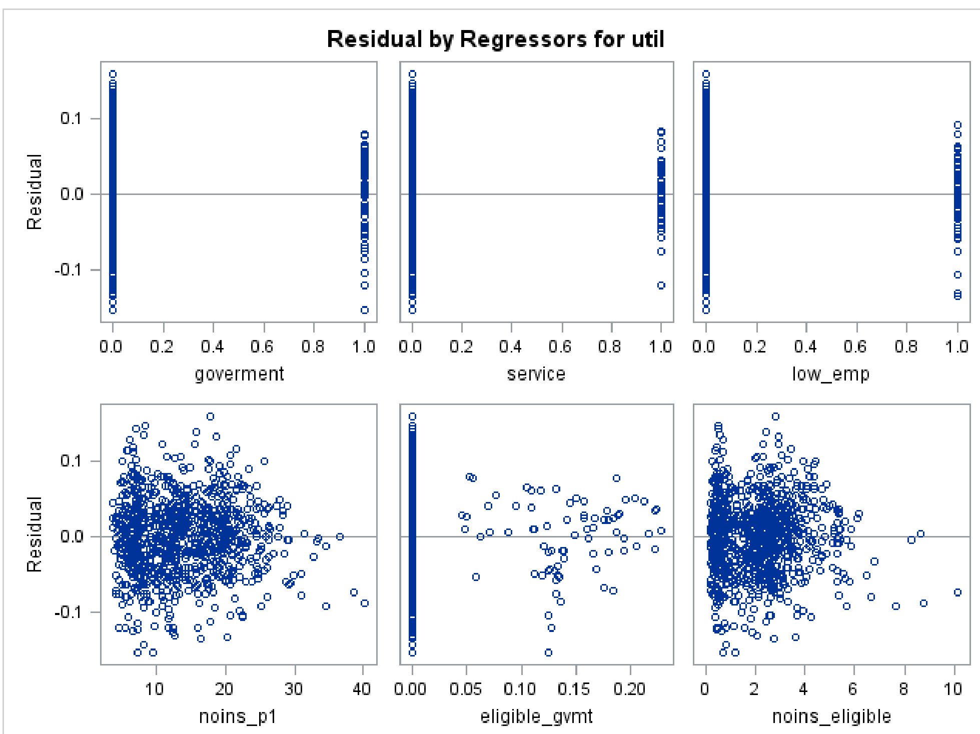
ru2
ru3
retire_dest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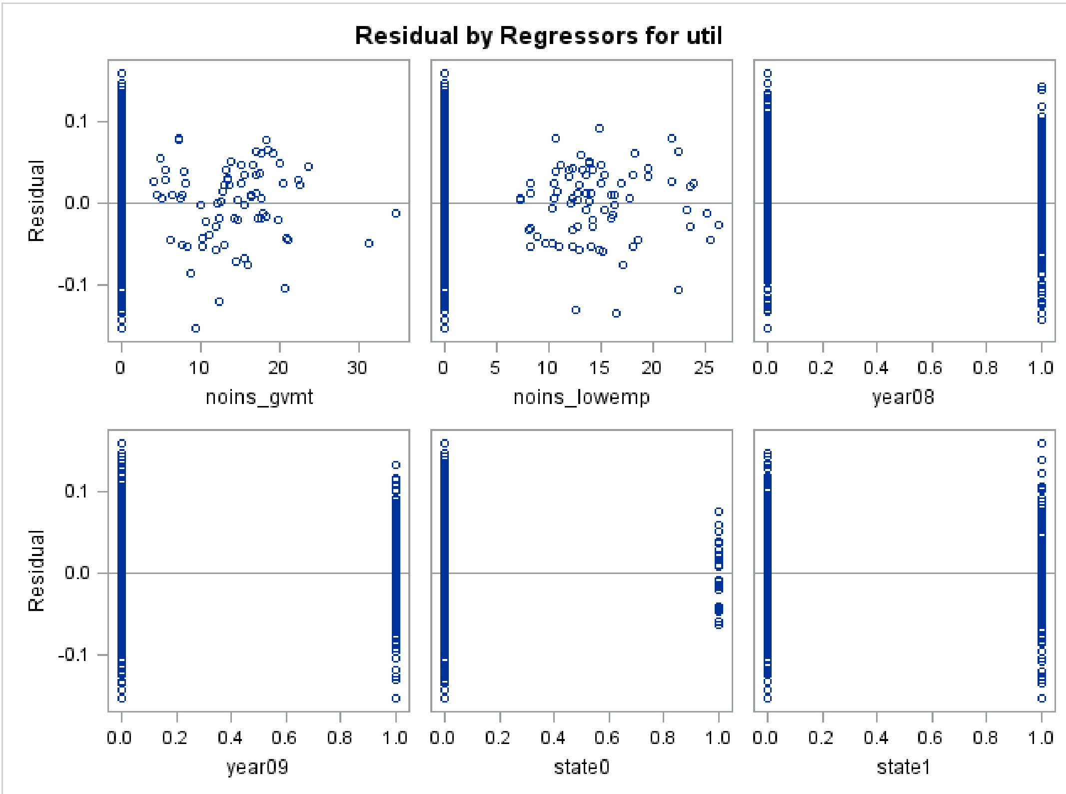
