The Allocation of Scarce Resources in Public Health

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SUMMARY

As health care costs continue to increase at rates higher than the general inflation rate, there is increased focus on controlling health care expenditures in the public and private sectors. In particular, there is a compelling need for more creative and informed allocation decisions for limited government public health funds. This thesis suggests several methods for better forecasting the demand for health care and allocating health care resources more efficiently. First, productivity of dental sealant programs is studied and suggestions are made for increased efficiency. Using simulation and data from several states' programs, guidelines are offered for optimal programs based on program size, distance to site, and practice act requirements. We find that under most conditions, it is better to carry an extra dental assistant to every program. The cost of satisfying practice act requirements is also quantified. Second, a model for allocating health resources to Community Health Centers (CHCs) is provided. Using the state of Georgia as a prototype, local estimation is used to forecast county insurance types, disease prevalence, and likelihood of using a clinic. Then, the optimal locations and service portfolios to be offered under financial constraints are determined using a developed mixed-integer programming model. Finally, shortcomings in current Markovian modeling of chronic disease are analyzed. Common forecasting techniques can overestimate or underestimate the population in need of care, as illustrated by analytic results and an example with lung cancer data. Suggestions are presented for improving such modeling. Each of these issues affect the planning models for scarce resources in health care, and improving those models can positively impact utilization of those services. Through this research, models are presented that can positively impact public health decisions in coming years, particularly those for growing high-risk and low-income populations.

CHAPTER I

INTRODUCTION

Public health decisions are extremely complex. Policy makers must balance society's interest in having a healthy, thriving population with economic constraints where limited budgets require the most efficient and cost-effective delivery of services possible.

Unfortunately, large gaps in services currently exist. For example, among 5 to 17-year-olds, the percentage of White children who have had one or more sealants applied to their permanent teeth is three times that of Black and Mexican-American children [33]. In addition, Black and Hispanic mothers are more likely to forego prenatal care - leading to higher rates of infant mortality [40].

Health spending as a proportion of GDP is expected to jump from an already astounding 14.9 percent (2002 figures) to 18.4 percent by 2013 [31]. In most years since its inception, Medicaid has had very rapid growth in expenditures. The growth can be attributed to several factors, including the increase in size of the Medicaid-covered populations as a result of U.S. Federal mandates, population growth, and economic recessions. Other factors leading to the growth in Medicaid and Medicare spending are the expanded coverage and utilization of services, the increase in the number of very old and disabled persons requiring extensive acute and/or long-term health care and various related services, and the increase in payment rates to providers of health care services, when compared to general inflation [25].

The growing population of medically uninsured ultimately leads to higher health care costs for all persons. Having no health insurance often means that persons will postpone necessary care and forego preventive care - such as childhood immunizations and routine checkups - completely, making them more likely to be hospitalized for health conditions that could have been avoided [27]. As these costs continue to increase, there is a need for more creative and/or informed allocation decisions for scarce government funds.

Pressing health care needs among the underinsured and uninsured can lead to policy decisions that reactively address those immediate concerns but have little hope of providing longer-term solutions. For example, as the large number of serious health problems take precedence in the community health centers (CHCs), this leaves little time for the preventative care that can lead to reduced incidence of disease in the future. In most cases, making preventive services available to more people would allow more efficient use of the medical workforce and ultimately free up more resources. In addition, primary prevention (e.g. preventative dental care) is often more effective, less costly, and requires less technology than more serious care [26]. As the government continues to look toward CHCs as an option for affordable health care, the decisions of where to locate the centers and what services they should offer become more important.

Along with the scarcity of funds to serve the growing demand, there is also a scarcity of resources, especially for dental health. For the last several years, there have been reports of a dwindling supply of dentists nationally. Whereas the supply of pediatricians is expected to grow relative to demand in the near future, the supply of dentists is expected to decrease [34]. A significant portion of the dentist population is nearing retirement - more than one third are over the age of 55 according to the American Dental Association. Further compounding this issue, many dental schools have closed over the past decade [61]. In June 1998, the National Institute of Health (NIH) Director announced that by 2005 there would be a shortage of dentists [7]. While rural areas have been dealing with these shortages for quite some time, the shortage of dentists now has the potential to become a national problem. In 2002, Oral Health America researched the dentist deficiency and found only 25 states and Washington, D.C. had a sufficient number of dentists available for the general public [2]. Relaxing dental practice act restrictions to better utilize dental hygienists is one possible solution.

This thesis examines three aspects of scarce resource allocation for public health, and the layout of the thesis is therefore divided into three parts. In Chapter 2, the productivity of dental sealant programs is studied and suggestions are made for increased efficiency.

Using simulation and data from several states' programs, guidelines are offered for optimal programs, based on program size, distance to site, and practice act requirements. In addition, the cost of state practice acts is quantified.

Chapter 3 suggests means of allocating health resources to Community Health Centers (CHCs). Using the state of Georgia as a prototype, the optimal locations and service portfolios to be offered under financial constraints are determined. Local estimation is used to forecast county insurance types, disease prevalence, and likelihood of using a clinic. Operating costs and other data are estimated from current CHC reports. A variant of a facility location model is proposed to make the location and allocation decisions. Changing various constraints, such as an overall budget constraint, minimum service levels for the uninsured, and the different number of the current locations to be kept open, are studied for their impact on the final solution.

In Chapter 4, shortcomings in Markovian modeling of chronic disease are discussed, and suggestions for improvement are made. As the population gets older in general, and as technology and medicine make improvements, people are living longer with chronic disease. This chapter illustrates how common forecasting techniques can underestimate or overestimate the population in need of care. The chapter concludes with a study from lung cancer data.

Each of these issues affect the planning models for scarce resources in health care, and improving those models can positively impact utilization of those services. Through this research, models are presented that can positively impact public health decisions in coming years, particularly those for growing high-risk and low-income populations.

CHAPTER II

EFFICIENCY OF SCHOOL-BASED SEALANT PROGRAMS AND THE COST OF DENTAL PRACTICE ACTS

2.1 Introduction and Literature Review

Dental sealants are clear or opaque plastic materials applied to the pits and fissures of teeth to prevent dental caries by providing a physical barrier that prevents debris and decay-causing bacteria from collecting in the pits and fissures of vulnerable teeth. Sealants are most frequently applied to first and second molars. These areas are often the first and most frequent sites to be affected by dental caries in children and adolescents. National estimates show that as much as 90% of schoolchildren's caries occur in the pits and fissures of permanent molars [48]. Sealants, delivered both clinically and in school-based programs, are effective in preventing caries on vulnerable tooth surfaces for as long as the sealant material remains in place [1, 33]. Through a systematic review of the literature in 2002, the Task Force on Community Preventative Services found that exposure to sealant programs results in a median relative decrease in caries experience of 60% [60].

To be most effective, sealants should be placed soon after the teeth erupt. For this reason, sealant programs typically target second grade for sealing first molars and sixth grade for second molars [48]. One of the objectives of the U.S. Government's Healthy People 2010 initiative is to increase the proportion of children with sealants on molar teeth to 50%, as measured at both 8 and 14 years of age [44]. The baseline in 1988-94 was 23% at age 8 and 15% at age 14 [44].

Currently, approximately 20 percent of the nation's children have sealants on their teeth. Unfortunately, that 20 percent does not include most of the low-income and minority children who have the greatest problem with tooth decay [26]. Among 5 to 17-year-olds, the percentage of White children who have had one or more sealants applied to their permanent teeth is three times that of Black and Mexican-American children [33]. The mean fee charged by general practitioners in private practice for sealant application in 1995 was $24.42 per tooth in 1995, compared to the mean cost of providing a sealant in a school-based program of $8.17 per tooth in the mid-1990s [9].

School-based sealant programs (SBSP) typically target high-risk children, especially those less likely to receive private dental care. Students participating in free or reduced-cost meal programs (where the cutoff is generally 185% of the federal poverty guideline) is the most common proxy for this need [60].

Children on Medicaid are unlikely to receive dental care in a dentist's office. Most Medicaid programs reimburse for sealants at rates well below those of private insurance companies and dentists' usual fees. This in some cases limits dentists' willingness to provide the service [33]. An alternative to clinical delivery of sealants are school-based programs. One potential barrier to SBSP is the requirement that dentists must prescribe sealants. For the majority of states, Dental Practice Acts passed by state legislatures prevent dental hygienists from performing this task autonomously [24]. According to the American Dental Association's (ADA) 1998 survey [3], Colorado is the only state that does not require supervision. Of the other 45 states and District of Columbia for which data is available, 26 have general supervision, 7 indirect, and 12 direct (defined below). However, some states are changing their practice requirements. In 1999, the North Carolina (NC) General Assembly revised the NC Dental Practice Act to allow specially trained public health dental hygienists to perform oral health screenings and preventive and educational services. The NC Institute of Medicine has begun exploring how to use dental hygienists to expand preventive dental services to underserved populations in federally-funded community or migrant health centers, state-funded health clinics, and the not-for-profit clinics that serve predominantly Medicaid, low-income or uninsured populations [57]. In addition, a lawsuit filed in September of 2003 [12] by the Federal Trade Commission (FTC) against the South Carolina State Board of Dentistry has the potential to impact the Practice Act in that state and others. The FTC alleges that the dentistry board violated federal laws by "illegally restricting the ability of dental hygienists to provide preventive dental services, including cleanings, sealants, and fluoride treatments, on-site to children in South Carolina schools". This is in response to the board regulation that a hygienist may only apply sealants to those who have been examined by a dentist in the last 45 days. This litigation is just one case in a national trend that may impact the regulations on dental hygienists nationwide. Thus it is important to capture the actual costs which are affiliated with these restrictions on sealant programs.

These changes, however, can be slow to take effect. Further, there have not been comprehensive studies examining how to most efficiently deliver sealants for each of the various levels of required dental supervision. With any limited resource, we need to be especially careful about how we handle those persons most in need. Effective SBSP will also lead to reduced long term costs for states, as illustrated in our example in section 2.4.1. Our goal is to determine efficient methods of distributing sealants in programs targeting schools and high-risk communities.

In the following, we compare four different types of practice act - no supervision for hygienists, general supervision, indirect supervision and direct supervision. We also investigate the cost differences for applying sealants in public health programs for these different practice acts. In section 2 we formally define the problem and in section 3 we explain the experiment. Section 4 contains our results and we conclude in section 5.

2.2 Methods

There are variations within states and programs, but the typical process for dental sealant programs is as follows. Once a school has been chosen, forms are given to the students for the parents to sign obtaining permission for screening and sealants if indicated to be applied. SBSP are typically targeted to delivering sealants to children from low-income families. Some SBSP target schools based on the percentage of children on free and reduced lunch and deliver sealants to all children who attend the school, while other events target children and thus only deliver sealants to children participating in the free and reduced lunch program. If a sufficient number of students sign up for the event, then the SBSP schedules a sealant event. Sometimes it is difficult to obtain parental consent for sealants for reasons such as language barriers or lack of education about dental care. Additionally, many of these schools have poor attendance and students may either miss screening or those who are screened may be absent from school the next day, missing their opportunity to be sealed.

States vary by who can prescribe and apply sealants. There are four possible levels of supervision, included in a state's Dental Practice Act. In some states, *no dentist supervision* (N) is required. Dental hygienists are allowed to both prescribe and apply sealants. Most states require *general supervision* (G) from a dentist. In this case, a dentist must screen all of the students and prescribe sealants as needed and then the hygienists can apply the sealants without further supervision. Some states also put time restrictions on how much time can elapse between the prescription and the application of sealant. With *indirect supervision* (I), the dentist must screen and prescribe the sealants and be present in the building during all sealing (though they do not need to directly supervise). Lastly, with *direct supervision* (D), the dentist must screen, be present in the building while sealing is going on, and inspect the sealant when it is completed. See Table A.10 in the Appendix for a list of each state's requirements.

Programs typically use the four-handed method (teams of two - a dental assistant and dentist or dental hygienist) to apply sealants. Several teams may operate together at a school. Figure 2.1 illustrates the process flow. The number of dental chairs brought for a program depends on the size of the school, the size of the room (and power capability) and the preference of the program. Volunteers are generally recruited to help with removing children from the classroom. Some programs remove all students from a given class at one time, while others remove students as they can be served. Under general supervision, on the first day of a sealant program the dentist typically screens all of the students with the help of a dental assistant to determine whether they are in need of sealant and hygienists come on later days. After screening or delivering sealants to a child, the chair and supplies must be prepared for the next child. In addition, instruments must be sterilized if programs do not use disposable instruments (referred to as the barrier change). Since additional instruments are used during sealant application, the barrier change after sealing takes longer. Finally, under direct supervision, the sealant must then be inspected by a dentist before the child is dismissed.

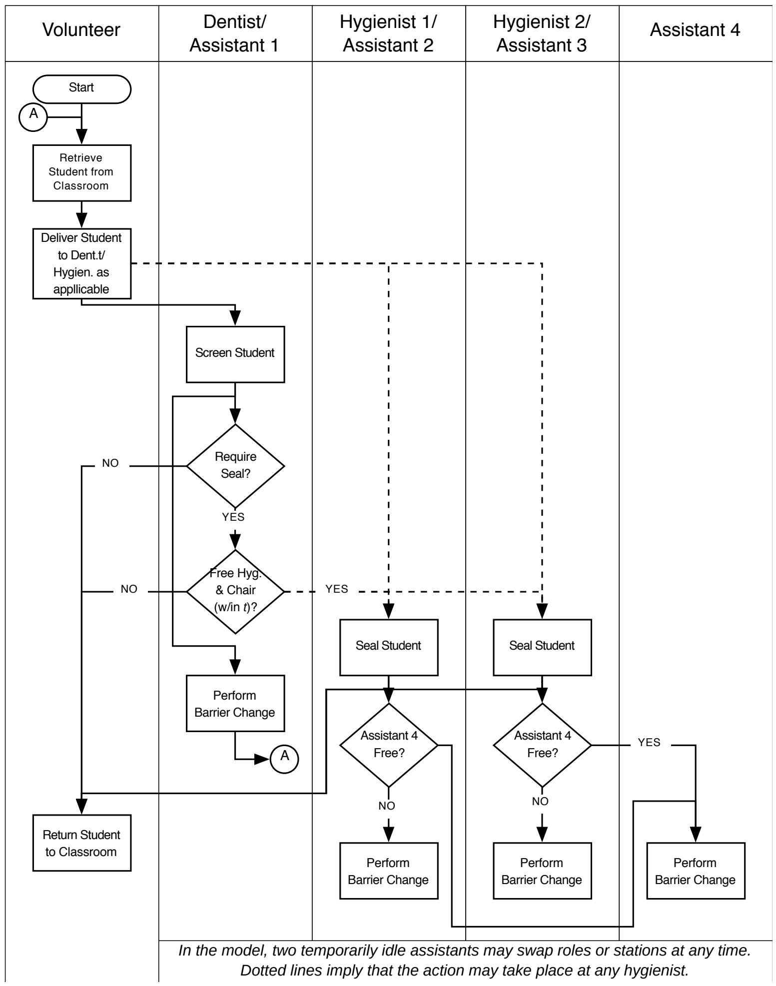

Figure 2.1: The Sealant Delivery Process

2.3 Experiment

We wish to determine the optimal quantity of labor (number of dentists, hygienists, assistants) and capital (specifically sealant stations) to minimize the costs of a program. These are the factors under a program's control, given the constraints of program size, travel distance to location, and practice acts. We estimate costs from a societal perspective. To study efficiency, we have modeled different methods in the simulation software package Automod and run 50 replications of each simulation (with no warmup). The code used is provided in Appendix A.1. We determine times and the associated costs, testing various combinations of program size and supervision requirements. For program size, we consider the range from 25 to 200 students screened (more specifically, 25, 50, 75, 100, 150 and 200 students) which, from our conversations with state program directors, seems to cover most school program sizes. For supervision requirements, we consider direct supervision (D), indirect supervision (I), general supervision (G), and no supervision (N) as defined in section 2.

We assume that programs use the four handed delivery method and that the average number of sealants delivered per child is four, as best practices recommends sealing only 1st permanent molars, which erupt around age 6 and 2nd permanent molars, which erupt around age 12 [55]. We assume that a child is always ready for screening or sealing when a chair and team are available. We also assume that sealant retention rates do not vary between dentists and dental hygienists and that both types of operators take the same time to screen or apply a sealant [9, 37].

We gathered data from several states on the times required to screen, seal, and perform barrier changes as well as the percentage of screened students who require sealants. We obtained data from the best practices document of the Association of State and Territorial Dental Directories (ASTDD) [48] for four states (two with indirect supervision, Illinois and Ohio, and two with general supervision, Arizona and New Mexico) and spoke directly with state dental personnel from three other states, chosen for their different types of practice act (one with no supervision, Colorado, one with general supervision, Wisconsin, and one with direct supervision, Alabama) [13, 14, 15].

Because the estimates for time to screen and seal varied for different states, we modelled three different combinations to test the robustness of our solutions. The first (No Supervision 1, General 1, Indirect 1, Direct 1) requires a constant 2 minutes to screen while the time to seal a child (4 sealed teeth) is drawn from a symmetric triangular probability distribution with a range of 15 to 20 minutes. The second (N2, G2, I2, D2) is a constant 2 minutes to screen and random triangular 20 to 30 minutes to seal. The last (N3, G3, I3, D3) is a constant 4 minutes to screen and random triangular 20 to 30 minutes to seal. For our model we assume that barrier changes for screening take a constant 1 minute and for sealing take a constant 7 minutes and that 70% of those students screened require sealants.

Using data from the Bureau of Labor Statistics, we assumed the hourly compensation for dental assistants and dental hygienists were $13.10 and $26.59, respectively [45]. Because the BLS does not have data on compensation for self-employed dentists we estimated this value to be $75 per hour based on input from some of the states we interviewed. In the indirect supervision case, we assume that once the dentist is finished screening, she helps with sealing. With direct supervision, we assume that the dentist does not do any sealing, so that she is always quickly available to inspect finished sealants. We assume that each team is able to do 7 hours of work per day, plus half an hour of set-up on the first day. We assume that the equipment remains set up for the duration of the event. Since travel can be a significant factor, especially in rural areas, we consider four different travel times to the site - 30 minutes and 1, 2, and 3 hours roundtrip. We do not include administrative costs or other equipment costs.

Since an assistant is able to perform the barrier change autonomously, we consider the option of having one additional assistant and chair than hygienist and dentist. Instead of having each hygienist keep their chair, when they finish a student, they would rotate to an available chair that had already had the barrier change completed. One assistant could be dedicated to barrier changes, or each assistant could keep their chair. None of the programs we spoke with have tried this, but all said it would be a possibility. Finally, from information from the programs with whom we spoke, we assume that no more than six chairs would be used for a program (due to electricity availability and/or space limitations in the schools).

2.4 Results

The entire results table is included in the Appendix in Tables A.11, A.12, and A.13. The optimal combination of hygienists and dental assistants for each of the practice acts and program sizes for one hour round-trip of travel time are in the chart below (Table 2.1), while the tables for 30 minutes and 2 hours are given in Appendix Tables A.14 and A.15. In each case for general, direct, and indirect supervision, it is optimal to have only one dentist. When no supervision is required, it is optimal to not use any dentists. For general supervision, the number of assistants and chairs below does not include the assistant that works on the first day with the dentist before the hygienists come to seal. In the direct and indirect cases, the assistant that works with the dentist is included. This is to capture the actual number of stations that would need to be set up for the program.

Table 2.1: Optimal Number of Hygienists and Assistants (Hygienists, Assistants) for Different Practice Acts for Various Program Sizes, Assuming 1 Hour Round-trip Travel Time to the Site

		Number of Students Screened					
Supervision	Data	25	50	75	100	150	200
N	1	(2,3)	(2,3)	(3,4)	(2,3)	(2,3)	(2,3)
N	2	(2,2)	(3,4)	(4,5)	(3,4)	(3,4)	(3,4)
N	3	(2,2)	(3,4)	(3,4)	(3,4)	(3,4)	(3,4)
G	1	(2,3)	(2,3)	(3,4)	(2,3)	(2,3)	(2,3)
G	2	(2,2)	(3,4)	(2,3)	(3,4)	(4,5)	(3,4)
G	3	(2,2)	(3,4)	(2,3)	(3,4)	(4,5)	(3,4)
I	1	(2,4)	(2,4)	(2,4)	(4,6)	(2,4)	(4,6)
I	2	(2,4)	(2,4)	(4,6)	(3,5)	(4,6)	(3,5)
I	3	(2,4)	(2,4)	(4,6)	(3,5)	(3,5)	(4,6)
D	1	(2,4)	(3,5)	(4,6)	(4,6)	(4,6)	(4,6)
D	2	(3,5)	(4,6)	(4,6)	(4,6)	(4,6)	(4,6)
D	3	(3,5)	(4,6)	(4,6)	(4,6)	(4,6)	(4,6)

Our results clearly showed a significant cost savings for using an extra assistant and chair for the programs of size 50 or larger. The cost savings for adding an assistant and chair averaged over all of the program sizes and travel distances were 4.87% (se=1.57) for no supervision, 4.50% (se=0.89) for general supervision, 5.82% (se=0.65) for indirect supervision and 10.94% (se=0.56) for direct supervision. In general, these savings increase as the size of the program increases. This is intuitive, as the assistant will have a higher utilization when there are more hygienists working. However, there was a peak at 75 students, since at that level the extra assistant consistently saved the program one day of travel. See Table 2.2 and Figure 2.2.

One other aspect to take into consideration is the cost of purchasing the extra chair and equipment for an extra station. For small programs the cost savings may be eclipsed by the cost of the extra station. Assuming a total cost of $5,779 for a Pro Seal cart with compressor and hand piece, equipment cart, instrument tray, overhead light, curing light, operator stool, and assistant stool [62], a 10 year lifetime, and discounting at 3%, a program with no supervision would need to serve 771 students per year to break even, a program with general supervision would need to serve 671 students per year to break even, a program with indirect supervision would need to serve 520 students per year to break even, and a program with direct supervision would need to serve 209 students per year to break even.

As expected, a significant cost savings results from reducing the required supervision level, and thus the number of hours worked, by dentists. The cost savings of changing from general to no supervision averaged 21.86% (se=1.40) across all experiments. Changing from indirect to general supervision saves 8.72% (se=1.61), while changing from indirect to no supervision saves 28.03% (se=1.53). Changing from direct to indirect supervision saves 2.74% (se=1.92) and so is not significantly different. Changing from direct to general supervision saves 10.46% (se=1.74), and changing from direct to no supervision saves 29.96% (se=1.67). For the most part, these savings decrease as the size of the program increases. See Table 2.3 and Figure 2.3 for results for one hour of travel time and the Appendix for other results.

It is important to note that while these cost improvements are significant throughout, they are most dramatic for smaller, rural programs. As the distance to the site increases

Table 2.2: Savings from Adding an Extra Dental Assistant for Various Program Sizes

1/2 HOUR RT	Students	25	50	75	100	150	200
No	Diff	-0.02%	4.68%	5.50%	6.35%	6.73%	6.69%
Supervision	S.E.	1.67%	1.09%	0.78%	0.79%	0.66%	0.59%
General	Diff	0.52%	3.95%	6.38%	5.55%	6.67%	6.67%
Supervision	S.E.	0.88%	0.68%	0.51%	0.49%	0.41%	0.33%
Indirect	Diff	2.06%	6.24%	8.35%	7.25%	8.68%	9.07%
Supervision	S.E.	0.68%	0.44%	0.36%	0.34%	0.27%	0.26%
Direct	Diff	5.71%	10.44%	13.41%	12.38%	13.89%	13.88%
Supervision	S.E.	0.47%	0.42%	0.34%	0.34%	0.29%	0.23%
1 HOUR RT	Students	25	50	75	100	150	200
No	Diff	-1.14%	5.22%	5.61%	6.42%	6.83%	6.56%
Supervision	S.E.	1.50%	1.00%	0.72%	0.73%	0.62%	0.55%
General	Diff	-0.36%	3.32%	7.05%	5.09%	6.69%	6.40%
Supervision	S.E.	0.76%	0.62%	0.46%	0.45%	0.37%	0.30%
Indirect	Diff	0.99%	5.91%	7.99%	6.22%	8.27%	8.58%
Supervision	S.E.	0.60%	0.41%	0.34%	0.31%	0.25%	0.24%
Direct	Diff	4.39%	9.67%	14.19%	11.74%	13.91%	13.53%
Supervision	S.E.	0.42%	0.39%	0.31%	0.31%	0.27%	0.22%
2 HOUR RT	Students	25	50	75	100	150	200
No	Diff	-2.80%	6.07%	5.79%	6.53%	7.01%	6.35%
Supervision	S.E.	1.25%	0.86%	0.62%	0.64%	0.54%	0.49%
General	Diff	-1.59%	2.35%	8.08%	4.35%	6.71%	5.95%
Supervision	S.E.	0.61%	0.52%	0.39%	0.39%	0.32%	0.27%
Indirect	Diff	-0.53%	5.41%	7.40%	4.57%	7.60%	7.77%
Supervision	S.E.	0.48%	0.35%	0.29%	0.27%	0.22%	0.22%
Direct	Diff	2.47%	8.46%	15.41%	10.70%	13.94%	12.95%
Supervision	S.E.	0.35%	0.34%	0.26%	0.27%	0.23%	0.19%
3 HOUR RT	Students	25	50	75	100	150	200
No	Diff	-3.98%	6.72%	5.92%	6.61%	7.14%	6.17%
Supervision	S.E.	1.07%	0.75%	0.55%	0.57%	0.48%	0.44%
General	Diff	-2.40%	1.64%	8.85%	3.79%	6.73%	5.61%
Supervision	S.E.	0.50%	0.45%	0.34%	0.34%	0.28%	0.24%
Indirect	Diff	-1.57%	5.03%	6.94%	3.30%	7.06%	7.12%
Supervision	S.E.	0.41%	0.30%	0.26%	0.24%	0.20%	0.20%
Direct	Diff	1.14%	7.55%	16.32%	9.90%	13.97%	12.49%
Supervision	S.E.	0.29%	0.29%	0.23%	0.24%	0.20%	0.17%

and as the program size decreases, both characteristics of more rural programs, the cost improvements increase. These are also the areas that tend to have a higher shortage of dentists, yet they are the most negatively affected by the practice acts.

2.4.1 Example

Data is used from the Wisconsin's Seal-A-Smile program to illustrate the potential cost impact of reducing the practice act restriction on public health sealant programs for that

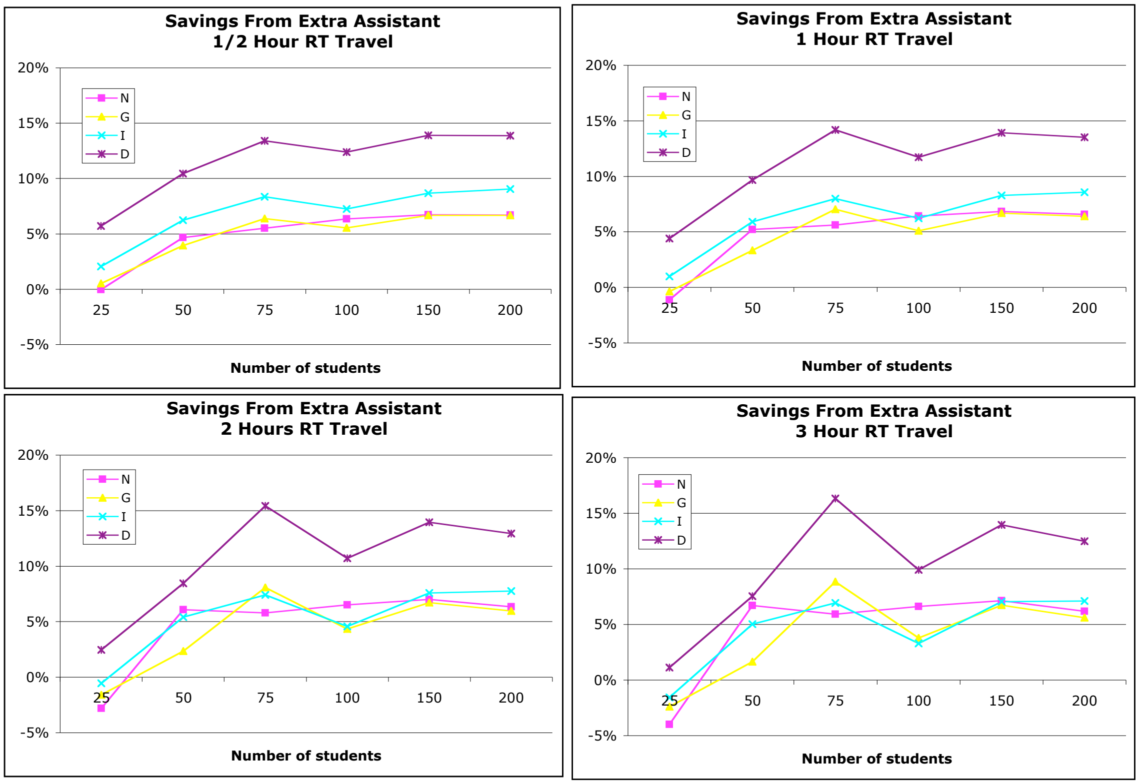

Figure 2.2: Savings from Adding an Extra Dental Assistant for Various Program Sizes

state. The state of Wisconsin during 2002/2003 required general supervision.

In 2002/2003, the Wisconsin Seal-A-Smile screened 4,367 children and applied a total of 10,697 sealants for 2,670 children [53]. There were 102 school events held, and so the average event size was approximately 43. The Children's Health Alliance of Wisconsin managed the budget of $59,456 for these community school-based/school-linked programs. The Seal-A-Smile cost per child sealed is then $20.51. Since some of the children sealed were Medicaid or State Children's Health Insurance Program (SCHIP) eligible (30.1%), and the Medicaid reimbursement is $67.96 per child, of which 29.19% is paid by the state of Wisconsin after

Table 2.3: Cost Savings from Different Practice Acts for Various Program Sizes Assuming 1 Hour Round-trip Travel to the Site

Number of Students	25	50	75	100	150	200
No supervision compared to general	29.17%	23.40%	19.07%	20.78%	20.65%	18.11%
Standard error	2.15%	1.75%	1.55%	1.31%	1.07%	0.96%
No supervision compared to indirect	37.39%	29.96%	24.52%	27.82%	25.02%	23.48%
Standard error	2.37%	1.94%	1.54%	1.34%	1.42%	0.96%
No supervision compared to direct	41.87%	32.59%	25.41%	28.81%	25.54%	25.24%
Standard error	2.51%	2.09%	1.87%	1.59%	1.35%	1.13%
General supervision compared to indirect	13.13%	9.37%	7.22%	9.75%	5.83%	7.01%
Standard error	2.45%	2.11%	1.66%	1.42%	1.49%	0.94%
General supervision compared to direct	17.93%	12.01%	7.84%	10.13%	6.15%	8.70%
Standard error	2.57%	2.24%	1.97%	1.66%	1.42%	1.11%
Indirect supervision compared to direct	7.15%	3.76%	1.18%	1.37%	0.68%	2.30%
Standard error	2.89%	2.48%	2.04%	1.76%	1.73%	1.16%

the Federal Medical Assistance Percentage (FMAP) and SCHIP are factored out, then the actual state cost is \$20.51 + (0.31)(.2919)(\$67.96)=\$26.66 per child sealed.

If Wisconsin were to go from general supervision to no supervision, the savings would be 23.40% (se=1.75) (Table 2.3). This would translate to an additional 1,120 extra children being sealed under the same budget, assuming the same sealant prescription rate. It is estimated that applying sealants for Seal-A-Smile saved 2.5 molars from decay per child sealed [30]. If the same proportion of the new students sealed were Medicaid or SCHIP eligible as the current student proportion (30.1%), the break even point for state funds would be only 1.56 molars saved per child sealed (see Appendix A.3 for calculations).

2.4.2 Additional Factors

Two factors that were not captured in the simulation of general, indirect, and direct supervision (referred to simply as 'supervision' below) were: i) the chance that a dentist or hygienist missed the sealant event appointment, and ii) the chance that a student is screened the first day, but is then absent the following day or absent the day of screening. Although

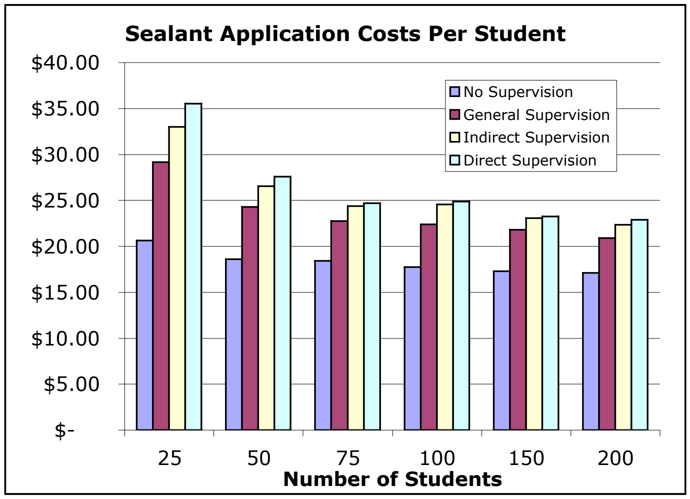

Figure 2.3: Sealant Application Cost per Student for Different Practice Acts for Various Program Sizes. (Assumes 1 Hour Round-Trip Travel to the Site.)

both of these cases do indeed occur, accurate data was not available to properly model this. However, there are several observations that we can make with respect to the relative impact of these factors.

For the case of the dentist not attending the sealant event, the primary effect on the results presented would be that the event would need to be rescheduled at a later date. This would therefore increase the cost of events where supervision was required relative to those events where supervision was not required (i.e., the reported savings from reducing the required supervision level by dentists would be at least as great as those reported). For the case of a hygienist not showing at a scheduled event, the effect would be an increase in the time to seal all of the students, but the effect would be the same regardless of the level of supervision. Finally, for the case where the student was absent, the impact would be in the form of cost savings of having sealed teeth versus not having sealed teeth. This cost would be higher for supervision where students are screened the first day and sealed the second day as compared to no supervision since in the later case the student could be screened and sealed on the second day. Therefore, the overall comparison results presented are conservative in that supervision could have higher costs than reported.

In addition, there is a cost associated with the lost productivity of the students. It is desirable to minimize the time spent out of class for the students, as well as the disruptions to the classroom from students entering and exiting. Removing students once for screening and again for sealing, as is done for general, indirect, and direct supervision, is less advantageous than simply removing them once, as when dental hygienists are allowed to do all of the work.

Finally, we have implicitly assumed that the longevity of sealants placed by dentists and hygienists does not differ. Most studies indicate that sealant retention rates do not differ between dentists and dental hygienists, however, one recent study by Folke et. al [21] showed that sealants placed on first molars by dentists had three times the risk of failure compared to those placed by hygienists. Therefore, there could potentially be additional cost savings not captured in our model if sealant delivery were delegated to hygienists rather than dentists.

2.5 Conclusions

These findings can be helpful in better allocating public health funds to dental sealant programs. This is especially important since the percentage savings outlined above is money that can be used to seal more children. States are interested in increasing the efficient of their SBSP as evidenced by the Best Practices Program sponsored by the ASTDD. This chapter identifies best practices regarding capital and labor usage and helps to quantify the benefits associated with implementing such practices given a program's operating constraints. In addition, it quantifies the costs associated with the practice acts that govern the sealant programs. This research should thus help policy makers plan more efficient sealant programs as well as evaluate the effectiveness of their state restrictions for sealant application.

Along with the savings shown above, there are additional costs that are more difficult to capture that increase the benefits of practice acts that do not require supervision of hygienists. This work only considers the actual labor costs of the dentists, and assumes that dentists are available to do the work. In reality, there is a significant opportunity cost, in terms of substituting a higher cost input for equally effective, less costly inputs. Dentists could be using their time to deliver treatment requiring a higher level skill. For the last several years there have been reports of a dwindling supply of dentists nationally. In 2002 Oral Health America researched the dentist deficiency and found only 25 states and Washington, D.C. had a sufficient number of dentists available for the general public [2]. These shortages do not exist for dental hygienists.

CHAPTER III

COMMUNITY HEALTH CENTERS: LOCATION AND SERVICE ALLOCATION DECISIONS

3.1 Introduction

Community Health Centers (CHCs) provide family-oriented health care services for people living in rural and urban medically underserved communities. Their services include primary and preventive health care, outreach, and dental care, as well as links to welfare; Medicaid; Medicare; Women, Infants and Children (WIC); mental health and substance abuse treatment; and related services [43]. CHCs were first funded by the federal government as part of the war on poverty in the mid-1960s. They are now an important part of President George W. Bush's 2004 plan to make health care more affordable [49].

In 2000, nearly 700 CHCs served 9.6 million users, of whom 3.9 million were uninsured. Congress has consistently increased funding for the program, but not enough to cover the increasing number of uninsured people and the reduced Medicare/Medicaid reimbursements [4]. Additionally, public health providers currently cannot meet the large need for oral health services. In fact, only about one third of community health centers offer comprehensive dental services [24].

CHCs are restricted to locations that are classified as medically underserved [43]. The criteria is based on a combination of the ratio of primary care physicians per 1,000 population, infant mortality numbers, the percentage of the population below the poverty level, and the percentage of the population above age 65 [8]. In addition, there is a preference for the centers to be geographically distributed and with a balance between urban and rural locations. These locating specifications may not be sufficient; note that currently, 95% of Georgia qualifies as being medically underserved [28]. Appendix B.1 contains maps of the above categories by county for Georgia. For the locations of current Georgia CHCs, see Figure 3.4. In the past, CHCs have been located incrementally, but here we solve the problem as a system.

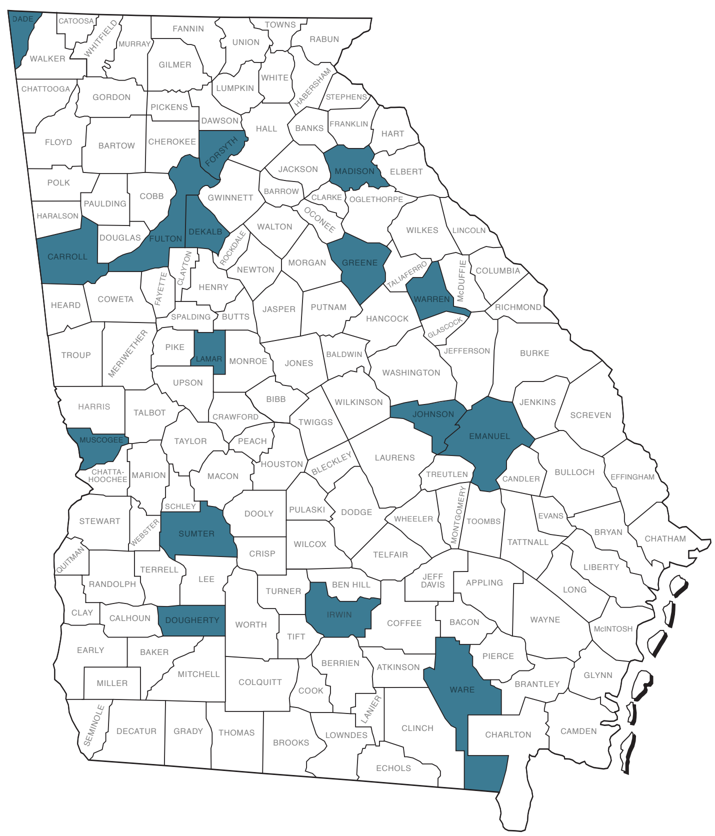

Figure 3.4: Current Locations of Community Health Centers in Georgia

The goal of this research is to analyze the impact of existing CHCs and develop a method for determining the best location and number of new CHCs, as well as what services each CHC should offer. We look at several competing factors, such as cost and level of service, using the state of Georgia as a prototype.

Some preliminary work has been done to model the optimal locations of CHCs in Georgia [28]. Several objective functions are considered in their work. The first maximizes the total number of individuals covered (without considering their health). Another objective maximizes the total number covered among those found to be unhealthy. Neither of these captures the revenue aspect or capacity constraints on the size of a CHC, and the second only begins to cover the actual need for the various services. We expand upon their work significantly by creating and using estimates of demand for the various services potentially offered at a CHC. We also relax assumptions, such as unlimited capacity, as well as consider the insurance coverage of the population served in the cost estimates.

One of the most difficult aspects of this location and service allocation problem is to characterize the objective. It is desirable to cover as large a percentage of the state, geographically, as possible. However, it is also desirable that a high percentage of these covered people are in need of the services offered at the CHCs that they are served by. It is important to reach uninsured members of the communities, but it is also necessary to bring in a portion of patients who are able to provide revenue to the centers in return for their service. Additionally, some types of services could be considered more important than others, for reasons such as their likelihood to prevent the spread of infectious diseases (HIV testing, for example) or their impact on key health benchmarks (such as prenatal care). In this research we make such trade-offs in our choice of objectives and constraints.

There is also no database of local prevalence of health conditions to aid in solving this problem. We take into consideration the demographics of each county and forecast the county prevalence of various health conditions. Using the method outlined in [29], we use the publicly available United States census database [11] and National Health and Nutrition Examination Survey (NHANES) database [42] to make county estimates of demand that currently are unavailable. In addition to aiding in future decisions of where to locate CHCs, the local demand estimates will be valuable in other public health decisions that are made at the local level.

The rest of the chapter is organized as follows. The optimization model is included in the next section, followed by an explanation of the data, including local estimations methods, in section 3.3. Section 3.4 contains the results, and conclusions are in section 3.5.

3.2 The Optimization Model

Our model determines both locations and service offerings for Community Health Centers. We use a location optimization model that incorporates demand, costs, and facility size.

Along with those services handled by a general practitioner, our model can choose to offer prenatal care and gynecology (OBGyn), dentistry, and mental health and substance abuse counseling (M/SA). These correspond with types of services currently offered by CHCs [47]. The specific services currently offered at CHCs in Georgia include general primary medical care, diagnostic procedures (including labs, x-rays, tests, and screenings), HIV testing and counseling, immunizations, prenatal and gynecological care, dental care (preventative, restorative, emergency, and rehabilitative), and mental health and substance abuse treatment and counseling.

We attempt to account for the relative importance of the different services by assigning a constant weight to each service in the objective function. There is no readily apparent way to quantify the importance of the different services offered by CHCs. For this reason, we study several different sets of values. First, we assume that each type of service is equally important and set all of the weights equal to one. Next we increase the weights of prenatal care, since infant mortality is a target area of CHCs [47]. Lastly, we decrease the weights associated with dental care and mental health and substance abuse, since they seldom lead to critical health problems. Our objective is then to maximize the number of annual weighted patient encounters, summed over the various locations and services.

In the constraints, we include the cost, demand, and geographical considerations. Costs are split into their fixed and variable components as detailed below, and the model has an overall budget constraint. The model is constrained by the demand for services as a function of county-level need data that we forecast. We also determine how many people a CHC serves by placing limits on how far a person would travel to use the CHC as well as on the total capacity of the CHC. We examine the impact of changes in those constraints on the number of patients that we are able to serve and on the corresponding location choices.

In the model we make the following assumptions. Capacities are available only in discrete levels for each service and there is a maximum capacity for each service. A person's willingness to travel to a CHC for service is a linearly declining function of distance between the center of their county and the center of the CHC's county and this value does not vary between services. We also assume that adding new CHC locations will not change the expected behavior of an individual. That is, the prediction of whether a person will use a CHC is based on demographic estimates that do not vary with the location of available CHCs.

3.2.1 Notation

i = locations index (note: We also use z when we are comparing two locations)

j = services index

k = index of levels for each service

Decision variables

s_{ijk}= binary variable for what level each service j is offered at a center i

x_{izj} = percentage of location z's population that is served by a center in i for service j

p_{ij}= variable for the number of patients of service type j served at i (relaxed to linear)

c_i= binary variable for whether a center exists at i

Data

u_i= urban indicator for each i

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

w_j = the weight associated with serving a customer of type j

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

$UrbanMax, UrbanMin$ = maximum and minimum percentage of urban locations allowed

MP_{izj} = maximum percentage of z's population that can be served at i for service j

$=max\left(0, 1 - \frac{d_{iz}}{D}\right)$ where d_{iz} = set of distances between tract i and z

and D is some maximum travel distance

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

$=\frac{\sum_{zjm} MP_{iz} IP_{zm} n_{zj} v_{jm}}{\sum_z MP_{iz}}$

where IP_{zm} is the percentage of patients at i that have insurance type m and

v_{jm} is the variable cost of the service j at insurance level m

Model

$$\max \sum_{ij} w_j p_{ij} \tag{1}$$

$$\textbf{s.t.} \sum_{i} FL_i c_i + \sum_{ijk} FS_{jk} s_{ijk} + \sum_{ij} VS_{ij} p_{ij} \leq B \tag{2}$$

$$p_{ij} \leq \sum_{k} s_{ijk} CAP_{jk} \qquad \forall i, j \tag{3}$$

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

$$x_{izj} \leq MP_{izj} \qquad \forall i, z, j \tag{5}$$

$$\sum_{i} x_{izj} \leq 1 \qquad \forall z, j \tag{6}$$

$$p_{ij} \leq \sum_{z} x_{izj} n_{zj} \qquad \forall i, j \tag{7}$$

$$UrbanMin \sum_{i} c_i \leq \sum_{i} c_i u_i \leq UrbanMax \sum_{i} c_i \tag{8}$$

$$x_{izj}, p_{ij} \geq 0 \tag{9}$$

$$s_{ijk}, c_i \in \{0, 1\} \tag{10}$$

This is an integer optimization problem with linear constraints. Due to the large size of the problem using all 1,618 census tracts in Georgia as the possible locations (more than 2.6 million variables and 5.2 million constraints before preprocessing), we relaxed the problem to allow the set of locations, indexed by i, to be the 159 counties in Georgia. The service choices, indexed by j, are general, obstetrics/gynecology (OBGyn), dentistry, and mental health and substance abuse (M/SA). There are three size levels of service allowed, indexed by k, and three types of insurance, indexed by m (private, government, and none).

The objective is to maximize the total weighted number of patients served. Constraint (2) is the budget constraint, (3) that patients can only be served if there is capacity available for them at that service level, (4) 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 and (6) prevents the same person from being served by two CHCs. Constraint (7) requires that people can only be served with demand for the service who are within the range of location i, and (8) places a restriction on the maximum and minimum percentage of CHCs located in urban locations.