noins_eligible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noins_lowemp
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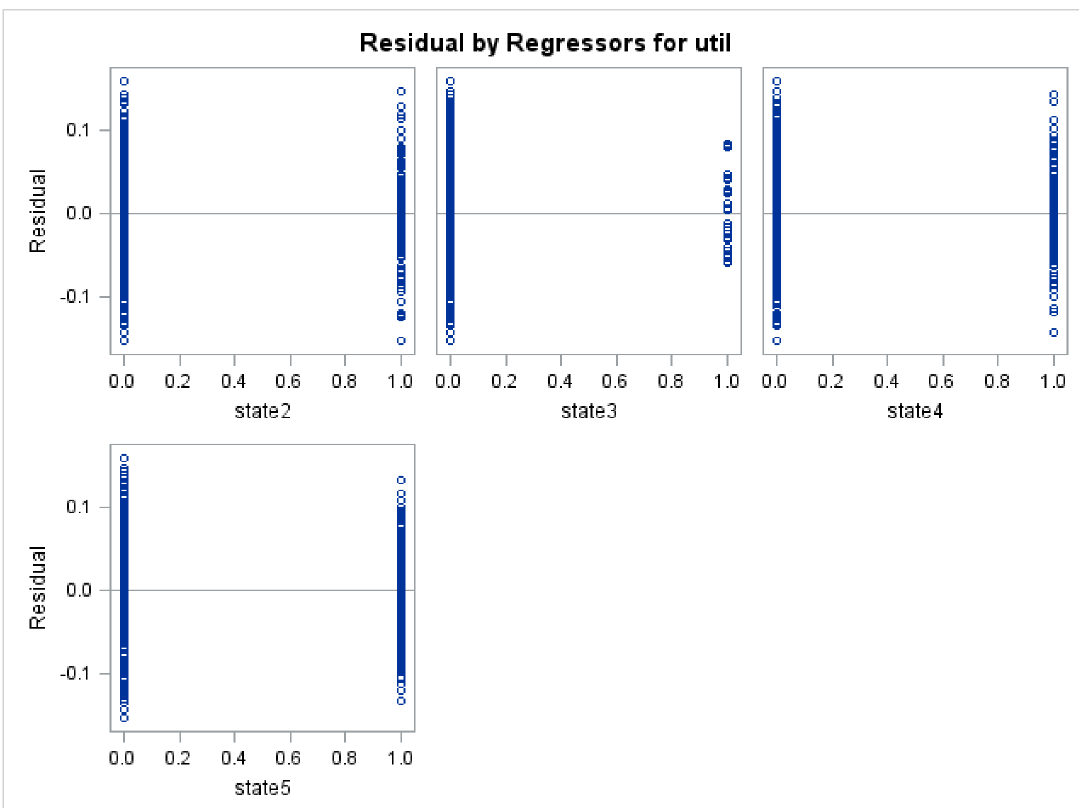
year09
state0
state1