3.3 Data Estimation

3.3.1 Demand

While there is national data publicly available for the prevalence of health conditions (NHANES [42], for example), there is very little data available for smaller regions. The Behavioral Risk Factor Surveillance System (BRFSS) [58] is one example that contains some data for states and metropolitan areas, but certainly not all counties. Therefore, we needed to develop a way to estimate local prevalence figures for our model from national level data.

From Georgia census data [11], we know the number of each county's population in each demographic. We use logistic regression with data from the fourth NHANES survey (1999-2002) [42] in SAS callable SUDAAN. We model insurance type (private, government, and uninsured), and demand for mental health and substance abuse services as a function of gender (male, female), race/ethnicity (white, black, Hispanic/latino), income (above and below the federal poverty income ratio), and age (younger than 18, 18-35, 35-65, and older than 65 years). We model likelihood of using a clinic as a function of the same demographics plus insurance type. The text of the NHANES questions used can be found in Appendix B.2.

We start with the full model that contains all of the two-way interaction terms and then remove insignificant ($p > 0.1$) variables to obtain the coefficients for insurance type (Appendix Tables B.18, B.19, and B.20), mental health (Table B.22), substance abuse (Tables B.23 and B.24) and likelihood of using a clinic (Table B.21) - each as a function of national demographics values.

The samples used were all people who answered the demographic questions and the question or examination pertaining to what was being predicted. Sample sizes are included in the tables. The Appendix Table B.25 also includes the summary prevalence predictions. We then multiply these prevalence estimates by county census data values for population in each demographic category to predict the number of people within each county in Georgia with each health condition. For example, since the prevalence of private insurance for white females above the poverty level and younger than 18 is 0.81, we multiply the number in Fulton county in that demographic (36,008) by 0.81 to determine the expected number of white females above the poverty level and younger than 18 in Fulton county. We do this for each of the 48 demographics groups and sum them to predict the total number of people in Fulton county with private insurance. In addition, we obtained the actual number of births per year in Georgia by county [59] and estimates for the prevalence of untreated dental decay by county from [29], which used a similar estimation method.

Once the number of people with each health condition are estimated, that value is converted into the number of people who will likely go to a county's CHC with that need. This is likely an underestimate, since not all areas may have a clinic in close proximity, and people would potentially use a CHC if one was located closer to them. To estimate the demand, in number of patient encounters, for dental services at a CHC in a county, we weight the untreated dental decay by the prevalence of clinic use for the demographics in that county. We then multiply by 1.60, which was the average number of annual dental encounters per dental user in Georgia in 2002 [47]. To estimate the demand 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 [46], as many women receiving care at CHCs do not visit until their second or third trimester [47] 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 3.28, which was the average number of annual mental health encounters per mental health user in Georgia in 2002 [47]. Finally, 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, 81% [23], by the number of encounters per medical user from the CHC report, 3.01 [47]. Figure 3.5 illustrates this demand estimation process.

Along with people who live in the county where a CHC is located, some additional demand will come from nearby counties. To account for this, distances between counties were determined from census latitude and longitude data [11], measured from the center of each county. We assume the portion of county z's population that will have demand for county i's CHC is represented by:

$$\text{Maximum portion} = \text{Max}\{0, 1 - \tfrac{\text{distance between } i \text{ and } z}{\text{a maximum distance constant}}\}$$

The likelihood of using a nearby county's CHC is then a decreasing linear function of distance to the county. The maximum total demand for each service in a CHC in county i is the maximum portion of all counties multiplied by their demands for the services. Patients from a county can be served by more than one CHC location. However, the total number of a county's patients served by all CHCs is constrained by the total demand from

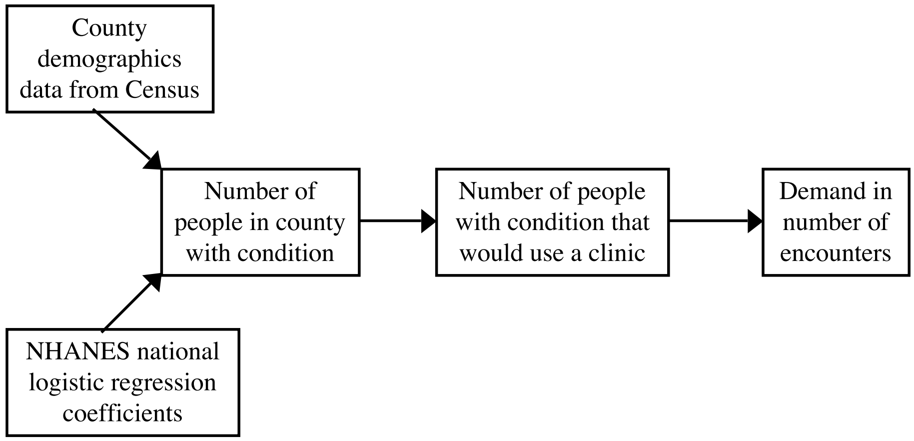

Figure 3.5: Demand Estimation Process

that county.

3.3.2 Costs

From the 2002 Georgia CHC report [47] a doctor on average served approximately 4,200 patients per year while a dentist served 2,639. We used these figures along with Georgia census median salary data to obtain estimates of the variable cost of each service. For general practitioners and obstetricians (mean annual salary $131,000) we include a nurse ($26,000), and for the dentist ($105,000) we include a dental assistant ($23,000). This equates to $37.38 per medical encounter and $48.50 per dental encounter. Mental health and substance abuse encounters are a separate line item in the Georgia CHC report, and averaged $26.64 per encounter.

Table 3.4: Variable Costs per Encounter

	General	OBGyn	Dental	M/SA
Staffing	\$37.38	\$37.38	\$48.50	\$26.64
Equipment/Supplies	\$10.92	\$10.92	\$16.14	-
Lab/X-ray	\$4.78	\$4.78	\$6.20	-
Admin/Pharmacy/Enabling	\$16.98	\$16.98	\$22.04	\$9.37
TOTAL	\$70.06	\$70.06	\$92.88	\$36.01

Also from the CHC report, dividing the dollars spent on equipment and supplies by the total dollars spent on staffing, we estimate the portion of the cost of equipment and supplies to be \$10.92 per general and OBGyn encounters and \$16.14 per dental encounter. Similarly, we estimate the average cost for laboratory and x-ray to be \$4.78 per general and OBGyn encounter and \$6.20 per dental encounter. Dividing the total cost for pharmacy, administration, and enabling (translation during visits, transportation, etc.) by the sum of the costs above per service type, we estimate an allocation of \$16.98 per general and OBGyn encounter, \$22.04 per dental, and \$9.37 per mental and substance abuse encounter. This is a total variable cost of \$70.06 per general and OBGyn encounter, \$92.88 per dental encounter, and \$36.01 per mental health and substance abuse encounter.

We classified CHCs by size to determine appropriate service levels for the four service types using data from the CHC report [47]. For the general category, total encounters in Georgia ranged from 3,391 to 97,633 with a mean of 29,438, so we set the capacity of a small clinic at 8,000 encounters, medium 30,000, and large 70,000. For dentistry, the number of dentists ranged from 0.5 to 2.6 in Georgia CHCs. Since a dentist serves 2,639 per year, we let a small clinic serve 1,320, medium 3,959 and large 6,598. Disregarding one outlier at 41,583, the number of mental health and substance abuse encounters in the data ranged from 262 to 3,476, so we chose levels of 300, 1000, and 3000 encounters. Data was not available on

Table 3.5: Example Maximum Portion Matrix

	A	B	C	D
A	1	0.5	0.1	0
B	0.5	1	0	0
C	0.1	0	1	0
D	0	0	0	1

OBGyn encounters, so we estimated that small clinics serve 2,100, medium 4,200 and large 8,400, which is roughly equal to one-half, one, and two full-time obstetricians.

The final variable cost of service of a patient from county i, is dependent upon the insurance coverage estimates from above weighted by the probabilities of each insurance type to use a CHC. To determine the variable cost of service in county i, we calculate the weighted average of the variable costs for the service for each type of insurance coverage. In 2002, CHC users with public insurance (Medicare, Medicaid, etc.) paid 74.0% of their charges, users with private insurance paid 64.1% of their charges, and uninsured users paid 22.3% of their charges [47]. We assume these reimbursement values are on the above costs.

The last step in calculating the total variable cost in a county, VS_{ij}, is to take a weighted average of the costs from the mix of counties that would be served by a CHC in county i (from the maximum portion calculation above). For example, if counties A through D have the maximum portion matrix found in Table 3.5, then the total demand for a CHC in county A will be:

$$\textit{county A demand} + .5 \textit{ county B demand} + .1 \textit{ county C demand}$$

and the total variable cost will be:

$$\frac{\textit{variable cost in county A} + .5 \textit{ variable cost in B} + .1 \textit{ variable cost in C}}{1+.5+.1=1.6}$$

Due to constraint (6) above, the actual mix of patients in A, for example, may change slightly if all of county B's patients are served by a CHC in some other county E, but it should not be enough to alter the variable cost of service significantly.

Finally, the fixed cost per service (FS_{jk}) is \$5,000 per small service, \$10,000 per medium service and \$15,000 per large sized service offered, and the fixed cost per location (FL_i) is estimated to be \$100,000 per location. We do not have any specific data on those costs besides the \$5.2 million annual facility cost for the 22 grantees in Georgia [47]. Therefore, the values are simply chosen to ensure that locations would not be opened or services offered without having a reasonable number of people to serve.

3.3.3 Other Data

In 2003, the total budget for CHCs in Georgia was approximately \$80 million and revenue was \$36 million [47]. Most of the remainder of the budget was provided by grants from the government. We initially use a budget of \$44 million for constraint (2) to represent the government's subsidy of CHCs, and also study the effect of changes in that budget.

We consider three values for the maximum distance willing to travel used in the maximum portion calculation - 0 miles (i.e., a person will only use a CHC in their own county), 30 miles and 60 miles. As a reference, the average distance between centers of counties in Georgia is 128 miles, with a maximum of 355 miles. On average, each county has 6.23 other county centers within 30 miles of its center.

We first run the model for equal weights (1.0) for each of the services. Then we study the effect of increasing the weight for OBGyn services (by tenths up to 1.5) and decreasing the weight for dentistry and mental health and substance abuse (by tenths down to 0.5).

3.3.4 Validation

The results are clearly dependent upon reasonable data inputs. While it is impossible to obtain the exact data for several of the inputs detailed above, we perform some sensitivity analysis and provide some general insights.

As previously mentioned, BRFSS has a limited amount of state and county level data. Unfortunately, this does not include any of the health factors that we used in our model. However, two health conditions that they do measure (in 2002 and 2003 only) that are also measured at the national level in NHANES are the prevalence of asthma and diabetes. They also measure the percentage of the population without insurance. To get some indication of the accuracy of our local estimation procedure, we estimated the number of people with asthma and diabetes in Georgia, Fulton county, and Dekalb county (the only Georgia counties in BRFSS) and compared with BRFSS' estimates along with our estimates for uninsured population. The comparison is in Table 3.6. (Appendix B.2 contains the text of the questions used for both NHANES and BRFSS.) We are unsure why our estimate for diabetes in Georgia is so low when compared to BRFSS, despite being very close for the two largest counties, and will continue to attempt to verify our data by making comparisons with other states.

Additionally, while the actual number of births per county for 2000 was available [59], we also calculated our local estimates of pregnancies per year from NHANES national data (lab results for pregnancy) for comparison. Realizing that the number of pregnancies and births are not identical, due to issues such as multiple births and miscarriages, they still provide some opportunity for comparison. Our estimates of pregnancies are on average 1.51% higher than the actual number of births. The correlation between the two is 98.6%. The mean actual number of births was 838 per county while our mean estimate of pregnancies was

Table 3.6: Comparison Between Local Estimates and BRFSS Data: Predicted Prevalence of Disease as a Percentage of the Population

		Local Estimate (2000)	2002 BRFSS Data	2003 BRFSS Data
Asthma	Georgia	12.8	11.7	11.8
	Fulton County	13.1	13.2	16.1
	Dekalb County	13.4	8.6	12.5
Diabetes	Georgia	4.6	7.1	7.8
	Fulton County	4.9	5.0	5.6
	Dekalb County	5.1	4.7	5.2
Uninsured	Georgia	14.9	15.7	16.5
	Fulton	16.0	13.8	17.2
	Dekalb	16.7	15.1	18.9

851 per county.

3.4 Results

3.4.1 Solution to the Primary Problem

Our "base" model, chosen to closely represent the actual data in Georgia, constrains the annual budget to $44 million, service weights all equal to 1.0, and a maximum driving distance of 30 miles. We then compare the impact of changes to the data and constraints on the solution of the problem. To keep solution times reasonable, all of the models below were run for solutions guaranteed to be within 1% of optimal. Summary results for the number of locations, number of encounters, cost per encounter, and the percentage of each service offered are included in Table 3.7. Detailed results of the counties chosen are included in Appendix Table B.26.

Table 3.7: CHC Model Summary Results

Distance	Budget	Special Constraints	Number of Locations	Number of Encounters	Cost per Encounter	% General Encounters	% OBGyn Encounters	% Dental Encounters	% M/SA Encounters	% Counties > 30mi from CHC	% Counties > 60mi from CHC	% of uninsured demand met
30	44		21	1,418,726	31.01	95.6	0.0	0.0	4.4	55.3	14.5	26.1
0	44		19	1,267,287	34.72	90.1	5.4	0.0	4.5	53.5	8.2	23.4
60	44		21	1,438,769	30.58	95.6	0.0	0.0	4.4	57.9	29.6	27.7
30	88		39	28,261,23	31.14	93.2	2.7	0.0	4.1	42.1	11.9	53.6
30	22		10	717,190	30.68	95.8	0.0	0.0	4.2	68.6	29.6	13.4
30	44	all current CHCs must be included	26	1,383,691	31.80	94.4	0.0	0.0	5.6	28.9	0.0	26.2
30	44	only the current CHCs may be included	17	898,258	48.98	79.4	5.6	9.3	5.7	37.7	0.0	17.0
0	44	only the current CHCs may be included	17	604,700	72.76	78.4	5.8	9.1	6.6	37.7	0.0	11.5
30	44	at least 10 of current included	22	1,409,695	31.21	95.3	0.0	0.0	4.7	44.0	12.6	26.7
30	88	all current CHCs must be included	46	2,789,934	31.54	94.8	0.3	0.0	4.9	20.1	0.0	52.9
30	44	weights: (1.0,1.1,0.9,0.9)	19	1,419,496	31.00	90.2	6.0	0.0	3.8	53.5	15.7	26.1
30	44	weights: (1.0,1.2,0.8,0.8)	19	1,345,778	32.69	88.3	7.6	0.0	4.0	56.6	17.0	24.7
30	44	weights: (1.0,1.3,0.7,0.7)	19	1,400,812	31.41	91.2	8.8	0.0	0.0	55.3	27.0	25.7
30	44	weights: (1.0,1.4,0.8,0.8)	19	1,399,723	31.43	91.4	8.6	0.0	0.0	57.9	32.1	25.8
30	44	weights: (1.0,1.5,0.5,0.5)	19	1,398,460	31.46	90.8	9.2	0.0	0.0	59.7	25.8	25.7
30	44	at least 30% from most rural	24	1,394,297	31.56	94.4	2.2	0.0	3.4	44.0	8.8	25.6

Twenty-one CHC locations are chosen in the base model solution. Figure 3.6 is a map of the counties chosen. Each location offers mental health/substance abuse at the largest level and operates at maximum capacity (3,000 encounters). Fifteen of the locations operate at maximum capacity of general care (70,000), while 5 offered the highest level but were not at the maximum capacity, and 1 offered at the maximum capacity of the middle level (30,000). No location offered prenatal care or dentistry. Four of the chosen counties currently have CHCs - Carroll, Dougherty, Lamar, and Muscogee. No CHC is located in one of the 16 (10%) most rural counties and only one is located in one of 16 counties with the most uninsured persons. Seven locations are chosen among the 16 most urban counties, and several more are from counties bordering the most urban counties. Total patient encounters are approximately 1.43 million.

3.4.2 Comparison to Current CHC Locations

When we constrain the model to choose the exact same locations as are currently open, with the same annual budget, and assume that patients are willing to travel at most 30 miles, the model chooses to offer each service at every location with approximately 898,000 total patient encounters (compared to 683,000 from Georgia in 2002 [47]). However, if we assume that patients will only visit a CHC in their own county, the number served decreases to approximately 605,000.

If we constrain the model to keep the same 17 CHCs open while allowing new locations as well and keeping the budget at $44 million, 9 new CHCs are added, and all of the CHCs only offer general and mental health/substance abuse services. If we require that the same 17 CHCs be kept open but double the budget to $88 million, 29 new CHCs are added, and all of the CHCs still only offer general and mental health/substance abuse services.

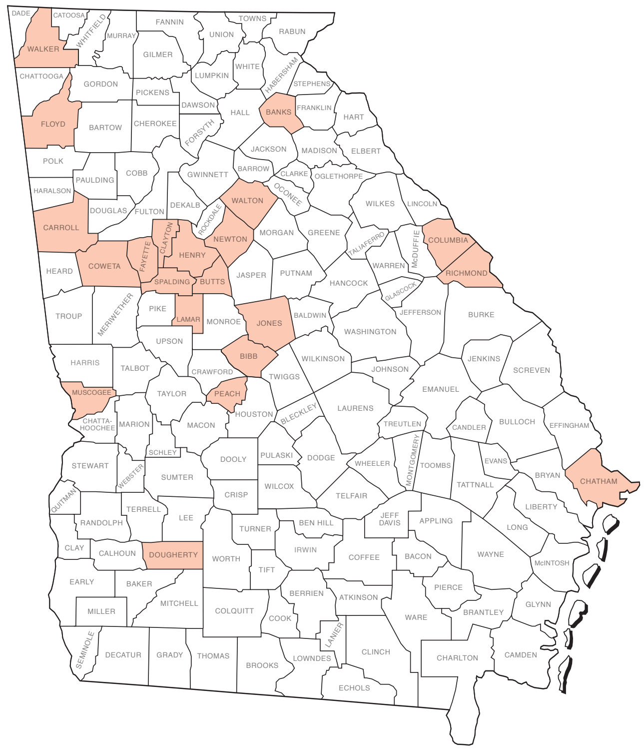

Figure 3.6: Selected Counties for Community Health Centers

3.4.3 Sensitivity to Maximum Distance Input

When we assume that a person will only visit a CHC in their own county, demand values become significantly lower at each location and the fixed cost of opening a location becomes more significant. The model chooses to open 19 locations, 9 of which are the same as those chosen when the maximum distance is 30 miles. The model chooses the 13 counties with the highest estimated general need, and the other six locations are chosen in the top 24. This is almost without regard to the variable cost of service in each location, as 6 of the locations are in the top 10% of uninsured persons. Total patient encounters decrease to approximately 1.27 million.

However, when the maximum distance willing to travel is increased to 60 miles the solution changes dramatically from the base model. Only one location, Dougherty County, is the same as in the 30 miles case. Total patient encounters increase to approximately 1.45 million.

We also measured what percentage of the counties do not have a CHC within 30 miles or within 60 miles of their center for each solution of the model. These results are in Table 3.7. This shows that the current CHC locations are spread more geographically around the state.

3.4.4 Sensitivity to the Budget Constraint

When the budget constraint is relaxed to $88 million, 39 locations are chosen. All but one of the locations from the base case is kept open and 19 new ones are added. Each location offers general services and mental health/substance abuse at the highest level. Twenty-two locations offer OBGyn services, at a mix of the three service levels. None offer dentistry. Total patients encounters are approximately 2.83 million.

When the budget is halved to $22 million, only 10 locations are chosen and they are a subset of the locations opened with the $44 million budget. All of the locations offer general services and mental health and substance abuse at the highest level. Total patient encounters decrease to approximately 718,000.

3.4.5 Impact of Weights on Services

The two least expensive services per encounter are mental health/substance abuse (since the variable cost is the lowest) and general services (since the higher demand lowers the fixed cost portion per encounter). Dentistry has the highest variable cost and has not been chosen by any of the models unless the other services have already been used to their fullest capacity. As mentioned in the data section, we study the impact of increasing the weight on OBGyn by tenths up to 1.5 and the impact of decreasing the weights on dentistry and mental health and substance abuse by tenths to 0.5.

As expected, as the weights for OBGyn increase, the number of encounters increase steadily, from no encounters at a weight of 1.0, to 85,472 at a weight of 1.1, up to 128,290 at a weight of 1.5. Mental health decreases from 54,000 at weights of 1.0, 0.9, and 0.8 to no encounters at a weight of 0.7. Dentistry is unaffected, since it was not selected even at a weight of 1.0.

3.4.6 Impact on Rural Counties

The model seldom chooses the most rural counties because they have less total demand, which causes the fixed costs to have a more significant impact per encounter. However, since one of the objectives of the community health center program is to have a mix of urban and rural locations [43], we added the constraint to the base model that at least 25% of CHC locations be from the 10% most rural counties. The model chose to open 24 locations, 6 of which were rural, with approximately 1.39 million encounters.

3.4.7 Impact on the Uninsured Population

As one of the purposes of the CHC program is to reach uninsured persons, we also approximated the percentage of the demand from uninsured persons that would be met with each of our solutions (included in Table 3.7). This ranged from 11% to 54% and was heavily influenced by the budget allocated.

We also changed our model to minimize cost subject to serving a minimum percentage of the uninsured population's estimated demand. The results from this model are shown in Figure 3.7. The costs represented are costs after insurance reimbursements and payments, and therefore represent the budget that would need to come from (mainly government) grants. We include demand for all four services. We still assume people will travel a maximum distance of 30 miles. The increase in cost is fairly linear until the last 10% of the population needs to be served.

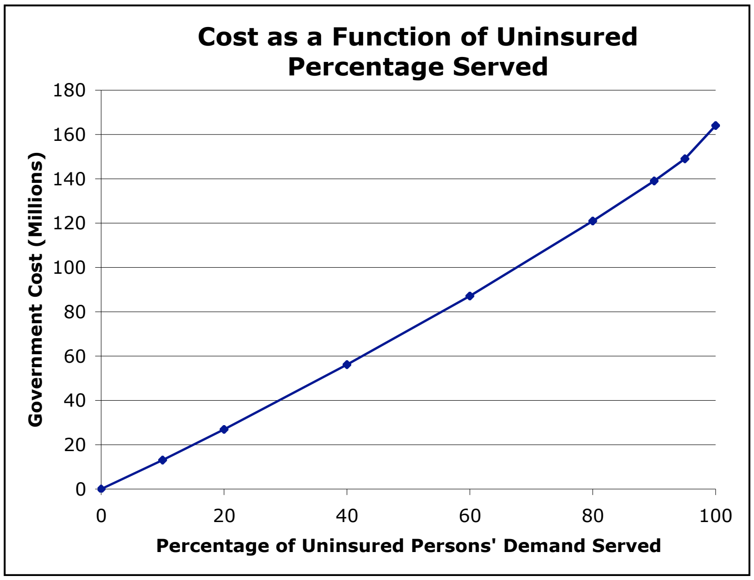

Figure 3.7: Effect of Increase in Government Subsidy of CHC Budget on Percentage of Uninsured Persons' Demand Met

This model can be useful in the debate over access to healthcare for the uninsured versus universal insurance. Offering service to the uninsured at CHCs is an alternative to increasing insurance and is an interesting public health topic.

3.4.8 Considerations for Dental Coverage

As mentioned above, dental services are not chosen by our model, due to the high variable cost. However, if we wish to offer dental services at all to the uninsured, it may be that CHCs are the most cost-efficient way to do so. We should also note that the predictions of insurance above are for health insurance, which does not always include dental, so the costs could be even higher.

We tested adding an additional constraint to our model that requires a portion of the budget to be spent on dental care to see how that affects the overall solution. If an additional 10% ($4.4 million) is allocated to the base model to be used only for dental costs (variables costs as well as fixed cost for the service), 106,405 dental patients are served. The model chooses one fewer location than without the dental constraint, and of the 20 locations chosen, 13 are the same as the locations chosen in the base model.

3.5 Conclusions

There are many that would argue that Community Health Centers should be more financially self-sufficient. This chapter illustrates some of the negative ramifications associated with that prospect. Making decisions only on budget considerations leaves out some of those most in need of services - namely those who are uninsured and those who live in very rural areas. Rural areas do not have enough demand to achieve the economies of scale that overcome the fixed costs. It is less cost effective to serve the uninsured population, since they tend to pay significantly less for services than those who are insured. This parodox must be handled appropriately in policy decisions.

In addition, since the model is choosing to maximize the number of encounters with a limited budget, some services (i.e. OBGyn and dentistry) are excluded in favor of more cost-efficient options. In general, the model chooses general services, due to the economies of scale of the fixed costs, and mental health/substance abuse services, due to the low cost per encounter. Since there is a huge amount of need for CHC services in Georgia, it is possible in reality that it may be most effective to only offer the most inexpensive services so that more people can be reached. However, if this is not an acceptable option, then there should be a compelling reason to offer additional services. For example, as shown above, if CHCs are more effective at delivering dental care than some other methods this can be addressed by allocating a separate budget to dentistry or weighting each of the services. We also illustrate how obstetrics and gynecology services are chosen when the weights are increased.

When making comparisons between our model and the current CHC locations, it is clear that the current location and service decisions are not the most cost-efficient. Locations chosen by our model would allow significantly more encounters per year. While current locations of CHCs capture some of the targets not chosen by our base model, such as offering prenatal care shown to reduce infant mortality figures, it is clear that there is a benefit to being able to consider the location and allocation decision as part of a larger network approach to decision making.

3.5.1 Limitations

There are several limitations to our model. First, the solutions resulting from our model are dependent upon the input data for costs and demands, much of which we had to estimate. Also, while there is a preference for geographic dispersion of CHCs [43], it may actually be more effective to have more than one CHC in certain urban counties, which is not allowed in our model. Finally, solving the model for counties assumes that all of the population of a county is located at the center of the county. While we do not believe this to be a significant problem for Georgia's relatively small counties, this could result in bad solutions if the counties are large and sparsely populated or if the county is large and the population is densely located in a small off-center area.

3.5.2 Future Research

There are many opportunities to expand upon this research. After determining a way to computationally solve a larger version of the problem (in terms of number of possible locations) we could look at the more detailed problem of which census tracts would be the best locations in Georgia. Additionally, we could solve the network at the national level and study the tradeoffs throughout the country. More work can be done on the local estimate problem - expanding the estimates to more states and using BRFSS data or other methods such as NHANES subsampling to validate. In addition, some rural counties do not have doctors available. Including a constraint for modeling likeliness to get doctors in short supply would be an interesting addition to the model.

Finally, we suggest that this model could also be used to help make decisions that take future migration patterns into consideration. For example, the Hispanic population is currently increasing in Georgia. Being Hispanic is a risk factor for certain health conditions and they are more likely to be uninsured than white individuals [42]. By using forecasts of future demographics, we can forecast future need for CHCs' services to take into account in policy decision making.

CHAPTER IV

MARKOV CHAINS AND CHRONIC DISEASE

4.1 Introduction

Discrete time Markov chains are currently a very popular model for evaluating interventions aimed at treating chronic diseases [5, 17]. The valuable information that can be gleaned from these types of models can be used to help in public policy decisions. Resources often limit formal studies, and when true experiments are infeasible or impractical to determine the effect of a particular intervention, Markov models can be used to simulate experiments and explore alternative scenarios. In health economic evaluation, models are typically used to extrapolate beyond the data observed in a trial, linking intermediate clinical endpoints to final outcomes, generalizing to other settings, synthesizing head-to-head comparisons where relevant trials do not exist and informing decisions in the absence of hard data [10, 16]. The use of these models provides estimates that would otherwise be unavailable. This is especially important since there is such high demand for allocating limited funds for public health issues.

There are several examples in the literature of using Markov models to forecast the prevalence of disease. For example, Markovian modeling has been used for forecasting diabetes prevalence [32, 39], the future cost of children born with HIV [52], and the future status of molar teeth [35]. Another context is to measure the impact of interventions on disease prevalence, including the impact of bleach programs for preventing AIDS among IV drug users [56], strategies to decrease tuberculosis among the homeless [6], and the effect of blood pressure-lowering on life expectancy [54]. Often Markov chains are used to model the cost-effectiveness of various interventions, such as Hepatitis B vaccination programs [36], helical computed tomography for lung cancer screening [38] or Hepatitis C treatments [51]. In each of these cases, a model is made of the probabilities of various circumstances based on data from past experiments or expert opinion.

Unfortunately, there is a significant room for error in the estimation of these probabilities, especially in turning panel data into single year probabilities or using short-term data to extrapolate over long periods of time. Beck and Pauker state that constant transition probabilities are realistic only for diseases with a short time horizon [5]. In this chapter, we illustrate some of the potential biases associated with the use of Markov modeling in chronic disease. In section 2, we provide some background on Markov chains. We offer some analytic results in sections 3 and 4, include a specific example using lung cancer data in section 5, and conclude with a discussion of the results.

4.2 Markov Models

The primary assumption required when using Markov chains is that the probability of an event occurring at a given time is not dependent on what has happened in the past, but only on its current state, i [50]. This "memoryless property" is what allows us to describe the entire model in a single matrix. The progression of a disease is captured in distinct states (for example: health, presence of risk factors for disease, presence of disease, death). In a discrete time Markov chain, transition probabilities, p_{ij}, are the probabilities of moving between states i and j in a cycle per discrete time period. These are captured in a transition matrix, P, in which the rows represent the states at the beginning of the period and the columns are the states at the end of the period. The sum across each row of the matrix must be one, since all of the possibilities in the disease progression are accounted for in the matrix. The probability of being in one state n periods later is obtained by raising the one-period matrix to the n^{th} power. For example, the probability of progression between states in two periods is found by simply multiplying the transition matrix by itself. One benefit of using Markov models to study disease progression is that diseases are generally well-captured by distinct health states.

Markov models can be appropriately applied to infectious disease. For example, the probability of a person contracting malaria from a mosquito bite during a particular year is not affected by how many years that person has been there before, but only whether that person is exposed that year. This is not true for chronic disease. Often there is a correlation between the amount of time a person spends in a risk state for a disease and their probability of getting that disease. For example, a person who has been obese for fifty years has a higher probability of obtaining diabetes than someone who has been obese for only one year, all else being equal [19, 20]. If we try to represent this probability with just one value, there will be bias in the estimate of the number of people in the disease state, as explained below.

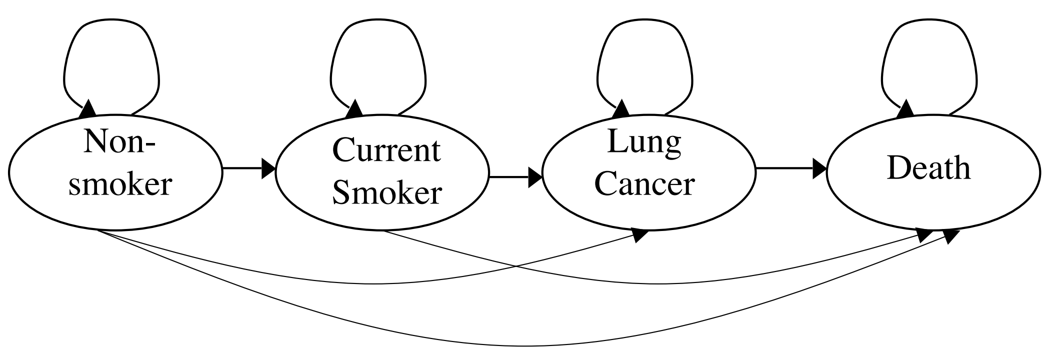

Figure 4.8: Typical Markov Chain - Lung Cancer Average Case

A typical Markov chain for a chronic disease is illustrated by the following lung cancer example (Figure 4.8). The arrows represent possible transitions between states within a given year. For example, a person who is healthy (non-smoker) can remain healthy, begin the risk behavior (smoking), contract the disease (lung cancer), or die. Obviously, once a person dies, they remain in the death state, and the only arrow from death goes back to death, i.e., it is an absorbing state. We also assume for our example that no one quits smoking. Let n represent the non-smoking state, s smoking, l lung cancer, and d death, and the transition matrix for this example is:

$$\begin{array}{c} \\ n \\ s \\ l \\ d \end{array} \begin{array}{c} \begin{array}{cccc} n & s & l & d \end{array} \\ \begin{pmatrix} \theta_{nn} & \theta_{ns} & \theta_{nl} & \theta_{nd} \\ 0 & \theta_{ss} & \theta_{sl} & \theta_{sd} \\ 0 & 0 & \theta_{ll} & \theta_{ld} \\ 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

However, the probability of contracting a disease often depends on how long a person has been in the risk state (smoking, in our example). In that case, the Markov chain would need to be modified (Figure 4.9). Although this Markov chain is more complicated, we show in the next section that using the simplified chain can lead to significant bias in the forecast.

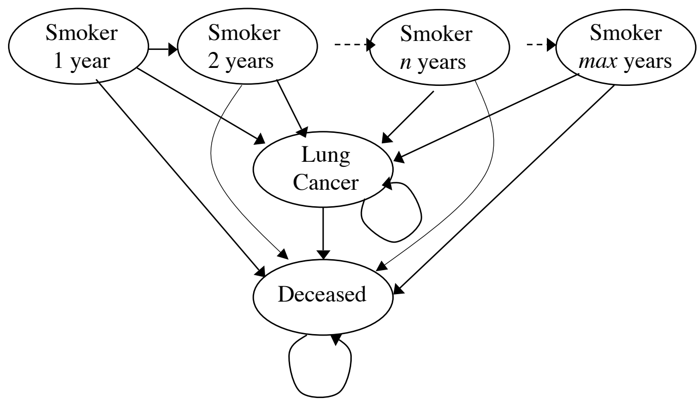

Figure 4.9: Markov Chain for Lung Cancer as a Function of Time Smoking

$$
\begin{array}{c} \\ n \\ s_1 \\ s_2 \\ \ldots \\ s_n \\ l \\ d \end{array}
\begin{array}{c}
\begin{array}{ccccccc} n & s_1 & s_2 & \ldots & s_n & l & d \end{array} \\
\begin{pmatrix}
\theta_{nn} & \theta_{ns_1} & 0 & \ldots & 0 & \theta_{nl} & \theta_{nd} \\
0 & 0 & \theta_{s_1 s_2} & \ldots & 0 & \theta_{s_1 l} & \theta_{s_1 d} \\
0 & 0 & 0 & \ldots & 0 & \theta_{s_2 l} & \theta_{s_2 d} \\
\ldots & & & & & & \\
0 & 0 & 0 & \ldots & \theta_{s_{n-1} s_n} & \theta_{s_{n-1} l} & \theta_{s_{n-1} d} \\
0 & 0 & 0 & 0 & 0 & \theta_{ll} & \theta_{ld} \\
0 & 0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}
\end{array}
$$

There are several methods commonly used in the literature to estimate a transition matrix from a given data set. For example, study data showing what percentage of a population obtained a disease in one particular year (incidence rate) might be used directly as the transition probability from risk to disease [35]. Often incidence is determined by looking at prevalence at two discrete points in time. When looking at n-year panel data where x

people obtain the disease over the course of the n years, it might be assumed that a constant x/n people contract the disease each year. Or, as several authors have shown, it is more accurate to assume that $\sqrt[n]{x}$ get the disease each year [5, 17]. The problem remains that, with chronic diseases, one transition probability cannot capture the actual progression from risk state to disease.

4.3 Analytic Results

In this section we demonstrate some of the causes of bias introduced by using a single transition probability from risk to disease instead of the whole probability function related to each risk state's progression to disease. Let p_{id} represent the probability of contracting the disease from risk state i.

Case 1: Using **ANY** average of past data from a population to predict future spread of disease.

Consider the transition probability function in Figure 4.10. The transition probability from risk to disease increases as the time spent in the risk state increases. If early data from time in risk states 1 and 2 is averaged to determine the transition probability for the future, the probability will be calculated somewhere to the left of R_2, even though the actual probability will be to the right of R_2 in the future. $\frac{(x-\alpha)+(x+\beta)}{2} < x + \beta$ for all positive values of α, β. This method will underestimate the number of people contracting the disease.

Case 2: Using the arithmetic mean of panel data to predict behavior in an identical population.

The formal proofs of the following are included in the Appendix. The following results all refer to using the arithmetic mean of the correct risk states to determine one transition

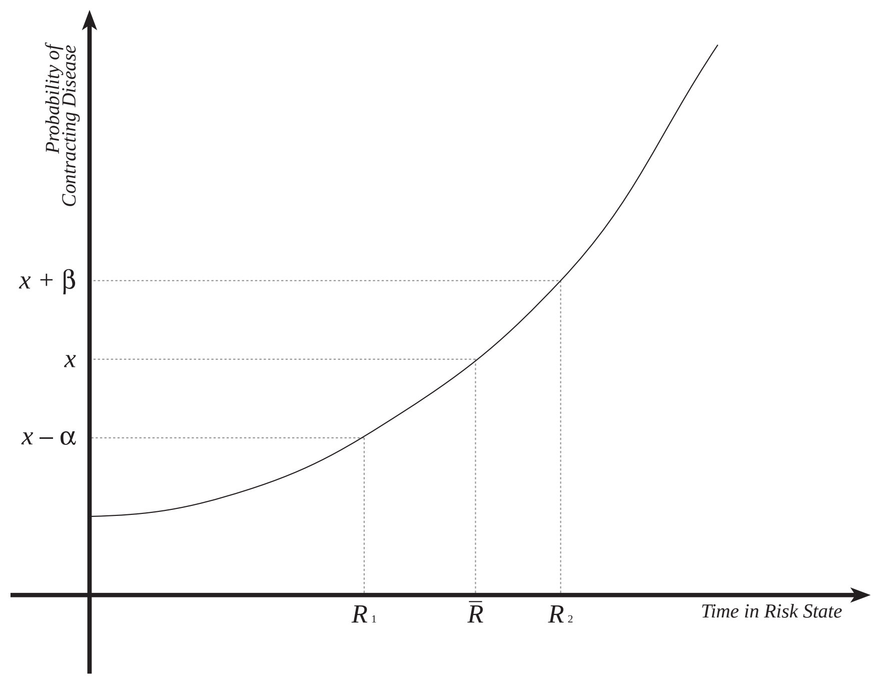

Figure 4.10: Convex Increasing Transition Probability Function

probability from n-year panel data (e.g. $\frac{p_{1d}+p_{2d}+...+p_{nd}}{n}$).

Proposition 4.1 If the transition probability function is convex and increasing {concave and decreasing} as a function of the time spent in the risk state, and the population all begins in state risk 1, then the single transition probability obtained from the arithmetic mean of the actual transition probabilities always underestimates {overestimates} the number of people who end up in the disease state when compared to the calculation when risk states are taken into consideration.

Proposition 4.2 Whenever the transition probability function is convex and increasing as a function of the time spent in the risk state, and the population begins evenly split between two risk states, then the single transition probability obtained from the arithmetic mean of the actual transition probabilities always underestimates the number of people who end up in the disease state when compared to the calculation when risk states are taken into consideration. Whenever the probability function is concave and decreasing, the average overestimates.

Proposition 4.3 If the transition probability function is increasing linearly with time, then the single transition probability obtained from the arithmetic mean of the actual transition probabilities always underestimates the number of people who end up in the disease state, independently of what proportion of the population began in each of two risk states.

Case 3: Using the ROOT method of panel data to predict behavior for a different population mix or for forecasting future behavior.

While taking the n^{th} root of n-year panel data will give the correct forecast when used on n years of the exact same initial population, it is not guaranteed to do so for even a slightly different initial population. It also is not guaranteed when forecasting the future, which is commonly what is being done with the estimate (e.g., in [32, 39]). If the n^{th} root is used to forecast into the future, it has the same effect as Case 1 above. Using any value obtained from early risk states will underestimate the behavior in the later risk states when the transition probabilities are increasing.

These results show that bias can exist when risk states are averaged. In the following section we give an example of the magnitude of the bias.

4.4 Experimental Results

Several different methods are used in the literature to determine the average transition probability. While we have shown above that none of them work perfectly, here we test the relative quality of a few different averages. We use three 2-factor designs, with "A" as the factor that we are testing (probability, concavity, duration - defined below) and "B" as the initial population distribution used (10 experiments each of uniform, left triangular, right triangular, and full triangular). We verified that at a confidence level of 99%, there is no interaction between A and B, so we can accurately test the factors.

AVERAGE1 is obtained by taking the total number that contract the disease at the end of n years for the actual (CORRECT) case divided by n (arithmetic mean). AVERAGE2 is the transition probability associated with the average risk state (p_{ad} where $a = \frac{n}{2}$), for the initial distribution in the CORRECT case, but used for every year. Full results are in Table 4.8.

Table 4.8: Experimental Results: Percent of Population in Disease State

FACTORS STUDIED			CORRECT		AVERAGE1		AVERAGE2		AVG1 - CORR		AVG2 - CORR	
Concavity	Duration	Probability	Avg	SD	Avg	SD	Avg	SD		SE		SE
LINEAR	SHORT	LOW	0.07	0.04	0.07	0.03	0.04	0.02	0.00	0.008	0.03	0.006
LINEAR	MED	LOW	0.18	0.06	0.16	0.05	0.08	0.06	0.02	0.013	0.10	0.014
LINEAR	LONG	LOW	0.34	0.09	0.27	0.07	0.15	0.14	0.07	0.018	0.19	0.026
CONCAVE	SHORT	LOW	0.05	0.04	0.05	0.03	0.02	0.01	0.00	0.008	0.03	0.006
CONCAVE	MED	LOW	0.13	0.07	0.12	0.05	0.04	0.04	0.01	0.013	0.09	0.012
CONCAVE	LONG	LOW	0.27	0.08	0.22	0.06	0.07	0.08	0.05	0.015	0.20	0.018
CONVEX	SHORT	LOW	0.09	0.04	0.09	0.03	0.06	0.03	0.00	0.008	0.03	0.007
CONVEX	MED	LOW	0.22	0.07	0.19	0.06	0.12	0.09	0.03	0.014	0.10	0.018
CONVEX	LONG	LOW	0.40	0.11	0.30	0.09	0.23	0.21	0.10	0.022	0.17	0.037
LINEAR	SHORT	MED	0.22	0.06	0.20	0.06	0.18	0.08	0.02	0.014	0.05	0.016
LINEAR	MED	MED	0.42	0.13	0.33	0.11	0.36	0.27	0.10	0.027	0.07	0.048
LINEAR	LONG	MED	0.57	0.20	0.39	0.14	0.65	0.58	0.18	0.038	-0.08	0.097
CONCAVE	SHORT	MED	0.19	0.05	0.17	0.05	0.14	0.06	0.01	0.012	0.05	0.013
CONCAVE	MED	MED	0.37	0.11	0.29	0.09	0.27	0.20	0.08	0.023	0.10	0.036
CONCAVE	LONG	MED	0.53	0.18	0.37	0.13	0.50	0.45	0.16	0.035	0.03	0.077
CONVEX	SHORT	MED	0.26	0.08	0.23	0.07	0.22	0.10	0.03	0.017	0.04	0.020
CONVEX	MED	MED	0.47	0.16	0.35	0.12	0.44	0.35	0.12	0.031	0.03	0.060
CONVEX	LONG	MED	0.59	0.22	0.40	0.15	0.80	0.72	0.19	0.041	-0.21	0.119
LINEAR	SHORT	HIGH	0.42	0.14	0.35	0.12	0.41	0.20	0.07	0.029	0.01	0.038
LINEAR	MED	HIGH	0.59	0.22	0.41	0.15	0.82	0.61	0.18	0.042	-0.23	0.103
LINEAR	LONG	HIGH	0.63	0.24	0.41	0.15	1.52	1.42	0.21	0.045	-0.90	0.227
CONCAVE	SHORT	HIGH	0.39	0.13	0.33	0.11	0.35	0.15	0.06	0.026	0.04	0.032
CONCAVE	MED	HIGH	0.57	0.21	0.40	0.15	0.70	0.55	0.17	0.040	-0.13	0.092
CONCAVE	LONG	HIGH	0.62	0.24	0.41	0.15	1.26	1.14	0.21	0.045	-0.64	0.184
CONVEX	SHORT	HIGH	0.46	0.16	0.38	0.13	0.48	0.24	0.08	0.032	-0.01	0.045
CONVEX	MED	HIGH	0.61	0.23	0.42	0.15	0.94	0.71	0.19	0.043	-0.33	0.119
CONVEX	LONG	HIGH	0.63	0.24	0.41	0.16	1.76	1.66	0.22	0.045	-1.13	0.265

We studied high [0.3,0.6], medium [0.1,0.3] and low [0,0.1] probability ranges for transition from risk to disease, and compared both averages to the correct value. In general, when compared to the correct value, AVERAGE1 performs worse at higher probabilities than medium probabilities, and it performs worse at medium than low probabilities at a confidence level of 99%. With AVERAGE2, it performs worse at low than medium and at medium than high probabilities, also at a confidence level of 99%.

We also studied simulations over long (10 periods), medium (5 periods), and short (2 periods) durations. At a confidence level of 99% AVERAGE1 performs worse for longer durations than for medium durations which are worse than short. AVERAGE2 performs worse at the medium duration than the long duration at a confidence level of 99%, but (even at confidence of 90%) comparisons to the short duration are statistically insignificant.

Finally, we studied linear, convex, and concave transition probability functions. To randomize the probabilities for linear, we let $P(x) = a + \frac{(n-1)(b-a)}{N-1}$, where $[a, b]$ is the probability range from above, n is the risk state, and N is the total number of risk states. For the convex case, we used the function $P(x) = a + \frac{(n-1)^2(b-a)}{(N-1)^2}$ and for the concave case we used $P(x) = a + \frac{(n-1)^{1/2}(b-a)}{(N-1)^{1/2}}$. For AVERAGE1, performance is worse for concave probability functions than convex (99% confidence), and (even at confidence of 90%) linear is statistically insignificant when compared to the concave and convex cases. AVERAGE2 performs worse on convex cases than concave, which is worse than linear.

In general, AVERAGE1 performed much better than AVERAGE2 compared to the true rates. AVERAGE1 had a mean difference from CORRECT of 0.10 (s.e. = 0.026), while AVERAGE2's mean difference from CORRECT was 0.19 (s.e. = 0.064).