Residual by Regressors for util
Residual
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0.0
-0.1
state2
state3
state4
state5

APPENDIX K: EFFECTS OF INCREASING REIMBURSEMENT FEE

County	No intervention			Intervention : Increase Reimbursement fee (+$10)					
	Supply	Demand	Beneficiary	Incremental DPMC	Incmt. supply	New supply	New beneficiary	Incmt. beneficiary	cost
1	1320	3412	1320	5.2	73	1392	1392	73	114,795
2	1637	1523	1523	9.9	60	1697	1523	-	106,620
3	11638	14053	11638	3.4	428	12066	12066	428	946,630
4	5326	7125	5326	4.4	223	5549	5549	223	441,612
5	4595	3906	3906	3.4	224	4818	3906	-	273,451
6	29092	28421	28421	2.7	841	29933	28421	-	1,989,439
7	359	239	239	9.3	19	378	239	-	16,703
8	7997	8340	7997	5.8	265	8262	8262	265	641,281
9	2920	3222	2920	5.6	128	3048	3048	128	243,846
10	492	535	492	10.9	22	513	513	22	41,108
11	5463	10851	5463	8.9	161	5624	5624	161	431,884
12	183	130	130	10.2	10	193	130	-	9,078
13	6873	10804	6873	7.0	216	7089	7089	216	547,664
14	5722	5393	5393	6.2	199	5921	5393	-	377,486
15	6265	2696	2696	5.6	224	6490	2696	-	188,719
16	2351	1246	1246	5.9	106	2456	1246	-	87,203
17	16957	10921	10921	3.3	558	17515	10921	-	764,490
18	3090	1770	1770	7.9	111	3200	1770	-	123,912
19	1619	1498	1498	9.0	63	1682	1498	-	104,843
20	5845	5990	5845	6.2	204	6049	5990	145	453,753
21	852	562	562	7.2	43	896	562	-	39,322
22	4348	3937	3937	8.3	141	4489	3937	-	275,568
23	3274	4508	3274	5.4	141	3415	3415	141	272,629
24	1578	1267	1267	11.0	55	1633	1267	-	88,670
25	946	938	938	11.7	35	981	938	-	65,640
26	55805	49447	49447	2.6	1268	57073	49447	-	3,461,284
27	1055	504	504	4.7	65	1120	504	-	35,265
28	8434	9546	8434	3.7	334	8768	8768	334	693,304
29	699	544	544	12.9	26	725	544	-	38,065
30	47173	37055	37055	2.5	1156	48329	37055	-	2,593,878
31	29664	32072	29664	2.3	892	30557	30557	892	2,351,325
32	3302	3265	3265	6.1	134	3436	3265	-	228,535
33	16673	12095	12095	2.9	577	17251	12095	-	846,635
34	350	195	195	9.2	18	368	195	-	13,661
35	4137	4022	4022	4.1	192	4329	4022	-	281,523
36	13972	10887	10887	3.3	490	14462	10887	-	762,106
37	3465	1244	1244	8.4	117	3583	1244	-	87,093
38	17680	34171	17680	4.0	537	18217	18217	537	1,403,079
State Total (Average cost/incremental beneficiary)								3,565	21,442,098 (6,014)

APPENDIX L : EFFECTS OF INCREASING ENROLLMENT

County	No intervention			Intervention : Increase enrollment(+10,000)						
	Supply	Demand	Beneficiary	Incmt. Enroll	Incremental Util	Incmt. demand	New demand	New beneficiary	Incmt. beneficiary	Cost
1	1320	3412	1320	69.7	0.000015	43	3455	1320	-	104,550
2	1637	1523	1523	38.0	0.000020	21	1544	1544	21	62,062
3	11638	14053	11638	358.6	0.000002	203	14256	11638	-	537,900
4	5326	7125	5326	208.3	0.000005	122	7247	5326	-	312,450
5	4595	3906	3906	144.6	0.000007	77	3984	3984	77	235,283
6	29092	28421	28421	857.7	0.000001	471	28891	28891	471	1,398,612
7	359	239	239	8.7	0.000118	5	243	243	5	14,156
8	7997	8340	7997	203.4	0.000004	114	8454	7997	-	305,100
9	2920	3222	2920	116.4	0.000009	65	3287	2920	-	174,600
10	492	535	492	21.6	0.000057	11	546	492	-	32,400
11	5463	10851	5463	330.9	0.000004	192	11043	5463	-	496,350
12	183	130	130	4.1	0.000247	2	132	132	2	6,680
13	6873	10804	6873	308.9	0.000004	175	10979	6873	-	463,350
14	5722	5393	5393	173.2	0.000006	93	5486	5486	93	281,988
15	6265	2696	2696	118.8	0.000006	59	2755	2755	59	192,350
16	2351	1246	1246	44.2	0.000021	23	1269	1269	23	71,882
17	16957	10921	10921	388.7	0.000002	205	11126	11126	205	631,793
18	3090	1770	1770	69.8	0.000013	36	1806	1806	36	113,196
19	1619	1498	1498	56.5	0.000021	31	1528	1528	31	92,033
20	5845	5990	5845	147.7	0.000005	81	6071	5845	-	221,550
21	852	562	562	21.7	0.000041	11	573	573	11	35,212
22	4348	3937	3937	129.0	0.000008	70	4007	4007	70	210,165
23	3274	4508	3274	147.0	0.000010	86	4594	3274	-	220,500
24	1578	1267	1267	45.0	0.000025	24	1291	1291	24	73,291
25	946	938	938	25.0	0.000033	13	951	946	8	39,383
26	55805	49447	49447	1487.9	0.000000	815	50262	50262	815	2,425,793
27	1055	504	504	30.1	0.000039	15	519	519	15	48,813
28	8434	9546	8434	309.3	0.000003	177	9724	8434	-	463,950
29	699	544	544	23.4	0.000040	12	556	556	12	38,068
30	47173	37055	37055	1249.5	0.000001	680	37735	37735	680	2,036,110
31	29664	32072	29664	657.2	0.000001	361	32432	29664	-	985,800
32	3302	3265	3265	112.1	0.000009	60	3325	3302	38	177,106
33	16673	12095	12095	422.0	0.000002	225	12320	12320	225	686,645
34	350	195	195	7.3	0.000129	4	199	199	4	11,860
35	4137	4022	4022	141.5	0.000007	75	4097	4097	75	230,102
36	13972	10887	10887	422.8	0.000002	227	11114	11114	227	688,214
37	3465	1244	1244	57.4	0.000013	27	1271	1271	27	92,593
38	17680	34171	17680	1041.8	0.000001	627	34798	17680	-	1,562,700
State Total (Average cost/incremental beneficiary)									3,256	15,774,589 (4,845)