4.5 Specific Example: Lung Cancer

Lung cancer is one case that may result in bias if the limited Markov chain is used. It is well documented that smoking is the major cause of lung cancer. Lung cancer risks increase with age, duration of smoking, and number of cigarettes smoked (and decrease with time since cessation of smoking) [41]. To study all three of these effects, a four-dimensional matrix would need to be made. While this can certainly be done, to simplify notation, we focus below only on the effect of the duration of smoking. We study current male smokers, ages 40 to 79, who smoke 20 cigarettes per day and we model the expected incidence of lung cancer over time as a function of how many years they have been smoking. This is equivalent to Figure 4.9, with everyone beginning in one of the smoking risk states. We then compare our method to estimates obtained by more typical ways of modeling Markov chains in the literature.

Doll and Peto [18] estimated that among smokers who started smoking between the ages of 16 and 25 and who smoked 40 or less cigarettes per day, the annual lung cancer incidence in the age range 40-79 is:

$$(0.273X10^{-12})(\text{number of cigarettes per day} + 6)^2(\text{age} - 22.5)^{4.5} \quad (11)$$

Note that 22.5 is an estimate that comes from the average duration of smoking, since the participants began between the ages of 16 and 25. Since we are looking at smokers of 20 cigarettes per day, equation 11 reduces to:

$$1.845X10^{-10}(\text{duration of smoking in years})^{4.5} \quad (12)$$

Thus, the one year transition probability from smoking for n years to lung cancer is

$$T_{R_n,D} = 1.845X10^{-10}n^{4.5} \quad (13)$$

We use that resulting transition matrix to determine the expected prevalence of lung cancer in three different hypothetical populations that have been smoking 20 cigarettes per day since they were 16-25 years of age and are currently between 40 and 79 years of age. First we assume that the entire population was initially in state R_1, which corresponds to the shortest duration of smoking in the relevant groups (CONSTANT). Next we assume the population was uniformly distributed among - all of the risk states, R_1 to R_{40} (UNIFORM). Finally, we assume that the population was distributed as follows: R_1 to R_5 and R_{36} to R_{40}, each with 0.625%, R_6 to R_{10} and R_{31} to R_{35}, each 1.875%, R_{11} to R_{15} and R_{26} to R_{30}, each with 3.125%, and R_{16} to R_{25}, each with 4.375% (BLOCK). For each of these three cases, we run the Markov model for 2, 5, 10, and 20 years. These results can be found under the CORRECT columns in table 4.9.

We then compare this to several ways of characterizing the risk that do not differentiate by the duration of smoking. This is equivalent to Figure 4.8 that we discussed earlier. The first comparison (AVERAGE1) is to use the correct results from the base case for the number of people who have lung cancer, divided by the number of years the model was run. This is similar to what might happen if one uses multi-year survey data, and assumes that the number of people contracting the disease were the same in each year. This will always underestimate, as we showed in section 4.3. For the second comparison (AVERAGE2), we take the arithmetic mean of the initial correct risk states and use that single transition probability for the duration of the run. The last comparison (ROOT) is to take the n^{th} root of the correct results from the base case for the number of people who have lung cancer, where n is the number of years run. We then test these averages on several types of transition probability distributions.

Table 4.9: Lung Cancer Simulation Results

	2 years			**5 years**			**10 years**			**20 years**		
	CORRECT	AVG1	AVG2	CORRECT	AVG1	AVG2	CORRECT	AVG1	AVG2	CORRECT	AVG1	AVG2
DOLL-PETO												
constant	0.017%	0.017%	0.015%	0.061%	0.062%	0.036%	0.23%	0.23%	0.07%	1.39%	1.38%	0.14%
normal	3.22%	3.19%	0.40%	4.52%	4.43%	0.99%	7.21%	6.98%	1.96%	14.33%	13.40%	3.88%
block	1.89%	1.88%	0.40%	3.08%	3.05%	0.99%	5.73%	5.58%	1.96%	13.36%	12.54%	3.88%
POWER4												
constant	0.004%	0.004%	0.004%	0.014%	0.014%	0.009%	0.048%	0.048%	0.017%	0.25%	0.25%	0.035%
normal	2.61%	2.59%	0.066%	2.80%	2.76%	0.16%	3.20%	3.15%	0.33%	4.29%	4.20%	0.65%
block	1.35%	1.34%	0.066%	1.52%	1.52%	0.16%	1.92%	1.90%	0.33%	3.08%	3.04%	0.65%
HALF												
constant	0.008%	0.008%	0.007%	0.031%	0.031%	0.018%	0.12%	0.12%	0.036%	0.70%	0.69%	0.072%
normal	2.86%	2.84%	0.20%	3.52%	3.47%	0.49%	4.90%	4.80%	0.98%	8.68%	8.33%	1.96%
block	1.57%	1.57%	0.20%	2.17%	2.15%	0.49%	3.53%	3.47%	0.98%	7.55%	7.29%	1.96%
DOUBLE												
constant	0.033%	0.033%	0.029%	0.12%	0.12%	0.072%	0.46%	0.46%	0.14%	2.75%	2.72%	0.29%
normal	3.93%	3.90%	0.79%	6.46%	6.30%	1.96%	11.56%	10.98%	3.89%	24.25%	21.65%	7.62%
block	2.53%	2.51%	0.79%	4.87%	4.78%	1.96%	9.91%	9.48%	3.89%	23.64%	21.17%	7.62%

4.5.1 Using the same data as the base run

We begin by running the CORRECT DOLL-PETO case and then using that information to obtain our various average transition probabilities. For sensitivity analysis, we then run the same experiment for variations on Doll and Peto's equation 11. We test the original equation, but with an exponent of 4 instead of 4.5 (POWER4), as well as double and half the original transition probability (DOUBLE and HALF).

At a confidence level of 99%, we found that AVERAGE1 is closest to correct with the CONSTANT initial distribution and furthest with the UNIFORM initial distribution. Performance does not seem to change in relation to length of the study. Additionally (confidence 99%), AVERAGE1 performs best on DOUBLE, followed by DOLL-PETO, HALF, then POWER4. It has errors of up to 11%, and an average error of 2%. AVERAGE2 does the worst overall, and gets worse as the duration increases. The average error is 70%, with a maximum error of 98%. (See Table 4.9.)

Earlier we stated that the ROOT average yields an accurate value when run with the same data, but is sensitive to the initial distribution. In this case, since we are running the experiment again on exactly the same data, the ROOT case would give us the correct answer.

4.5.2 Using past data to forecast the future

To test the accuracy of the ROOT average, we next use values for ROOT obtained from the CORRECT case at 2, 5, and 10 years to test the accuracy of longer runs. If the transition probability from the square root of the 2-year CORRECT result matrix is used, it yields the correct value for 2 years, but underestimates disease prevalence by 33% at 5 years, 64% at 10 years, and 88% at 20 years. If the transition probability from the square root of the

5-year CORRECT result matrix is used, it underestimates by 48% at 10 years and 82% at 20 years. Lastly, if the 10-year result is used, it underestimates by 67% at 20 years.

4.5.3 Changing the initial distribution

To test the change in the initial distribution with the ROOT average, we run a sensitivity analysis on the effect of the starting distribution on the number of people expected to develop lung cancer over the study. We assume that all members start in the same risk state and then study the effect of changing to the adjacent risk state. We run this for each of the four durations of the previous study, and for the first ten initial risk states. Results are in Figure 4.11. For example, if the ROOT method of finding the average transition probability was used for participants in risk state 1, but then the forecast was applied to people who were actually in risk state 2, the forecast would be off by between 15 and 28 percent, depending on how long the study was run for. The second chart compares everyone in one period versus half in that period and half in the next. In that case, the forecast would be off by between 6 and 14 percent.

4.6 Discussion

Markov chains are frequently used to study the growth of disease in a population. Several different methods exist in the literature to determine the transition probabilities for a Markov chain. We have shown that some of these methods can lead to significant errors in forecasting for chronic diseases. We have illustrated that using too few risk states will incorrectly forecast the percentage of population with disease under many circumstances. Through experimental design we have shown the effect of duration, probability range, and the shape of the probability curve on the magnitude of the errors. Additionally, we have

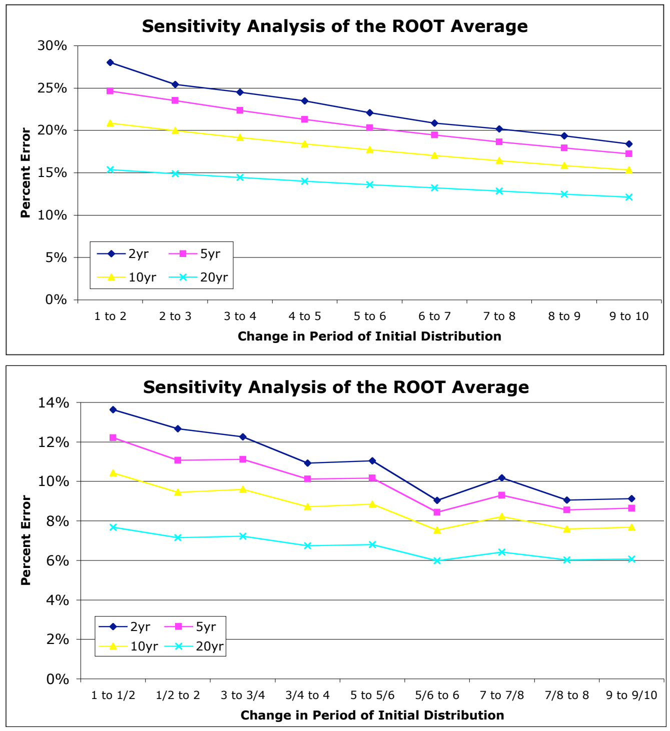

Figure 4.11: Lung Cancer Example Sensitivity Analysis

shown that while the root method is more accurate than other averages, it is still very sensitive to the input data. We further illustrated the problems of these averages in a simulation using lung cancer data.

The results of forecasts from Markov chains are often used to allocate funds for various diseases. The accuracy of these forecasts is essential to make these decisions wisely. Therefore, it is important to be aware of the need to consider the impact of the time spent in a risk state on the probability of a person obtaining a chronic disease.

These forecasts are especially important as medical technology and medications improve, increasing the length of time that people can live while at risk for or having chronic diseases. The increasing elderly population is one such example, as is the recent classification of HIV as a chronic disease [22]. Having correct forecasts of the prevalence of many of these health conditions will be vital in making the best decisions with limited public health funds.

CHAPTER V

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This thesis suggests several methods for better forecasting the demand for health care and allocating health care resources more efficiently. These results were organized into three sections.

In Chapter 2, we studied the productivity of dental sealant programs and made suggestions for increased efficiency. Using simulation and data from several states' programs, we offered guidelines for optimal programs based on program size, distance to site, and practice act requirements. We showed that significant cost savings can be attained from using an extra sealant station and dental assistant to perform the barrier changes in most cases. We quantified the cost of satisfying practice act requirements and showed that significantly more students can be sealed by reducing practice act restrictions. The magnitude of the benefit depends on several factors, including current practice act, program size, and travel distance to the site. Future research possibilities in this area included modeling the effect of the decreasing supply of dentists on obtaining dentists to apply sealants for public health programs and quantifying the cost of the lost student productivity under the different practice acts.

In Chapter 3 we presented a model for allocating health resources to Community Health Centers (CHCs). Local estimation was used to forecast county insurance types, disease prevalence, and likelihood of using a clinic in the state of Georgia, and we demonstrated that these estimates were close to available data. We developed a mixed-integer programming model to determine optimal locations and service portfolios to be offered under financial constraints. We demonstrated that the impact of cost-based decision making would be to avoid locations with the greatest number of uninsured persons and the most rural areas. More expensive services would also be avoided entirely when all service types are weighted equally. There are many potential directions for additional research related to this problem. More work is remaining to be done on local estimates of demand, and we would like to expand the results to the national level to study how this approach to locating CHCs performs at that level. This work could also be expanded to help quantify the cost differences between access and insurance in public health policy debates or to make decisions based on population migration patterns.

In Chapter 4, we analyzed shortcomings in current Markovian modeling of chronic disease. We showed three types of common forecasting techniques that can overestimate or underestimate the population in need of care. Through experimental results we showed how the magnitude of the bias can vary as a function of the transition probability level, duration of the forecast, and shape of the probability function. We then presented an example with lung cancer data that illustrated this bias. We showed how bias occurs even when taking the n^{th} root of the n-year outcome when that single probability from past data is used to forecast the future or when it is used on a different initial distribution than the one used to calculate it.

Each of the issues addressed affect the planning models for scarce resources in health care. Improving those models can positively impact utilization of those services. It is our hope that the models presented will positively impact public health decisions in coming years, particularly those for growing high-risk and low-income groups.

APPENDIX A

SUPPLEMENTARY MATERIAL FOR EFFICIENCY OF SCHOOL-BASED SEALANT PROGRAMS AND THE COST OF DENTAL PRACTICE ACTS

A.1 Automod Code

```
/*INITIALIZING & SCREENING*/
begin P_screening_NS1 arriving /*short screen, short seal*/
if V_temp_NS1 = 0 then
begin
increment V_temp_NS1 by 1 /*tracks what student we are on*/
send to P_dummy_NS1 /* to time when the runs complete*/
end
move into Q_inspect_wait(1) /*infinite queue*/
move into Q_chair(1) /*capacity = capacity of R_assist*/
get R_hyg(1)
get R_assist(1)
wait for 2 sec /* time to screen */
send to oneof (3:P_die_NS1, 7:P_dental_NS1)/*30% don't need seal*/
end

begin P_screening_NS2 arriving /*short screen, long seal*/
if V_temp_NS2 = 0 then
begin
increment V_temp_NS2 by 1
send to P_dummy_NS2
end
move into Q_inspect_wait(2)
move into Q_chair(2)
get R_hyg(2)
get R_assist(2)
wait for 2 sec
send to oneof (3:P_die_NS2, 7:P_dental_NS2)
end

begin P_screening_NS3 arriving /*long screen, long seal*/
if V_temp_NS3 = 0 then
begin
```

```
increment V_temp_NS3 by 1
send to P_dummy_NS3
end
move into Q_inspect_wait(3)
move into Q_chair(3)
get R_hyg(3)
get R_assist(3)
wait for 4 sec
send to oneof (3:P_die_NS3, 7:P_dental_NS3)
end

begin P_screening_G1 arriving /*N/A screen, short seal*/
if V_temp_G1 = 0 then
begin
increment V_temp_G1 by 1
send to P_dummy_G1
end
send to oneof (3:P_die_G1, 7:P_dental_G1)
end

begin P_screening_G2 arriving /*N/A screen, long seal*/
if V_temp_G2 = 0 then
begin
increment V_temp_G2 by 1
send to P_dummy_G2
end
send to oneof (3:P_die_G2, 7:P_dental_G2)
end

begin P_screening_I1 arriving /*short screen, short seal*/
if V_temp_I1 = 0 then
begin
increment V_temp_I1 by 1
send to P_dummy_I1
end
move into Q_inspect_wait(6)
move into Q_dent(6)
get R_dentist(6)
get R_assist(6)
wait for 2 sec
increment V_dentist_I1 by 1
if V_dentist_I1 = (MAX-1) then
begin
order 1 load from OL_Dent(1) to continue
end
send to oneof (3:P_die_I1, 7:P_dental_I1)
end
```

```
begin P_screening_I2 arriving /*short screen, long seal*/
if V_temp_I2 = 0 then
begin
increment V_temp_I2 by 1
send to P_dummy_I2
end
move into Q_inspect_wait(7)
move into Q_dent(7)
get R_dentist(7)
get R_assist(7)
wait for 2 sec
increment V_dentist_I2 by 1
if V_dentist_I2 = (MAX-1) then
begin
order 1 load from OL_Dent(2) to continue
end
send to oneof (3:P_die_I2, 7:P_dental_I2)
end

begin P_screening_I3 arriving /*long screen, long seal*/
if V_temp_I3 = 0 then
begin
increment V_temp_I3 by 1
send to P_dummy_I3
end
move into Q_inspect_wait(8)
move into Q_dent(8)
get R_dentist(8)
get R_assist(8)
wait for 4 sec
increment V_dentist_I3 by 1
if V_dentist_I3 = (MAX-1) then
begin
order 1 load from OL_Dent(3) to continue
end
send to oneof (3:P_die_I3, 7:P_dental_I3)
end

/*******************************************************/
/* SEALING */
begin P_dental_NS1 arriving
wait for triangular 15,17.5,20 sec /*time to seal*/
free R_hyg(1)
wait for 7 sec /*barrier change*/
free R_assist(1)
increment V_temp_NS1 by 1
if V_temp_NS1 = MAX then order 1 load from OL_assem(1) to continue
send to die
```

```
end

begin P_dental_NS2 arriving
wait for triangular 20,25,30 sec
free R_hyg(2)
wait for 7 sec
free R_assist(2)
increment V_temp_NS2 by 1
if V_temp_NS2 = MAX then order 1 load from OL_assem(2) to continue
send to die
end

begin P_dental_NS3 arriving
wait for triangular 20,25,30 sec
free R_hyg(3)
wait for 7 sec
free R_assist(3)
increment V_temp_NS3 by 1
if V_temp_NS3 = MAX then order 1 load from OL_assem(3) to continue
send to die
end

begin P_dental_G1 arriving
move into Q_inspect_wait(4)
move into Q_chair(4)
get R_hyg(4)
get R_assist(4)
wait for triangular 15,17.5,20 sec
free R_hyg(4)
wait for 7 sec
free R_assist(4)
increment V_temp_G1 by 1
if V_temp_G1 = MAX then order 1 load from OL_assem(4) to continue
send to die
end

begin P_dental_G2 arriving
move into Q_inspect_wait(5)
move into Q_chair(5)
get R_hyg(5)
get R_assist(5)
wait for triangular 20,25,30 sec
free R_hyg(5)
wait for 7 sec
free R_assist(5)
increment V_temp_G2 by 1
if V_temp_G2 = MAX then order 1 load from OL_assem(5) to continue
send to die
```

```
end

begin P_dental_I1 arriving
free R_dentist(6)
wait for 1 sec /*screening barrier change*/
free R_assist(6)
move into Q_inspect_wait(6)
move into Q_chair(6)
get R_hyg(6)
get R_assist(6)
wait for triangular 15,17.5,20 sec
free R_hyg(6)
wait for 7 sec
free R_assist(6)
increment V_temp_I1 by 1
if V_temp_I1 = MAX then order 1 load from OL_assem(6) to continue
send to die
end

begin P_dental_I2 arriving
free R_dentist(7)
wait for 1 sec
free R_assist(7)
move into Q_inspect_wait(7)
move into Q_chair(7)
get R_hyg(7)
get R_assist(7)
wait for triangular 20,25,30 sec
free R_hyg(7)
wait for 7 sec
free R_assist(7)
increment V_temp_I2 by 1
if V_temp_I2 = MAX then order 1 load from OL_assem(7) to continue
send to die
end

begin P_dental_I3 arriving
free R_dentist(8)
wait for 1 sec
free R_assist(8)
move into Q_inspect_wait(8)
move into Q_chair(8)
get R_hyg(8)
get R_assist(8)
wait for triangular 20,25,30 sec
free R_hyg(8)
wait for 7 sec
free R_assist(8)
```

```
increment V_temp_I3 by 1
if V_temp_I3 = MAX then order 1 load from OL_assem(8) to continue
send to die
end

/****************************************************/
/* TRACKING WHEN JOB IS DONE */
begin P_dummy_NS1 arriving
move into Q_dummy(1)
wait to be ordered on OL_assem(1)
send to die
end

begin P_dummy_NS2 arriving
move into Q_dummy(2)
wait to be ordered on OL_assem(2)
send to die
end

begin P_dummy_NS3 arriving
move into Q_dummy(3)
wait to be ordered on OL_assem(3)
send to die
end

begin P_dummy_G1 arriving
move into Q_dummy(4)
wait to be ordered on OL_assem(4)
send to die
end

begin P_dummy_G2 arriving
move into Q_dummy(5)
wait to be ordered on OL_assem(5)
send to die
end

begin P_dummy_I1 arriving
get R_hyg(6) /*this is a dummy hygienist to track when dentist available to help with seal-
ing*/
move into Q_dummy(6)
wait to be ordered on OL_Dent(1)
free R_hyg(6)
wait to be ordered on OL_assem(6)
send to die
end

begin P_dummy_I2 arriving
```

```
get R_hyg(7)
move into Q_dummy(7)
wait to be ordered on OL_Dent(2)
free R_hyg(7)
wait to be ordered on OL_assem(7)
send to die
end

begin P_dummy_I3 arriving
get R_hyg(8)
move into Q_dummy(8)
wait to be ordered on OL_Dent(3)
free R_hyg(8)
wait to be ordered on OL_assem(8)
send to die
end

/************************************************/
/*HANDLES STUDENTS THAT DON'T NEED SCREENING*/
begin P_die_NS1 arriving
free R_hyg(1)
wait for 1 sec
free R_assist(1)
increment V_temp_NS1 by 1
if V_temp_NS1 = MAX then
order 1 load from OL_assem(1) to continue
send to die
end

begin P_die_NS2 arriving
free R_hyg(2)
wait for 1 sec
free R_assist(2)
increment V_temp_NS2 by 1
if V_temp_NS2 = MAX then
order 1 load from OL_assem(2) to continue
send to die
end

begin P_die_NS3 arriving
free R_hyg(3)
wait for 1 sec
free R_assist(3)
increment V_temp_NS3 by 1
if V_temp_NS3 = MAX then
order 1 load from OL_assem(3) to continue
send to die
end
```

```
begin P_die_G1 arriving
increment V_temp_G1 by 1
if V_temp_G1 = MAX then
order 1 load from OL_assem(4) to continue
send to die
end

begin P_die_G2 arriving
increment V_temp_G2 by 1
if V_temp_G2 = MAX then
order 1 load from OL_assem(5) to continue
send to die
end

begin P_die_I1 arriving
free R_dentist(6)
wait for 1 sec
free R_assist(6)
increment V_temp_I1 by 1
if V_temp_I1 = MAX then
order 1 load from OL_assem(6) to continue
send to die
end

begin P_die_I2 arriving
free R_dentist(7)
wait for 1 sec
free R_assist(7)
increment V_temp_I2 by 1
if V_temp_I2 = MAX then
order 1 load from OL_assem(7) to continue
send to die
end

begin P_die_I3 arriving
free R_dentist(8)
wait for 1 sec
free R_assist(8)
increment V_temp_I3 by 1
if V_temp_I3 = MAX then
order 1 load from OL_assem(8) to continue
send to die
end
```

A.2 Results

Table A.10: State Supervision Requirements for Application of Dental Sealants

State	Required Supervision
Alabama	Direct
Alaska	General
Arizona	General
Arkansas	Direct
California	General
Colorado	None
Connecticut	General
Delaware	General
D.C.	Direct
Florida	Direct
Georgia	Direct
Hawaii	Direct
Idaho	General
Illinois	Indirect
Indiana	Not Reported
Iowa	General
Kansas	Not Reported
Kentucky	Indirect
Louisiana	Direct
Maine	General
Maryland	Indirect
Massachusetts	General
Michigan	General
Minnesota	General
Mississippi	Direct
Missouri	General
Montana	General
Nebraska	General
Nevada	General
New Hampshire	General
New Jersey	Not Reported
New Mexico	General
New York	General
North Carolina	Indirect
North Dakota	General
Ohio	Indirect
Oklahoma	General
Oregon	General
Pennsylvania	General
Puerto Rico	Direct
Rhode Island	General
South Carolina	Direct
South Dakota	Indirect
Tennessee	Indirect
Texas	General
Utah	Not Reported
Vermont	Not Reported
Virginia	Direct
Washington	General
West Virginia	Direct
Wisconsin	General
Wyoming	Direct

Table A.11: Per Person Costs for Different Practice Acts for Various Program Sizes, Assuming 1 Hour Round-trip Travel to Site

Number of hygienists Number of assistants & chairs (+1 for (I), (D))		2 2	2 3	3 3	3 4	4 4	4 5	5 5	5 6	6 6
#students		25	25	25	25	25	25	25	25	25
Cost per student	N1	$17.87	$17.58	$20.96	$20.65	$23.17	$23.72	$25.60	$26.64	$28.70
Standard deviation		$1.46	$1.32	$1.34	$1.31	$1.60	$1.44	$1.55	$1.43	$1.65
Cost per student	N2	$21.69	$21.97	$23.98	$24.72	$26.96	$27.40	$30.05	$30.29	$32.37
Standard deviation		$1.56	$1.43	$2.22	$1.87	$2.30	$1.78	$2.54	$1.69	$2.45
Cost per student	N3	$22.68	$23.17	$25.45	$25.87	$29.07	$29.13	$31.69	$32.46	$34.01
Standard deviation		$2.26	$2.06	$2.32	$1.56	$1.96	$2.01	$1.82	$1.59	$2.13
Cost per student	G1	$25.80	$25.35	$28.56	$28.43	$31.22	$31.46	$33.86	$34.40	$36.53
Standard deviation		$1.39	$1.12	$1.42	$1.20	$1.62	$1.30	$1.59	$1.49	$1.97
Cost per student	G2	$29.59	$29.73	$32.35	$32.49	$34.98	$35.39	$38.02	$38.41	$40.89
Standard deviation		$2.28	$2.09	$2.55	$2.23	$2.51	$2.10	$2.66	$2.35	$2.80
Cost per student	G3	$32.53	$32.67	$35.29	$35.43	$37.92	$38.33	$40.96	$41.34	$43.83
Standard deviation		$2.28	$2.09	$2.55	$2.23	$2.51	$2.10	$2.66	$2.35	$2.80
Cost per student	I1	$29.33	$28.62	$30.68	$30.65	$30.92	$32.56	$35.89	N/A[1]	N/A
Standard deviation		$4.09	$2.21	$2.46	$2.32	$1.32	$1.39	$1.53	N/A	N/A
Cost per student	I2	$34.66	$34.16	$35.60	$35.69	$32.61	$34.34	$37.85	N/A	N/A
Standard deviation		$4.06	$3.27	$4.61	$2.47	$1.57	$1.65	$1.82	N/A	N/A
Cost per student	I3	$36.52	$36.17	$37.32	$37.53	$38.64	$40.69	$44.86	N/A	N/A
Standard deviation		$3.32	$2.60	$2.99	$2.38	$1.32	$1.40	$1.54	N/A	N/A
Cost per student	D1	$33.99	$30.57	$32.83	$31.24	$33.47	$32.93	$34.90	N/A	N/A
Standard deviation		$2.94	$2.19	$2.47	$2.01	$2.51	$1.97	$2.30	N/A	N/A
Cost per student	D2	$41.98	$39.13	$39.43	$38.00	$39.33	$38.88	$40.91	N/A	N/A
Standard deviation		$4.81	$4.09	$4.43	$3.72	$3.90	$3.17	$3.84	N/A	N/A
Cost per student	D3	$41.98	$39.13	$39.43	$38.00	$39.33	$38.88	$40.91	N/A	N/A
Standard deviation		$4.81	$4.09	$4.43	$3.72	$3.90	$3.17	$3.84	N/A	N/A
#students		50	50	50	50	50	50	50	50	50
Cost per student	N1	$16.83	$14.57	$16.68	$15.86	$18.18	$17.68	$19.36	$18.84	$20.79
Standard deviation		$1.07	$0.84	$0.98	$1.00	$1.09	$1.05	$0.98	$0.88	$1.11
Cost per student	N2	$20.37	$20.79	$22.84	$19.93	$21.79	$21.31	$23.50	$22.85	$24.58
Standard deviation		$1.29	$1.11	$1.37	$1.20	$1.23	$1.37	$1.48	$1.21	$1.43
Cost per student	N3	$22.04	$21.95	$24.00	$21.29	$23.08	$22.75	$24.48	$24.40	$25.97
Standard deviation		$1.26	$1.52	$1.32	$1.11	$1.37	$1.33	$1.48	$1.23	$1.37
Cost per student	G1	$22.47	$19.74	$22.28	$21.21	$23.57	$22.90	$24.89	$24.46	$26.20
Standard deviation		$1.13	$0.93	$1.15	$0.96	$1.17	$1.02	$1.30	$1.03	$1.22
Cost per student	G2	$25.98	$25.69	$25.78	$25.08	$27.27	$26.60	$28.84	$28.34	$30.19
Standard deviation		$1.74	$1.71	$1.87	$1.61	$1.78	$1.56	$1.80	$1.57	$1.78
Cost per student	G3	$28.92	$28.63	$28.72	$28.01	$30.21	$29.54	$31.78	$31.28	$33.13
Standard deviation		$1.74	$1.71	$1.87	$1.61	$1.78	$1.56	$1.80	$1.57	$1.78
Cost per student	I1	$24.22	$22.36	$24.14	$23.07	$24.66	$24.00	$25.43	N/A	N/A
Standard deviation		$2.53	$1.58	$1.53	$1.55	$1.24	$0.98	$1.29	N/A	N/A
Cost per student	I2	$32.49	$27.64	$28.98	$27.82	$29.58	$28.77	$30.24	N/A	N/A
Standard deviation		$2.99	$2.03	$3.46	$2.11	$2.22	$2.01	$1.69	N/A	N/A
Cost per student	I3	$34.35	$29.65	$30.71	$29.65	$31.23	$30.50	$31.83	N/A	N/A
Standard deviation		$3.03	$1.87	$2.20	$1.87	$1.43	$0.91	$1.18	N/A	N/A
Cost per student	D1	$32.54	$24.78	$26.51	$23.61	$25.68	$23.97	$25.76	N/A	N/A
Standard deviation		$2.39	$1.82	$1.99	$1.61	$1.82	$1.54	$1.88	N/A	N/A
Cost per student	D2	$39.95	$36.40	$32.60	$30.05	$31.45	$29.58	$31.47	N/A	N/A
Standard deviation		$3.67	$3.33	$3.26	$2.68	$2.77	$2.36	$2.59	N/A	N/A
Cost per student	D3	$39.95	$36.40	$32.60	$30.05	$31.45	$29.58	$31.47	N/A	N/A
Standard deviation		$3.67	$3.33	$3.26	$2.68	$2.77	$2.36	$2.59	N/A	N/A

[1] Not Applicable: would require more than the allowed 6 chairs with the dentist's chair.

Table A.11 (Cont.)

Number of hygienists Number of assistants & chairs (+1 for (I), (D))		2 2	2 3	3 3	3 4	4 4	4 5	5 5	5 6	6 6
#students		75	75	75	75	75	75	75	75	75
Cost per student	N1	$15.58	$14.92	$17.09	$14.57	$16.65	$15.71	$17.46	$16.59	$18.24
Standard deviation		$0.75	$0.66	$0.78	$0.64	$0.77	$0.76	$0.89	$0.79	$0.83
Cost per student	N2	$20.17	$18.76	$20.79	$20.22	$22.02	$19.17	$20.91	$19.89	$22.31
Standard deviation		$1.08	$0.94	$1.02	$0.92	$1.03	$1.12	$0.97	$1.15	$1.15
Cost per student	N3	$21.50	$21.58	$21.87	$21.48	$23.50	$22.71	$25.14	$21.81	$23.28
Standard deviation		$1.14	$1.02	$1.01	$1.00	$0.98	$1.06	$1.06	$0.82	$1.17
Cost per student	G1	$20.17	$19.02	$21.60	$18.80	$20.93	$20.02	$21.84	$21.15	$22.71
Standard deviation		$1.04	$0.86	$1.02	$0.83	$1.02	$0.90	$1.00	$0.92	$1.06
Cost per student	G2	$24.82	$23.25	$25.23	$24.38	$26.80	$23.71	$25.59	$24.87	$26.61
Standard deviation		$1.33	$1.24	$1.36	$1.29	$1.31	$1.18	$1.43	$1.28	$1.42
Cost per student	G3	$27.76	$26.19	$28.16	$27.32	$29.73	$26.65	$28.52	$27.80	$29.54
Standard deviation		$1.33	$1.24	$1.36	$1.29	$1.31	$1.18	$1.43	$1.28	$1.42
Cost per student	I1	$24.49	$20.27	$21.86	$20.51	$21.97	$21.01	$22.29	N/A	N/A
Standard deviation		$1.90	$1.18	$1.30	$1.38	$1.03	$0.77	$1.07	N/A	N/A
Cost per student	I2	$29.60	$27.89	$29.51	$28.18	$26.62	$25.58	$26.98	N/A	N/A
Standard deviation		$2.18	$1.91	$2.55	$1.73	$1.90	$1.84	$1.31	N/A	N/A
Cost per student	I3	$31.46	$29.90	$31.24	$30.01	$31.56	$27.31	$28.58	N/A	N/A
Standard deviation		$2.55	$1.39	$1.72	$1.67	$1.31	$0.68	$1.03	N/A	N/A
Cost per student	D1	$29.53	$25.09	$26.85	$21.05	$22.96	$20.96	$22.64	N/A	N/A
Standard deviation		$2.20	$1.67	$1.78	$1.38	$1.59	$1.36	$1.44	N/A	N/A
Cost per student	D2	$39.36	$33.35	$33.16	$30.35	$32.08	$26.54	$28.04	N/A	N/A
Standard deviation		$2.81	$2.43	$2.36	$2.14	$2.04	$1.79	$2.06	N/A	N/A
Cost per student	D3	$39.36	$33.35	$33.16	$30.35	$32.08	$26.54	$28.04	N/A	N/A
Standard deviation		$2.81	$2.43	$2.36	$2.14	$2.04	$1.79	$2.06	N/A	N/A
#students		100	100	100	100	100	100	100	100	100
Cost per student	N1	$15.73	$14.04	$16.24	$14.90	$17.05	$14.53	$16.25	$15.38	$16.94
Standard deviation		$0.77	$0.60	$0.63	$0.55	$0.80	$0.58	$0.70	$0.72	$0.70
Cost per student	N2	$19.17	$18.90	$19.39	$18.77	$20.79	$19.65	$21.85	$20.88	$22.80
Standard deviation		$0.82	$0.80	$1.14	$0.90	$0.86	$0.96	$0.97	$0.98	$0.96
Cost per student	N3	$21.26	$20.37	$22.09	$20.35	$21.94	$21.02	$23.16	$22.59	$24.36
Standard deviation		$0.91	$0.91	$0.88	$0.81	$0.87	$0.91	$0.83	$0.78	$1.06
Cost per student	G1	$19.81	$17.71	$20.10	$18.90	$21.21	$18.56	$20.30	$19.47	$20.92
Standard deviation		$0.86	$0.73	$0.84	$0.72	$0.87	$0.77	$0.90	$0.76	$0.82
Cost per student	G2	$23.55	$22.96	$23.81	$22.79	$24.93	$23.99	$26.02	$23.14	$24.76
Standard deviation		$1.12	$1.01	$1.15	$1.01	$1.12	$1.02	$1.11	$0.99	$1.07
Cost per student	G3	$27.37	$26.77	$27.63	$26.61	$28.75	$27.81	$29.84	$26.96	$28.58
Standard deviation		$1.12	$1.01	$1.15	$1.01	$1.12	$1.02	$1.11	$0.99	$1.07
Cost per student	I1	$23.01	$21.01	$22.79	$21.41	$20.59	$19.49	$20.67	N/A	N/A
Standard deviation		$1.72	$1.03	$0.97	$1.18	$0.99	$0.78	$0.83	N/A	N/A
Cost per student	I2	$29.90	$26.33	$27.65	$26.17	$27.71	$26.60	$28.16	N/A	N/A
Standard deviation		$1.73	$1.45	$2.67	$1.35	$1.69	$1.71	$1.15	N/A	N/A
Cost per student	I3	$30.09	$28.33	$29.37	$28.00	$29.36	$28.33	$29.75	N/A	N/A
Standard deviation		$2.22	$1.19	$1.34	$1.15	$1.02	$0.50	$0.84	N/A	N/A
Cost per student	D1	$29.72	$23.39	$25.01	$21.96	$24.07	$19.42	$21.04	N/A	N/A
Standard deviation		$1.82	$1.43	$1.46	$1.19	$1.36	$1.16	$1.29	N/A	N/A
Cost per student	D2	$37.61	$33.64	$31.47	$28.44	$29.86	$27.63	$29.30	N/A	N/A
Standard deviation		$2.35	$1.97	$2.01	$1.68	$1.74	$1.55	$1.61	N/A	N/A
Cost per student	D3	$37.61	$33.64	$31.47	$28.44	$29.86	$27.63	$29.30	N/A	N/A
Standard deviation		$2.35	$1.97	$2.01	$1.68	$1.74	$1.55	$1.61	N/A	N/A

Table A.11 (Cont.)

Number of hygienists Number of assistants & chairs (+1 for (I), (D))		2 2	2 3	3 3	3 4	4 4	4 5	5 5	5 6	6 6
#students		150	150	150	150	150	150	150	150	150
Cost per student	N1	$15.26	$13.74	$15.76	$13.79	$15.66	$14.64	$16.37	$15.50	$17.18
Standard deviation		$0.66	$0.52	$0.53	$0.52	$0.65	$0.52	$0.58	$0.59	$0.53
Cost per student	N2	$19.51	$18.55	$19.28	$18.27	$20.32	$18.30	$19.89	$18.98	$20.89
Standard deviation		$0.71	$0.76	$0.87	$0.79	$0.79	$0.71	$0.66	$0.76	$0.68
Cost per student	N3	$20.68	$20.02	$21.57	$19.93	$21.58	$20.79	$21.37	$20.35	$21.93
Standard deviation		$0.70	$0.64	$0.68	$0.49	$0.84	$0.65	$0.70	$0.71	$0.68
Cost per student	G1	$19.58	$17.67	$20.03	$17.86	$19.96	$18.88	$20.68	$19.82	$21.35
Standard deviation		$0.73	$0.60	$0.72	$0.61	$0.72	$0.63	$0.72	$0.64	$0.68
Cost per student	G2	$23.65	$22.42	$23.61	$22.48	$24.58	$22.42	$24.30	$23.35	$25.02
Standard deviation		$0.89	$0.82	$0.90	$0.81	$0.89	$0.81	$0.88	$0.80	$0.86
Cost per student	G3	$26.59	$25.36	$26.54	$25.42	$27.52	$25.36	$27.24	$26.28	$27.96
Standard deviation		$0.89	$0.82	$0.90	$0.81	$0.89	$0.81	$0.88	$0.80	$0.86
Cost per student	I1	$22.71	$19.39	$20.97	$19.43	$20.89	$19.74	$21.02	N/A	N/A
Standard deviation		$1.36	$0.87	$0.76	$0.86	$0.75	$0.50	$0.57	N/A	N/A
Cost per student	I2	$28.85	$25.71	$27.01	$23.96	$25.39	$24.07	$25.43	N/A	N/A
Standard deviation		$1.72	$1.18	$1.67	$1.19	$1.14	$1.44	$0.91	N/A	N/A
Cost per student	I3	$28.48	$26.51	$27.35	$25.80	$27.04	$25.80	$27.02	N/A	N/A
Standard deviation		$1.81	$1.12	$1.23	$1.28	$0.80	$0.44	$0.48	N/A	N/A
Cost per student	D1	$28.92	$23.03	$24.63	$19.98	$21.90	$19.68	$21.38	N/A	N/A
Standard deviation		$1.53	$1.17	$1.26	$1.02	$1.12	$0.95	$1.04	N/A	N/A
Cost per student	D2	$37.51	$32.32	$30.85	$27.68	$29.09	$25.03	$26.61	N/A	N/A
Standard deviation		$1.87	$1.59	$1.56	$1.35	$1.38	$1.22	$1.27	N/A	N/A
Cost per student	D3	$37.51	$32.32	$30.85	$27.68	$29.09	$25.03	$26.61	N/A	N/A
Standard deviation		$1.87	$1.59	$1.56	$1.35	$1.38	$1.22	$1.27	N/A	N/A
#students		200	200	200	200	200	200	200	200	200
Cost per student	N1	$15.14	$13.66	$15.67	$13.85	$15.74	$13.76	$15.58	$14.64	$16.05
Standard deviation		$0.50	$0.45	$0.47	$0.39	$0.54	$0.39	$0.43	$0.42	$0.45
Cost per student	N2	$18.41	$18.11	$19.05	$18.14	$19.37	$18.37	$19.88	$19.16	$19.48
Standard deviation		$0.74	$0.67	$0.69	$0.68	$0.66	$0.54	$0.70	$0.56	$0.73
Cost per student	N3	$19.69	$19.65	$20.98	$19.54	$21.48	$19.59	$21.32	$20.48	$22.08
Standard deviation		$0.60	$0.63	$0.75	$0.65	$0.69	$0.45	$0.70	$0.52	$0.62
Cost per student	G1	$19.02	$16.73	$18.96	$17.57	$19.70	$17.73	$19.45	$18.49	$19.99
Standard deviation		$0.58	$0.49	$0.55	$0.48	$0.58	$0.49	$0.57	$0.52	$0.55
Cost per student	G2	$22.56	$21.79	$23.11	$21.29	$23.26	$22.09	$24.02	$21.93	$23.58
Standard deviation		$0.68	$0.65	$0.74	$0.61	$0.70	$0.62	$0.68	$0.67	$0.72
Cost per student	G3	$25.93	$25.17	$26.49	$24.67	$26.64	$25.47	$27.40	$25.31	$26.96
Standard deviation		$0.68	$0.65	$0.74	$0.61	$0.70	$0.62	$0.68	$0.67	$0.72
Cost per student	I1	$22.55	$19.49	$21.11	$19.52	$19.82	$18.56	$19.82	N/A	N/A
Standard deviation		$1.24	$0.75	$0.77	$0.99	$0.62	$0.48	$0.58	N/A	N/A
Cost per student	I2	$28.39	$25.48	$26.79	$24.01	$25.50	$24.08	$25.57	N/A	N/A
Standard deviation		$1.43	$0.96	$1.66	$1.11	$0.86	$1.09	$0.79	N/A	N/A
Cost per student	I3	$27.74	$25.68	$26.45	$24.74	$25.91	$24.51	$25.73	N/A	N/A
Standard deviation		$1.40	$0.96	$0.94	$0.90	$0.61	$0.32	$0.46	N/A	N/A
Cost per student	D1	$28.52	$21.92	$23.41	$20.10	$22.07	$18.49	$20.14	N/A	N/A
Standard deviation		$1.22	$0.95	$0.96	$0.80	$0.90	$0.75	$0.83	N/A	N/A
Cost per student	D2	$35.97	$31.80	$30.63	$26.31	$27.61	$25.09	$26.74	N/A	N/A
Standard deviation		$1.43	$1.27	$1.28	$1.02	$1.09	$0.93	$0.99	N/A	N/A
Cost per student	D3	$35.97	$31.80	$30.63	$26.31	$27.61	$25.09	$26.74	N/A	N/A
Standard deviation		$1.43	$1.27	$1.28	$1.02	$1.09	$0.93	$0.99	N/A	N/A

Table A.12: Per Person Costs for Different Practice Acts for Various Program Sizes, Assuming 2 Hours Round-trip Travel to Site

Number of hygienists Number of assistants & chairs (+1 for (I), (D))		2 2	2 3	3 3	3 4	4 4	4 5	5 5	5 6	6 6
#students		25	25	25	25	25	25	25	25	25
Cost per student	N1	$21.05	$21.28	$25.72	$25.94	$29.52	$30.60	$33.53	$35.10	$38.23
Standard deviation		$1.46	$1.32	$1.34	$1.31	$1.60	$1.44	$1.55	$1.43	$1.65
Cost per student	N2	$24.86	$25.67	$28.75	$30.01	$33.31	$34.28	$37.99	$38.75	$41.90
Standard deviation		$1.56	$1.43	$2.22	$1.87	$2.30	$1.78	$2.54	$1.69	$2.45
Cost per student	N3	$25.86	$26.87	$30.21	$31.16	$35.42	$36.01	$39.63	$40.92	$43.54
Standard deviation		$2.26	$2.06	$2.32	$1.56	$1.96	$2.01	$1.82	$1.59	$2.13
Cost per student	G1	$32.50	$32.57	$36.85	$37.24	$41.09	$41.86	$45.33	$46.39	$49.58
Standard deviation		$1.39	$1.12	$1.42	$1.20	$1.62	$1.30	$1.59	$1.49	$1.97
Cost per student	G2	$36.29	$36.96	$40.64	$41.30	$44.86	$45.79	$49.48	$50.39	$53.94
Standard deviation		$2.28	$2.09	$2.55	$2.23	$2.51	$2.10	$2.66	$2.35	$2.80
Cost per student	G3	$39.22	$39.89	$43.57	$44.24	$47.80	$48.73	$52.42	$53.33	$56.88
Standard deviation		$2.28	$2.09	$2.55	$2.23	$2.51	$2.10	$2.66	$2.35	$2.80
Cost per student	I1	$36.03	$35.84	$38.97	$39.46	$40.79	$42.96	$47.35	N/A	N/A
Standard deviation		$4.09	$2.21	$2.46	$2.32	$1.32	$1.39	$1.53	N/A	N/A
Cost per student	I2	$41.36	$41.39	$43.88	$44.50	$42.48	$44.73	$49.31	N/A	N/A
Standard deviation		$4.06	$3.27	$4.61	$2.47	$1.57	$1.65	$1.82	N/A	N/A
Cost per student	I3	$43.22	$43.39	$45.61	$46.34	$48.52	$51.09	$56.32	N/A	N/A
Standard deviation		$3.32	$2.60	$2.99	$2.38	$1.32	$1.40	$1.54	N/A	N/A
Cost per student	D1	$40.69	$37.79	$41.11	$40.05	$43.35	$43.33	$46.37	N/A	N/A
Standard deviation		$2.94	$2.19	$2.47	$2.01	$2.51	$1.97	$2.30	N/A	N/A
Cost per student	D2	$48.68	$46.36	$47.71	$46.81	$49.20	$49.27	$52.37	N/A	N/A
Standard deviation		$4.81	$4.09	$4.43	$3.72	$3.90	$3.17	$3.84	N/A	N/A
Cost per student	D3	$48.68	$46.36	$47.71	$46.81	$49.20	$49.27	$52.37	N/A	N/A
Standard deviation		$4.81	$4.09	$4.43	$3.72	$3.90	$3.17	$3.84	N/A	N/A
#students		50	50	50	50	50	50	50	50	50
Cost per student	N1	$20.00	$16.42	$19.06	$18.51	$21.36	$21.11	$23.33	$23.07	$25.55
Standard deviation		$1.07	$0.84	$0.98	$1.00	$1.09	$1.05	$0.98	$0.88	$1.11
Cost per student	N2	$23.55	$24.49	$27.61	$22.57	$24.97	$24.74	$27.47	$27.08	$29.35
Standard deviation		$1.29	$1.11	$1.37	$1.20	$1.23	$1.37	$1.48	$1.21	$1.43
Cost per student	N3	$25.22	$25.65	$28.76	$23.93	$26.26	$26.19	$28.45	$28.64	$30.73
Standard deviation		$1.26	$1.52	$1.32	$1.11	$1.37	$1.33	$1.48	$1.23	$1.37
Cost per student	G1	$27.41	$23.35	$26.43	$25.62	$28.50	$28.10	$30.62	$30.45	$32.72
Standard deviation		$1.13	$0.93	$1.15	$0.96	$1.17	$1.02	$1.30	$1.03	$1.22
Cost per student	G2	$30.92	$31.15	$29.93	$29.48	$32.21	$31.80	$34.57	$34.34	$36.72
Standard deviation		$1.74	$1.71	$1.87	$1.61	$1.78	$1.56	$1.80	$1.57	$1.78
Cost per student	G3	$33.86	$34.09	$32.86	$32.42	$35.15	$34.74	$37.51	$37.27	$39.66
Standard deviation		$1.74	$1.71	$1.87	$1.61	$1.78	$1.56	$1.80	$1.57	$1.78
Cost per student	I1	$27.57	$25.97	$28.29	$27.47	$29.59	$29.19	$31.16	N/A	N/A
Standard deviation		$2.53	$1.58	$1.53	$1.55	$1.24	$0.98	$1.29	N/A	N/A
Cost per student	I2	$39.19	$31.25	$33.13	$32.22	$34.52	$33.97	$35.97	N/A	N/A
Standard deviation		$2.99	$2.03	$3.46	$2.11	$2.22	$2.01	$1.69	N/A	N/A
Cost per student	I3	$41.05	$33.26	$34.85	$34.06	$36.16	$35.70	$37.56	N/A	N/A
Standard deviation		$3.03	$1.87	$2.20	$1.87	$1.43	$0.91	$1.18	N/A	N/A
Cost per student	D1	$39.24	$28.39	$30.65	$28.01	$30.62	$29.17	$31.49	N/A	N/A
Standard deviation		$2.39	$1.82	$1.99	$1.61	$1.82	$1.54	$1.88	N/A	N/A
Cost per student	D2	$46.65	$43.63	$36.74	$34.45	$36.39	$34.78	$37.20	N/A	N/A
Standard deviation		$3.67	$3.33	$3.26	$2.68	$2.77	$2.36	$2.59	N/A	N/A
Cost per student	D3	$46.65	$43.63	$36.74	$34.45	$36.39	$34.78	$37.20	N/A	N/A
Standard deviation		$3.67	$3.33	$3.26	$2.68	$2.77	$2.36	$2.59	N/A	N/A

Table A.12 (Cont.)