APPENDIX M: EXAMPLE OF OPTIMAL SOLUTION BY COUNTY LEVEL

Additional Reimbursement fee : $32.6									
County	New Enroll. (E)	%uninsured	%Medicaid	util	Supply	Demand	Induced Supply	# Served	Improvement
1	0.00	0.049	0.321	0.509	405	257	463	257	(0)
2	0.00	0.065	0.404	0.502	197	178	238	178	(0)
3	0.00	0.072	0.381	0.5	656	664	729	664	8
4	0.00	0.056	0.535	0.506	673	793	778	778	105
5	0.00	0.07	0.264	0.503	316	184	355	184	(0)
6	0.00	0.04	0.242	0.523	1,368	857	1,552	857	0
7	0.00	0.044	0.416	0.491	5,232	6,446	5,954	5,954	722
8	0.00	0.043	0.312	0.511	1,307	979	1,463	979	0
9	0.00	0.037	0.193	0.521	1,009	557	1,191	557	0
10	0.00	0.059	0.267	0.503	1,000	777	1,137	777	0
11	0.00	0.075	0.455	0.461	990	1,251	1,134	1,134	144
12	0.00	0.051	0.311	0.507	590	519	671	519	(0)
13	0.00	0.056	0.345	0.5	517	357	593	357	(0)
14	0.00	0.047	0.253	0.499	886	651	1,047	651	0
15	0.00	0.053	0.428	0.508	643	698	760	698	55
16	0.00	0.044	0.217	0.502	758	478	891	478	0
17	0.00	0.04	0.393	0.512	1,602	1,920	1,911	1,911	310
18	0.00	0.057	0.363	0.508	466	473	561	473	7
19	0.00	0.058	0.272	0.494	539	408	626	408	0
20	0.00	0.061	0.441	0.511	476	513	538	513	37
21	0.00	0.056	0.367	0.5	572	724	712	712	139
22	0.00	0.067	0.259	0.493	830	522	975	522	0
23	0.00	0.041	0.414	0.518	2,327	2,516	2,633	2,516	190
24	0.00	0.072	0.473	0.469	881	1,088	1,001	1,001	120
25	0.00	0.036	0.19	0.538	2,526	1,739	2,907	1,739	0
26	0.00	0.084	0.245	0.49	406	284	449	284	0
27	0.00	0.061	0.496	0.498	406	488	482	482	76
28	0.00	0.054	0.27	0.5	723	586	853	586	0
29	0.00	0.044	0.51	0.396	1,679	2,576	1,960	1,960	281
30	0.00	0.05	0.274	0.506	605	463	739	463	0
31	0.00	0.042	0.311	0.49	2,943	3,714	3,479	3,479	535
32	0.00	0.059	0.42	0.509	527	537	613	537	10
33	0.00	0.05	0.401	0.504	988	942	1,140	942	0
34	0.00	0.055	0.375	0.509	852	745	979	745	0
35	0.00	0.068	0.395	0.505	565	517	654	517	0
36	0.00	0.053	0.418	0.511	365	366	407	366	1
37	0.00	0.055	0.376	0.51	509	411	585	411	(0)
38	0.00	0.041	0.183	0.519	590	266	681	266	(0)
39	0.00	0.055	0.277	0.517	541	365	619	365	0
40	0.00	0.048	0.358	0.507	698	651	820	651	0
41	0.00	0.056	0.329	0.507	518	435	603	435	(0)
42	0.00	0.058	0.346	0.506	803	723	940	723	0
43	0.00	0.048	0.359	0.531	778	703	881	703	0
44	0.00	0.039	0.444	0.506	922	1,037	1,075	1,037	115
45	0.00	0.065	0.337	0.5	467	381	548	381	0
46	0.00	0.055	0.359	0.507	454	400	541	400	(0)
47	0.00	0.06	0.342	0.508	330	276	382	276	(0)
48	0.00	0.041	0.29	0.51	727	577	837	577	0
49	0.00	0.056	0.331	0.503	810	773	954	773	0