Number of hygienists	2	2	3	3	4	4	5	5	6
Number of assistants & chairs (+1 for (I), (D))	2	3	3	4	4	5	5	6	6
#students	75	75	75	75	75	75	75	75	75
Cost per student N1	$17.70	$17.39	$20.27	$16.34	$18.77	$18.00	$20.11	$19.41	$21.42
Standard deviation	$0.75	$0.66	$0.78	$0.64	$0.77	$0.76	$0.89	$0.79	$0.83
Cost per student N2	$23.35	$21.22	$23.96	$23.74	$26.26	$21.46	$23.56	$22.71	$25.48
Standard deviation	$1.08	$0.94	$1.02	$0.92	$1.03	$1.12	$0.97	$1.15	$1.15
Cost per student N3	$24.67	$25.28	$25.05	$25.01	$27.74	$27.29	$30.43	$24.63	$26.46
Standard deviation	$1.14	$1.02	$1.01	$1.00	$0.98	$1.06	$1.06	$0.82	$1.17
Cost per student G1	$23.46	$22.66	$25.95	$21.74	$24.22	$23.49	$25.67	$25.14	$27.05
Standard deviation	$1.04	$0.86	$1.02	$0.83	$1.02	$0.90	$1.00	$0.92	$1.06
Cost per student G2	$29.17	$26.89	$29.58	$29.08	$32.21	$27.18	$29.41	$28.86	$30.96
Standard deviation	$1.33	$1.24	$1.36	$1.29	$1.31	$1.18	$1.43	$1.28	$1.42
Cost per student G3	$32.11	$29.83	$32.51	$32.01	$35.14	$30.11	$32.34	$31.80	$33.89
Standard deviation	$1.33	$1.24	$1.36	$1.29	$1.31	$1.18	$1.43	$1.28	$1.42
Cost per student I1	$28.96	$22.68	$24.62	$23.45	$25.26	$24.47	$26.11	N/A	N/A
Standard deviation	$1.90	$1.18	$1.30	$1.38	$1.03	$0.77	$1.07	N/A	N/A
Cost per student I2	$34.07	$32.71	$35.04	$34.05	$29.92	$29.05	$30.80	N/A	N/A
Standard deviation	$2.18	$1.91	$2.55	$1.73	$1.90	$1.84	$1.31	N/A	N/A
Cost per student I3	$35.93	$34.71	$36.76	$35.89	$38.14	$30.78	$32.40	N/A	N/A
Standard deviation	$2.55	$1.39	$1.72	$1.67	$1.31	$0.68	$1.03	N/A	N/A
Cost per student D1	$34.00	$29.90	$32.37	$23.99	$26.25	$24.43	$26.46	N/A	N/A
Standard deviation	$2.20	$1.67	$1.78	$1.38	$1.59	$1.36	$1.44	N/A	N/A
Cost per student D2	$46.06	$38.17	$38.69	$36.23	$38.66	$30.00	$31.86	N/A	N/A
Standard deviation	$2.81	$2.43	$2.36	$2.14	$2.04	$1.79	$2.06	N/A	N/A
Cost per student D3	$46.06	$38.17	$38.69	$36.23	$38.66	$30.00	$31.86	N/A	N/A
Standard deviation	$2.81	$2.43	$2.36	$2.14	$2.04	$1.79	$2.06	N/A	N/A
#students	100	100	100	100	100	100	100	100	100
Cost per student N1	$18.11	$15.89	$18.62	$17.54	$20.23	$16.24	$18.23	$17.50	$19.32
Standard deviation	$0.77	$0.60	$0.63	$0.55	$0.80	$0.58	$0.70	$0.72	$0.70
Cost per student N2	$21.55	$21.68	$21.78	$21.41	$23.96	$23.09	$25.82	$25.12	$27.57
Standard deviation	$0.82	$0.80	$1.14	$0.90	$0.86	$0.96	$0.97	$0.98	$0.96
Cost per student N3	$24.44	$23.15	$25.66	$23.00	$25.12	$24.45	$27.13	$26.83	$29.12
Standard deviation	$0.91	$0.91	$0.88	$0.81	$0.87	$0.91	$0.83	$0.78	$1.06
Cost per student G1	$23.08	$20.44	$23.36	$22.43	$25.26	$21.16	$23.16	$22.46	$24.18
Standard deviation	$0.86	$0.73	$0.84	$0.72	$0.87	$0.77	$0.90	$0.76	$0.82
Cost per student G2	$26.82	$26.61	$27.07	$26.32	$28.98	$28.31	$30.87	$26.14	$28.02
Standard deviation	$1.12	$1.01	$1.15	$1.01	$1.12	$1.02	$1.11	$0.99	$1.07
Cost per student G3	$31.51	$31.31	$31.77	$31.02	$33.68	$33.01	$35.57	$30.84	$32.72
Standard deviation	$1.12	$1.01	$1.15	$1.01	$1.12	$1.02	$1.11	$0.99	$1.07
Cost per student I1	$26.36	$24.62	$26.93	$25.81	$23.06	$22.08	$23.54	N/A	N/A
Standard deviation	$1.72	$1.03	$0.97	$1.18	$0.99	$0.78	$0.83	N/A	N/A
Cost per student I2	$34.93	$29.94	$31.79	$30.57	$32.65	$31.80	$33.89	N/A	N/A
Standard deviation	$1.73	$1.45	$2.67	$1.35	$1.69	$1.71	$1.15	N/A	N/A
Cost per student I3	$33.44	$31.95	$33.52	$32.41	$34.29	$33.53	$35.48	N/A	N/A
Standard deviation	$2.22	$1.19	$1.34	$1.15	$1.02	$0.50	$0.84	N/A	N/A
Cost per student D1	$34.75	$27.00	$29.15	$26.36	$29.01	$22.02	$23.90	N/A	N/A
Standard deviation	$1.82	$1.43	$1.46	$1.19	$1.36	$1.16	$1.29	N/A	N/A
Cost per student D2	$42.64	$39.06	$35.61	$32.85	$34.79	$32.83	$35.03	N/A	N/A
Standard deviation	$2.35	$1.97	$2.01	$1.68	$1.74	$1.55	$1.61	N/A	N/A
Cost per student D3	$42.64	$39.06	$35.61	$32.85	$34.79	$32.83	$35.03	N/A	N/A
Standard deviation	$2.35	$1.97	$2.01	$1.68	$1.74	$1.55	$1.61	N/A	N/A

Table A.12 (Cont.)

Number of hygienists		2	2	3	3	4	4	5	5	6
Number of assistants & chairs (+1 for (I), (D))		2	3	3	4	4	5	5	6	6
#students		150	150	150	150	150	150	150	150	150
Cost per student	N1	$17.38	$15.59	$18.14	$15.55	$17.77	$16.93	$19.01	$18.32	$20.35
Standard deviation		$0.66	$0.52	$0.53	$0.52	$0.65	$0.52	$0.58	$0.59	$0.53
Cost per student	N2	$22.15	$21.02	$21.67	$20.91	$23.49	$20.60	$22.54	$21.80	$24.07
Standard deviation		$0.71	$0.76	$0.87	$0.79	$0.79	$0.71	$0.66	$0.76	$0.68
Cost per student	N3	$23.32	$22.49	$24.75	$22.57	$24.75	$24.22	$24.02	$23.17	$25.10
Standard deviation		$0.70	$0.64	$0.68	$0.49	$0.84	$0.65	$0.70	$0.71	$0.68
Cost per student	G1	$22.87	$20.69	$23.59	$20.80	$23.25	$22.35	$24.50	$23.82	$25.70
Standard deviation		$0.73	$0.60	$0.72	$0.61	$0.72	$0.63	$0.72	$0.64	$0.68
Cost per student	G2	$27.47	$26.07	$27.16	$26.30	$28.93	$25.89	$28.12	$27.34	$29.37
Standard deviation		$0.89	$0.82	$0.90	$0.81	$0.89	$0.81	$0.88	$0.80	$0.86
Cost per student	G3	$30.41	$29.00	$30.10	$29.24	$31.87	$28.82	$31.06	$30.28	$32.31
Standard deviation		$0.89	$0.82	$0.90	$0.81	$0.89	$0.81	$0.88	$0.80	$0.86
Cost per student	I1	$26.06	$21.80	$23.73	$22.36	$24.18	$23.21	$24.84	N/A	N/A
Standard deviation		$1.36	$0.87	$0.76	$0.86	$0.75	$0.50	$0.57	N/A	N/A
Cost per student	I2	$33.32	$29.32	$31.15	$26.90	$28.68	$27.54	$29.25	N/A	N/A
Standard deviation		$1.72	$1.18	$1.67	$1.19	$1.14	$1.44	$0.91	N/A	N/A
Cost per student	I3	$30.71	$28.92	$30.11	$28.74	$30.33	$29.27	$30.84	N/A	N/A
Standard deviation		$1.81	$1.12	$1.23	$1.28	$0.80	$0.44	$0.48	N/A	N/A
Cost per student	D1	$33.39	$26.64	$28.78	$22.92	$25.19	$23.14	$25.20	N/A	N/A
Standard deviation		$1.53	$1.17	$1.26	$1.02	$1.12	$0.95	$1.04	N/A	N/A
Cost per student	D2	$43.09	$37.13	$35.00	$32.09	$34.03	$28.50	$30.43	N/A	N/A
Standard deviation		$1.87	$1.59	$1.56	$1.35	$1.38	$1.22	$1.27	N/A	N/A
Cost per student	D3	$43.09	$37.13	$35.00	$32.09	$34.03	$28.50	$30.43	N/A	N/A
Standard deviation		$1.87	$1.59	$1.56	$1.35	$1.38	$1.22	$1.27	N/A	N/A
#students		200	200	200	200	200	200	200	200	200
Cost per student	N1	$17.13	$15.51	$18.05	$15.83	$18.12	$15.48	$17.56	$16.75	$18.43
Standard deviation		$0.50	$0.45	$0.47	$0.39	$0.54	$0.39	$0.43	$0.42	$0.45
Cost per student	N2	$20.39	$20.43	$21.44	$20.78	$21.75	$20.95	$22.85	$22.34	$21.86
Standard deviation		$0.74	$0.67	$0.69	$0.68	$0.66	$0.54	$0.70	$0.56	$0.73
Cost per student	N3	$21.67	$21.96	$23.95	$22.18	$24.65	$22.16	$24.30	$23.66	$25.65
Standard deviation		$0.60	$0.63	$0.75	$0.65	$0.69	$0.45	$0.70	$0.52	$0.62
Cost per student	G1	$21.89	$19.00	$21.63	$20.43	$22.96	$20.33	$22.32	$21.49	$23.26
Standard deviation		$0.58	$0.49	$0.55	$0.48	$0.58	$0.49	$0.57	$0.52	$0.55
Cost per student	G2	$25.42	$24.99	$26.37	$24.16	$26.52	$25.55	$27.88	$24.93	$26.84
Standard deviation		$0.68	$0.65	$0.74	$0.61	$0.70	$0.62	$0.68	$0.67	$0.72
Cost per student	G3	$29.24	$28.80	$30.19	$27.97	$30.34	$29.37	$31.70	$28.74	$30.66
Standard deviation		$0.68	$0.65	$0.74	$0.61	$0.70	$0.62	$0.68	$0.67	$0.72
Cost per student	I1	$25.90	$22.20	$24.22	$22.82	$22.29	$21.16	$22.69	N/A	N/A
Standard deviation		$1.24	$0.75	$0.77	$0.99	$0.62	$0.48	$0.58	N/A	N/A
Cost per student	I2	$32.57	$29.09	$30.94	$27.31	$29.20	$27.98	$29.87	N/A	N/A
Standard deviation		$1.43	$0.96	$1.66	$1.11	$0.86	$1.09	$0.79	N/A	N/A
Cost per student	I3	$29.41	$27.49	$28.52	$26.95	$28.38	$27.11	$28.59	N/A	N/A
Standard deviation		$1.40	$0.96	$0.94	$0.90	$0.61	$0.32	$0.46	N/A	N/A
Cost per student	D1	$32.71	$24.62	$26.52	$23.40	$25.77	$21.09	$23.01	N/A	N/A
Standard deviation		$1.22	$0.95	$0.96	$0.80	$0.90	$0.75	$0.83	N/A	N/A
Cost per student	D2	$40.16	$36.32	$34.77	$29.61	$31.31	$28.99	$31.03	N/A	N/A
Standard deviation		$1.43	$1.27	$1.28	$1.02	$1.09	$0.93	$0.99	N/A	N/A
Cost per student	D3	$40.16	$36.32	$34.77	$29.61	$31.31	$28.99	$31.03	N/A	N/A
Standard deviation		$1.43	$1.27	$1.28	$1.02	$1.09	$0.93	$0.99	N/A	N/A

Table A.13: Per Person Costs for Different Practice Acts for Various Program Sizes, Assuming 1/2 Hour Round-trip Travel to Site

Number of hygienists Number of assistants & chairs (+1 for (I), (D))		2 2	2 3	3 3	3 4	4 4	4 5	5 5	5 6	6 6
#students		25	25	25	25	25	25	25	25	25
Cost per student	N1	$16.28	$15.73	$18.58	$18.01	$19.99	$20.29	$21.63	$22.41	$23.94
Standard deviation		$1.46	$1.32	$1.34	$1.31	$1.60	$1.44	$1.55	$1.43	$1.65
Cost per student	N2	$20.10	$20.12	$21.60	$22.08	$23.78	$23.97	$26.08	$26.06	$27.61
Standard deviation		$1.56	$1.43	$2.22	$1.87	$2.30	$1.78	$2.54	$1.69	$2.45
Cost per student	N3	$21.09	$21.32	$23.06	$23.23	$25.90	$25.69	$27.72	$28.23	$29.25
Standard deviation		$2.26	$2.06	$2.32	$1.56	$1.96	$2.01	$1.82	$1.59	$2.13
Cost per student	G1	$22.45	$21.74	$24.42	$24.03	$26.28	$26.26	$28.13	$28.41	$30.00
Standard deviation		$1.39	$1.12	$1.42	$1.20	$1.62	$1.30	$1.59	$1.49	$1.97
Cost per student	G2	$26.24	$26.12	$28.21	$28.09	$30.05	$30.19	$32.29	$32.42	$34.37
Standard deviation		$2.28	$2.09	$2.55	$2.23	$2.51	$2.10	$2.66	$2.35	$2.80
Cost per student	G3	$29.18	$29.06	$31.14	$31.02	$32.98	$33.13	$35.23	$35.35	$37.30
Standard deviation		$2.28	$2.09	$2.55	$2.23	$2.51	$2.10	$2.66	$2.35	$2.80
Cost per student	I1	$25.98	$25.01	$26.54	$26.25	$26.98	$27.36	$30.16	N/A	N/A
Standard deviation		$4.09	$2.21	$2.46	$2.32	$1.32	$1.39	$1.53	N/A	N/A
Cost per student	I2	$31.31	$30.55	$31.45	$31.29	$27.67	$29.14	$32.12	N/A	N/A
Standard deviation		$4.06	$3.27	$4.61	$2.47	$1.57	$1.65	$1.82	N/A	N/A
Cost per student	I3	$33.18	$32.56	$33.18	$33.12	$33.71	$35.49	$39.13	N/A	N/A
Standard deviation		$3.32	$2.60	$2.99	$2.38	$1.32	$1.40	$1.54	N/A	N/A
Cost per student	D1	$30.64	$26.96	$28.68	$26.83	$28.54	$27.73	$29.17	N/A	N/A
Standard deviation		$2.94	$2.19	$2.47	$2.01	$2.51	$1.97	$2.30	N/A	N/A
Cost per student	D2	$38.63	$35.52	$35.28	$33.59	$34.39	$33.68	$35.18	N/A	N/A
Standard deviation		$4.81	$4.09	$4.43	$3.72	$3.90	$3.17	$3.84	N/A	N/A
Cost per student	D3	$38.63	$35.52	$35.28	$33.59	$34.39	$33.68	$35.18	N/A	N/A
Standard deviation		$4.81	$4.09	$4.43	$3.72	$3.90	$3.17	$3.84	N/A	N/A
#students		50	50	50	50	50	50	50	50	50
Cost per student	N1	$15.24	$13.65	$15.49	$14.54	$16.60	$15.96	$17.38	$16.72	$18.41
Standard deviation		$1.07	$0.84	$0.98	$1.00	$1.09	$1.05	$0.98	$0.88	$1.11
Cost per student	N2	$18.78	$18.94	$20.46	$18.61	$20.21	$19.59	$21.51	$20.73	$22.20
Standard deviation		$1.29	$1.11	$1.37	$1.20	$1.23	$1.37	$1.48	$1.21	$1.43
Cost per student	N3	$20.45	$20.10	$21.62	$19.97	$21.50	$21.03	$22.50	$22.29	$23.58
Standard deviation		$1.26	$1.52	$1.32	$1.11	$1.37	$1.33	$1.48	$1.23	$1.37
Cost per student	G1	$20.00	$17.93	$20.21	$19.01	$21.10	$20.30	$22.02	$21.46	$22.93
Standard deviation		$1.13	$0.93	$1.15	$0.96	$1.17	$1.02	$1.30	$1.03	$1.22
Cost per student	G2	$23.51	$22.96	$23.71	$22.87	$24.80	$24.00	$25.98	$25.35	$26.93
Standard deviation		$1.74	$1.71	$1.87	$1.61	$1.78	$1.56	$1.80	$1.57	$1.78
Cost per student	G3	$26.45	$25.90	$26.65	$25.81	$27.74	$26.94	$28.91	$28.28	$29.87
Standard deviation		$1.74	$1.71	$1.87	$1.61	$1.78	$1.56	$1.80	$1.57	$1.78
Cost per student	I1	$22.54	$20.56	$22.07	$20.86	$22.19	$21.40	$22.56	N/A	N/A
Standard deviation		$2.53	$1.58	$1.53	$1.55	$1.24	$0.98	$1.29	N/A	N/A
Cost per student	I2	$29.14	$25.84	$26.91	$25.61	$27.11	$26.17	$27.37	N/A	N/A
Standard deviation		$2.99	$2.03	$3.46	$2.11	$2.22	$2.01	$1.69	N/A	N/A
Cost per student	I3	$31.00	$27.84	$28.64	$27.45	$28.76	$27.90	$28.97	N/A	N/A
Standard deviation		$3.03	$1.87	$2.20	$1.87	$1.43	$0.91	$1.18	N/A	N/A
Cost per student	D1	$29.19	$22.97	$24.43	$21.40	$23.21	$21.37	$22.89	N/A	N/A
Standard deviation		$2.39	$1.82	$1.99	$1.61	$1.82	$1.54	$1.88	N/A	N/A
Cost per student	D2	$36.60	$32.79	$30.53	$27.84	$28.98	$26.98	$28.60	N/A	N/A
Standard deviation		$3.67	$3.33	$3.26	$2.68	$2.77	$2.36	$2.59	N/A	N/A
Cost per student	D3	$36.60	$32.79	$30.53	$27.84	$28.98	$26.98	$28.60	N/A	N/A
Standard deviation		$3.67	$3.33	$3.26	$2.68	$2.77	$2.36	$2.59	N/A	N/A

Table A.13 (Cont.)