50	0.00	0.045	0.337	0.502	1,666	1,443	1,905	1,443	0
51	0.00	0.077	0.431	0.509	749	699	881	699	0
52	0.00	0.04	0.236	0.1	374	3,387	657	657	282
53	0.00	0.049	0.283	0.505	1,040	647	1,187	647	0
54	0.00	0.057	0.354	0.505	541	462	607	462	(0)
55	0.00	0.05	0.29	0.504	661	518	791	518	0
56	0.00	0.047	0.489	0.513	1,759	1,995	2,004	1,995	236
57	0.00	0.036	0.313	0.503	7,161	8,607	8,145	8,145	984
58	0.00	0.066	0.432	0.42	469	646	531	531	62
59	0.00	0.058	0.429	0.506	509	486	573	486	(0)
60	0.00	0.055	0.209	0.493	564	320	652	320	0
61	0.00	0.049	0.233	0.521	749	507	851	507	0
62	0.00	0.052	0.388	0.505	1,109	1,045	1,253	1,045	0
63	0.00	0.039	0.267	0.505	1,388	1,097	1,623	1,097	0
64	0.00	0.056	0.511	0.38	1,742	2,766	2,019	2,019	277
65	0.00	0.049	0.297	0.524	724	599	848	599	0
66	0.00	0.062	0.182	0.492	574	243	663	243	(0)
67	0.00	0.061	0.43	0.511	381	429	454	429	48
68	0.00	0.063	0.386	0.505	398	356	465	356	(0)
69	0.00	0.054	0.504	0.458	518	684	603	603	85
70	0.00	0.052	0.428	0.468	2,029	2,547	2,304	2,304	275
71	0.00	0.055	0.302	0.498	617	497	738	497	0
72	0.00	0.067	0.271	0.494	264	202	299	202	(0)
73	0.00	0.052	0.478	0.4	521	821	651	651	130
74	0.00	0.058	0.291	0.5	393	306	450	306	(0)
75	0.00	0.045	0.225	0.508	1,060	737	1,236	737	0
76	0.00	0.054	0.364	0.508	344	301	414	301	(0)
77	0.00	0.043	0.339	0.444	15,069	20,266	16,784	16,784	1,715
78	0.00	0.053	0.456	0.475	4,226	5,347	4,746	4,746	520
79	0.00	0.046	0.302	0.508	887	621	1,037	621	0
80	0.00	0.072	0.34	0.494	278	187	315	187	(0)
81	0.00	0.061	0.297	0.5	535	343	612	343	0
82	0.00	0.048	0.407	0.355	5,253	9,212	6,088	6,088	835
83	0.00	0.049	0.295	0.501	607	416	715	416	(0)
84	0.00	0.053	0.214	0.5	1,632	957	1,856	957	0
85	0.00	0.034	0.236	0.508	3,814	2,095	4,338	2,095	0
86	0.00	0.06	0.319	0.502	782	751	875	751	0
87	0.00	0.067	0.397	0.505	346	296	399	296	(0)
88	0.00	0.052	0.413	0.511	665	593	761	593	(0)
89	0.00	0.081	0.323	0.491	307	294	345	294	0
90	0.00	0.047	0.56	0.397	1,614	2,459	1,871	1,871	257
91	0.00	0.037	0.21	0.528	2,074	1,277	2,364	1,277	0
92	0.00	0.066	0.303	0.527	937	886	1,078	886	0
93	0.00	0.063	0.403	0.507	319	305	358	305	(0)
94	0.00	0.05	0.46	0.468	1,646	2,077	1,924	1,924	279
95	0.00	0.045	0.351	0.508	384	440	480	440	56
96	0.00	0.049	0.245	0.5	987	538	1,157	538	0
97	0.00	0.058	0.481	0.332	3,987	7,395	4,583	4,583	596
98	0.00	0.048	0.26	0.5	346	223	399	223	(0)
99	0.00	0.06	0.432	0.515	626	679	719	679	53

VITA

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