Number of hygienists		2	2	3	3	4	4	5	5	6
Number of assistants & chairs (+1 for (I), (D))		2	3	3	4	4	5	5	6	6
#students		75	75	75	75	75	75	75	75	75
Cost per student	N1	$14.52	$13.69	$15.51	$13.69	$15.60	$14.56	$16.14	$15.18	$16.65
Standard deviation		$0.75	$0.66	$0.78	$0.64	$0.77	$0.76	$0.89	$0.79	$0.83
Cost per student	N2	$18.58	$17.52	$19.20	$18.46	$19.91	$18.02	$19.59	$18.48	$20.72
Standard deviation		$1.08	$0.94	$1.02	$0.92	$1.03	$1.12	$0.97	$1.15	$1.15
Cost per student	N3	$19.91	$19.73	$20.29	$19.72	$21.39	$20.42	$22.49	$20.40	$21.70
Standard deviation		$1.14	$1.02	$1.01	$1.00	$0.98	$1.06	$1.06	$0.82	$1.17
Cost per student	G1	$18.52	$17.20	$19.42	$17.33	$19.29	$18.29	$19.93	$19.15	$20.53
Standard deviation		$1.04	$0.86	$1.02	$0.83	$1.02	$0.90	$1.00	$0.92	$1.06
Cost per student	G2	$22.65	$21.43	$23.05	$22.03	$24.09	$21.98	$23.68	$22.87	$24.43
Standard deviation		$1.33	$1.24	$1.36	$1.29	$1.31	$1.18	$1.43	$1.28	$1.42
Cost per student	G3	$25.58	$24.37	$25.99	$24.97	$27.03	$24.91	$26.61	$25.81	$27.37
Standard deviation		$1.33	$1.24	$1.36	$1.29	$1.31	$1.18	$1.43	$1.28	$1.42
Cost per student	I1	$22.26	$19.07	$20.48	$19.05	$20.32	$19.27	$20.38	N/A	N/A
Standard deviation		$1.90	$1.18	$1.30	$1.38	$1.03	$0.77	$1.07	N/A	N/A
Cost per student	I2	$27.37	$25.48	$26.75	$25.24	$24.98	$23.85	$25.07	N/A	N/A
Standard deviation		$2.18	$1.91	$2.55	$1.73	$1.90	$1.84	$1.31	N/A	N/A
Cost per student	I3	$29.23	$27.49	$28.47	$27.07	$28.27	$25.58	$26.67	N/A	N/A
Standard deviation		$2.55	$1.39	$1.72	$1.67	$1.31	$0.68	$1.03	N/A	N/A
Cost per student	D1	$27.30	$22.68	$24.08	$19.58	$21.31	$19.23	$20.73	N/A	N/A
Standard deviation		$2.20	$1.67	$1.78	$1.38	$1.59	$1.36	$1.44	N/A	N/A
Cost per student	D2	$36.01	$30.95	$30.40	$27.41	$28.79	$24.80	$26.13	N/A	N/A
Standard deviation		$2.81	$2.43	$2.36	$2.14	$2.04	$1.79	$2.06	N/A	N/A
Cost per student	D3	$36.01	$30.95	$30.40	$27.41	$28.79	$24.80	$26.13	N/A	N/A
Standard deviation		$2.81	$2.43	$2.36	$2.14	$2.04	$1.79	$2.06	N/A	N/A
#students		100	100	100	100	100	100	100	100	100
Cost per student	N1	$14.54	$13.12	$15.05	$13.58	$15.46	$13.67	$15.25	$14.32	$15.75
Standard deviation		$0.77	$0.60	$0.63	$0.55	$0.80	$0.58	$0.70	$0.72	$0.70
Cost per student	N2	$17.98	$17.51	$18.20	$17.45	$19.20	$17.94	$19.87	$18.77	$20.42
Standard deviation		$0.82	$0.80	$1.14	$0.90	$0.86	$0.96	$0.97	$0.98	$0.96
Cost per student	N3	$19.68	$18.99	$20.31	$19.03	$20.35	$19.30	$21.17	$20.48	$21.98
Standard deviation		$0.91	$0.91	$0.88	$0.81	$0.87	$0.91	$0.83	$0.78	$1.06
Cost per student	G1	$18.18	$16.34	$18.47	$17.14	$19.18	$17.26	$18.86	$17.97	$19.29
Standard deviation		$0.86	$0.73	$0.84	$0.72	$0.87	$0.77	$0.90	$0.76	$0.82
Cost per student	G2	$21.92	$21.13	$22.18	$21.03	$22.90	$21.83	$23.59	$21.64	$23.13
Standard deviation		$1.12	$1.01	$1.15	$1.01	$1.12	$1.02	$1.11	$0.99	$1.07
Cost per student	G3	$25.30	$24.51	$25.56	$24.41	$26.28	$25.21	$26.97	$25.02	$26.51
Standard deviation		$1.12	$1.01	$1.15	$1.01	$1.12	$1.02	$1.11	$0.99	$1.07
Cost per student	I1	$21.33	$19.21	$20.72	$19.20	$19.36	$18.19	$19.24	N/A	N/A
Standard deviation		$1.72	$1.03	$0.97	$1.18	$0.99	$0.78	$0.83	N/A	N/A
Cost per student	I2	$27.39	$24.52	$25.57	$23.96	$25.24	$24.00	$25.29	N/A	N/A
Standard deviation		$1.73	$1.45	$2.67	$1.35	$1.69	$1.71	$1.15	N/A	N/A
Cost per student	I3	$28.42	$26.53	$27.30	$25.80	$26.89	$25.73	$26.88	N/A	N/A
Standard deviation		$2.22	$1.19	$1.34	$1.15	$1.02	$0.50	$0.84	N/A	N/A
Cost per student	D1	$27.21	$21.59	$22.94	$19.76	$21.60	$18.12	$19.60	N/A	N/A
Standard deviation		$1.82	$1.43	$1.46	$1.19	$1.36	$1.16	$1.29	N/A	N/A
Cost per student	D2	$35.10	$30.93	$29.39	$26.24	$27.39	$25.03	$26.44	N/A	N/A
Standard deviation		$2.35	$1.97	$2.01	$1.68	$1.74	$1.55	$1.61	N/A	N/A
Cost per student	D3	$35.10	$30.93	$29.39	$26.24	$27.39	$25.03	$26.44	N/A	N/A
Standard deviation		$2.35	$1.97	$2.01	$1.68	$1.74	$1.55	$1.61	N/A	N/A

Table A.13 (Cont.)

Number of hygienists Number of assistants & chairs (+1 for (I), (D))		2 2	2 3	3 3	3 4	4 4	4 5	5 5	5 6	6 6
#students		150	150	150	150	150	150	150	150	150
Cost per student	N1	$14.20	$12.81	$14.57	$12.91	$14.60	$13.50	$15.04	$14.09	$15.59
Standard deviation		$0.66	$0.52	$0.53	$0.52	$0.65	$0.52	$0.58	$0.59	$0.53
Cost per student	N2	$18.18	$17.32	$18.09	$16.95	$18.73	$17.16	$18.57	$17.57	$19.31
Standard deviation		$0.71	$0.76	$0.87	$0.79	$0.79	$0.71	$0.66	$0.76	$0.68
Cost per student	N3	$19.35	$18.79	$19.99	$18.60	$19.99	$19.07	$20.05	$18.94	$20.34
Standard deviation		$0.70	$0.64	$0.68	$0.49	$0.84	$0.65	$0.70	$0.71	$0.68
Cost per student	G1	$17.94	$16.15	$18.25	$16.40	$18.31	$17.15	$18.77	$17.82	$19.18
Standard deviation		$0.73	$0.60	$0.72	$0.61	$0.72	$0.63	$0.72	$0.64	$0.68
Cost per student	G2	$21.74	$20.60	$21.83	$20.58	$22.41	$20.69	$22.39	$21.35	$22.84
Standard deviation		$0.89	$0.82	$0.90	$0.81	$0.89	$0.81	$0.88	$0.80	$0.86
Cost per student	G3	$24.68	$23.54	$24.76	$23.51	$25.35	$23.62	$25.33	$24.29	$25.78
Standard deviation		$0.89	$0.82	$0.90	$0.81	$0.89	$0.81	$0.88	$0.80	$0.86
Cost per student	I1	$21.03	$18.19	$19.59	$17.96	$19.24	$18.01	$19.11	N/A	N/A
Standard deviation		$1.36	$0.87	$0.76	$0.86	$0.75	$0.50	$0.57	N/A	N/A
Cost per student	I2	$26.62	$23.90	$24.93	$22.49	$23.75	$22.34	$23.52	N/A	N/A
Standard deviation		$1.72	$1.18	$1.67	$1.19	$1.14	$1.44	$0.91	N/A	N/A
Cost per student	I3	$27.36	$25.30	$25.97	$24.33	$25.39	$24.07	$25.11	N/A	N/A
Standard deviation		$1.81	$1.12	$1.23	$1.28	$0.80	$0.44	$0.48	N/A	N/A
Cost per student	D1	$26.69	$21.22	$22.56	$18.52	$20.26	$17.94	$19.47	N/A	N/A
Standard deviation		$1.53	$1.17	$1.26	$1.02	$1.12	$0.95	$1.04	N/A	N/A
Cost per student	D2	$34.71	$29.91	$28.78	$25.48	$26.62	$23.30	$24.70	N/A	N/A
Standard deviation		$1.87	$1.59	$1.56	$1.35	$1.38	$1.22	$1.27	N/A	N/A
Cost per student	D3	$34.71	$29.91	$28.78	$25.48	$26.62	$23.30	$24.70	N/A	N/A
Standard deviation		$1.87	$1.59	$1.56	$1.35	$1.38	$1.22	$1.27	N/A	N/A
#students		200	200	200	200	200	200	200	200	200
Cost per student	N1	$14.15	$12.74	$14.48	$12.86	$14.55	$12.90	$14.58	$13.58	$14.86
Standard deviation		$0.50	$0.45	$0.47	$0.39	$0.54	$0.39	$0.43	$0.42	$0.45
Cost per student	N2	$17.41	$16.96	$17.86	$16.81	$18.18	$17.08	$18.39	$17.58	$18.29
Standard deviation		$0.74	$0.67	$0.69	$0.68	$0.66	$0.54	$0.70	$0.56	$0.73
Cost per student	N3	$18.70	$18.49	$19.49	$18.21	$19.89	$18.30	$19.83	$18.90	$20.29
Standard deviation		$0.60	$0.63	$0.75	$0.65	$0.69	$0.45	$0.70	$0.52	$0.62
Cost per student	G1	$17.59	$15.60	$17.63	$16.14	$18.07	$16.43	$18.02	$17.00	$18.36
Standard deviation		$0.58	$0.49	$0.55	$0.48	$0.58	$0.49	$0.57	$0.52	$0.55
Cost per student	G2	$21.12	$20.20	$21.48	$19.86	$21.63	$20.36	$22.09	$20.43	$21.95
Standard deviation		$0.68	$0.65	$0.74	$0.61	$0.70	$0.62	$0.68	$0.67	$0.72
Cost per student	G3	$24.28	$23.35	$24.63	$23.02	$24.79	$23.52	$25.25	$23.59	$25.10
Standard deviation		$0.68	$0.65	$0.74	$0.61	$0.70	$0.62	$0.68	$0.67	$0.72
Cost per student	I1	$20.88	$18.13	$19.56	$17.87	$18.58	$17.26	$18.39	N/A	N/A
Standard deviation		$1.24	$0.75	$0.77	$0.99	$0.62	$0.48	$0.58	N/A	N/A
Cost per student	I2	$26.29	$23.68	$24.72	$22.36	$23.65	$22.13	$23.42	N/A	N/A
Standard deviation		$1.43	$0.96	$1.66	$1.11	$0.86	$1.09	$0.79	N/A	N/A
Cost per student	I3	$26.90	$24.78	$25.41	$23.64	$24.68	$23.21	$24.29	N/A	N/A
Standard deviation		$1.40	$0.96	$0.94	$0.90	$0.61	$0.32	$0.46	N/A	N/A
Cost per student	D1	$26.43	$20.56	$21.86	$18.45	$20.22	$17.19	$18.71	N/A	N/A
Standard deviation		$1.22	$0.95	$0.96	$0.80	$0.90	$0.75	$0.83	N/A	N/A
Cost per student	D2	$33.88	$29.54	$28.55	$24.66	$25.76	$23.14	$24.59	N/A	N/A
Standard deviation		$1.43	$1.27	$1.28	$1.02	$1.09	$0.93	$0.99	N/A	N/A
Cost per student	D3	$33.88	$29.54	$28.55	$24.66	$25.76	$23.14	$24.59	N/A	N/A
Standard deviation		$1.43	$1.27	$1.28	$1.02	$1.09	$0.93	$0.99	N/A	N/A

Table A.14: Optimal Number of Hygienists and Assistants (Hygienists, Assistants) for Different Practice Acts for Various Program Sizes, Assuming 30 Minutes Round-trip Travel Time to the Site

STUDENTS	25	50	75	100	150	200
N1	(2,3)	(2,3)	(2,3)	(2,3)	(2,3)	(2,3)
N2	(2,2)	(3,4)	(2,3)	(3,4)	(3,4)	(3,4)
N3	(2,2)	(3,4)	(3,4)	(3,4)	(3,4)	(3,4)
G1	(2,3)	(2,3)	(2,3)	(2,3)	(2,3)	(2,3)
G2	(2,3)	(3,4)	(2,3)	(3,4)	(3,4)	(3,4)
G3	(2,3)	(3,4)	(2,3)	(3,4)	(3,4)	(3,4)
I1	(2,3)	(2,3)	(3,4)	(4,5)	(3,4)	(4,5)
I2	(2,3)	(3,4)	(4,5)	(3,4)	(4,5)	(4,5)
I3	(2,3)	(3,4)	(4,5)	(4,5)	(4,5)	(4,5)
D1	(3,4)	(4,5)	(4,5)	(4,5)	(4,5)	(4,5)
D2	(3,4)	(4,5)	(4,5)	(4,5)	(4,5)	(4,5)
D3	(3,4)	(4,5)	(4,5)	(4,5)	(4,5)	(4,5)

Table A.15: Optimal Number of Hygienists and Assistants (Hygienists, Assistants) for Different Practice Acts for Various Program Sizes, Assuming 2 Hours Round-trip Travel Time to the Site

STUDENTS	25	50	75	100	150	200
N1	(2,2)	(2,3)	(3,4)	(2,3)	(3,4)	(4,5)
N2	(2,2)	(3,4)	(2,3)	(3,4)	(4,5)	(2,2)
N3	(2,2)	(3,4)	(5,6)	(3,4)	(2,3)	(2,2)
G1	(2,2)	(2,3)	(3,4)	(2,3)	(2,3)	(2,3)
G2	(2,2)	(3,4)	(2,3)	(5,6)	(4,5)	(3,4)
G3	(2,2)	(3,4)	(2,3)	(5,6)	(4,5)	(3,4)
I1	(2,3)	(2,3)	(2,3)	(4,5)	(2,3)	(4,5)
I2	(2,2)	(2,3)	(4,5)	(2,3)	(3,4)	(3,4)
I3	(2,2)	(2,3)	(4,5)	(2,3)	(3,4)	(3,4)
D1	(2,3)	(3,4)	(3,4)	(4,5)	(3,4)	(4,5)
D2	(2,3)	(3,4)	(3,4)	(4,5)	(4,5)	(4,5)
D3	(2,3)	(3,4)	(4,5)	(4,5)	(4,5)	(4,5)

Table A.16: Cost Savings from Different Practice Acts for Various Program Sizes Assuming 30 Minutes Round-trip Travel to the Site

Number of Students	25	50	75	100	150	200
No supervision compared to general	25.99%	21.61%	19.14%	19.72%	19.72%	18.31%
Standard error	2.35%	1.91%	1.65%	1.42%	1.16%	1.03%
No supervision compared to indirect	35.40%	29.07%	25.61%	26.94%	24.86%	23.70%
Standard error	2.66%	2.13%	1.67%	1.26%	1.25%	1.02%
No supervision compared to direct	39.45%	30.68%	26.01%	27.25%	25.07%	24.73%
Standard error	2.80%	2.28%	1.98%	1.74%	1.46%	1.22%
General supervision compared to indirect	14.56%	10.51%	8.70%	9.88%	6.84%	7.07%
Standard error	2.69%	2.31%	1.84%	1.37%	1.34%	1.00%
General supervision compared to direct	18.19%	11.57%	8.50%	9.38%	6.66%	7.86%
Standard error	2.82%	2.44%	2.12%	1.82%	1.54%	1.20%
Indirect supervision compared to direct	6.28%	2.28%	0.53%	0.44%	0.27%	1.35%
Standard error	3.24%	2.72%	2.24%	1.80%	1.66%	1.25%

Table A.17: Cost Savings from Different Practice Acts for Various Program Sizes Assuming 2 Hours Round-trip Travel to the Site

Number of Students	25	50	75	100	150	200
No supervision compared to general	33.56%	26.19%	20.73%	22.10%	22.24%	19.10%
Standard error	1.80%	1.50%	1.28%	1.13%	0.94%	0.84%
No supervision compared to indirect	40.41%	30.46%	24.62%	28.19%	24.28%	23.71%
Standard error	2.23%	1.71%	1.31%	1.21%	1.21%	0.99%
No supervision compared to direct	45.01%	35.07%	35.51%	31.22%	26.63%	27.22%
Standard error	2.18%	1.93%	1.56%	1.35%	1.21%	0.97%
General supervision compared to indirect	11.49%	6.14%	5.16%	8.47%	2.70%	6.04%
Standard error	2.29%	1.86%	1.47%	1.27%	1.27%	0.98%
General supervision compared to direct	17.24%	12.04%	18.65%	11.71%	5.65%	10.04%
Standard error	2.24%	2.05%	1.67%	1.41%	1.26%	0.97%
Indirect supervision compared to direct	7.72%	6.63%	14.45%	4.23%	3.10%	4.60%
Standard error	2.65%	2.24%	1.72%	1.53%	1.48%	1.12%

A.3 Calculations for Wisconsin Example

Program Budget: \$59,546

Children sealed: 2,670

Direct Cost per child: \$59,546/2,670 = \$20.51

Savings from decreasing practice act to no supervision: 23.40%

Cost per student after supervision savings: 0.766 * \$20.51 = \$15.71

Total students who could be sealed for same program cost: \$59,546/\$15.71 = 3,790

Increase in total students sealed: 3,790 - 2,670 = 1,120

Wisconsin Medicaid contribution percentage after FMAP & SCHIP: 29.19%

Medicaid sealant reimbursement rate per person: \$67.96

Percentage of program students on Medicaid/SCHIP: 31%

State's contribution to Medicaid reimbursements per Medicaid child:

    0.2919 * \$67.96 = \$19.84

Expected number of fillings averted per student: 2.5

Medicaid reimbursement per filling: \$43.60

Wisconsin's portion of Medicaid reimbursement per filling: 0.2919 * \$43.60 = \$12.73

Break-even point: \$19.84/\$12.73 = 1.56 fillings

APPENDIX B

SUPPLEMENTARY MATERIAL FOR COMMUNITY HEALTH CENTERS: LOCATION AND SERVICE ALLOCATION DECISIONS

B.1 Maps of Georgia Demographics

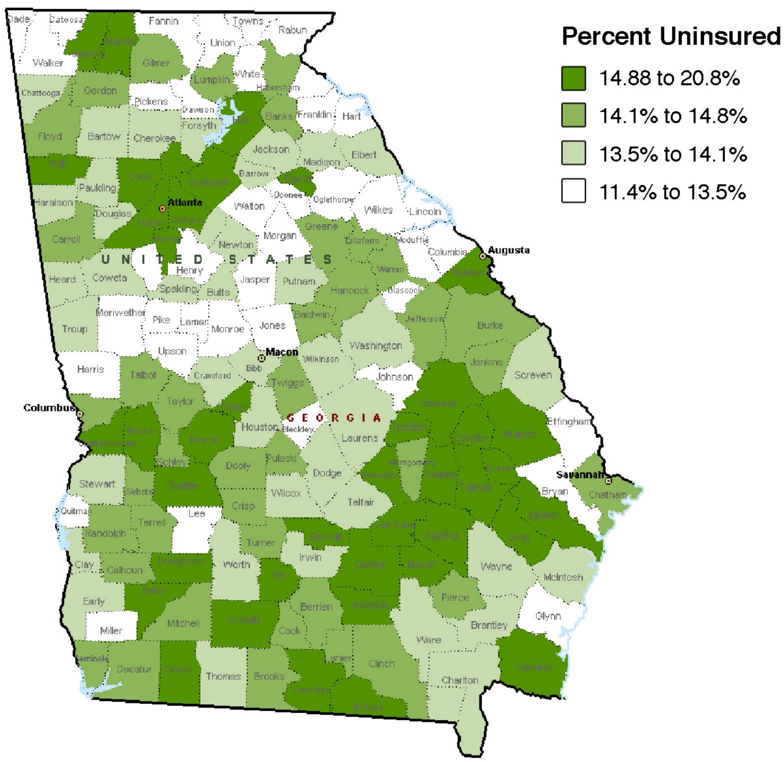

Figure B.12: Counties in Georgia with the Highest and Lowest Estimated Percentage of Uninsured People

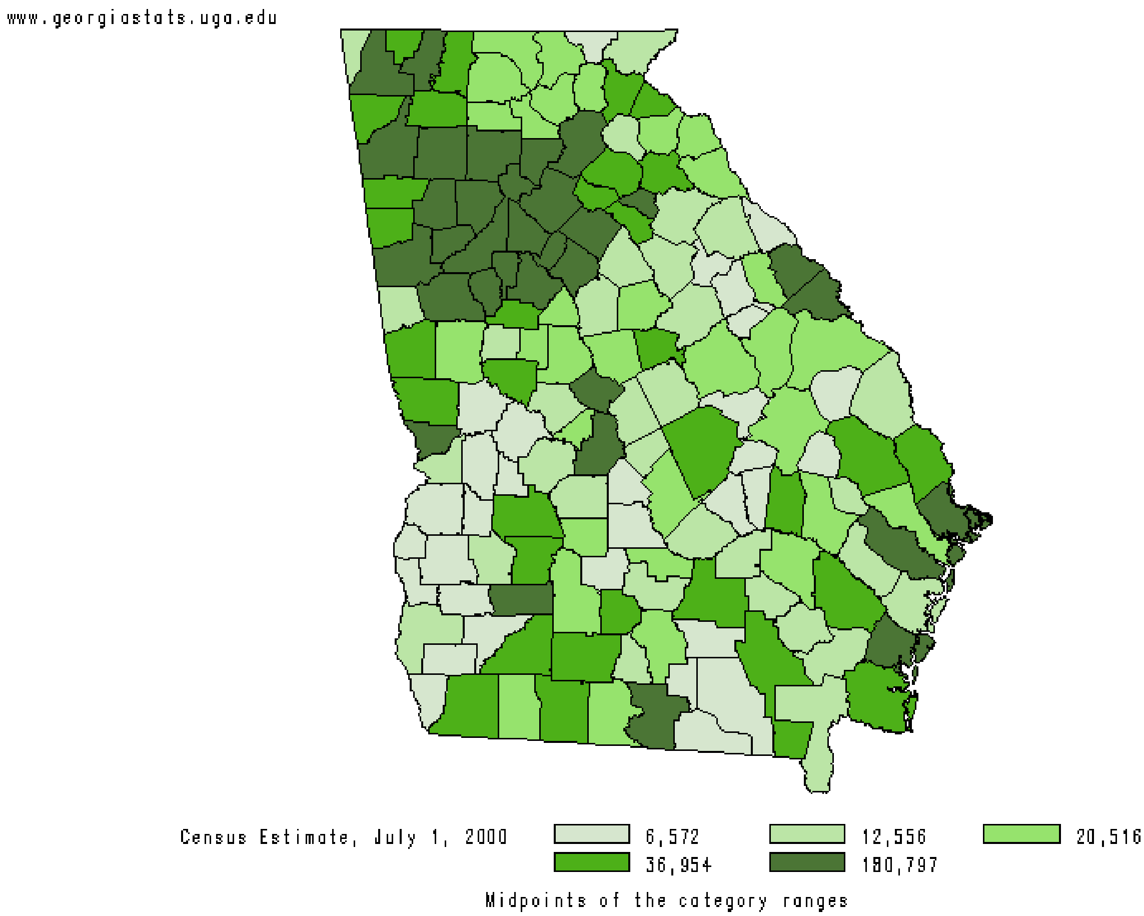

Figure B.13: Population Density of Georgia Counties

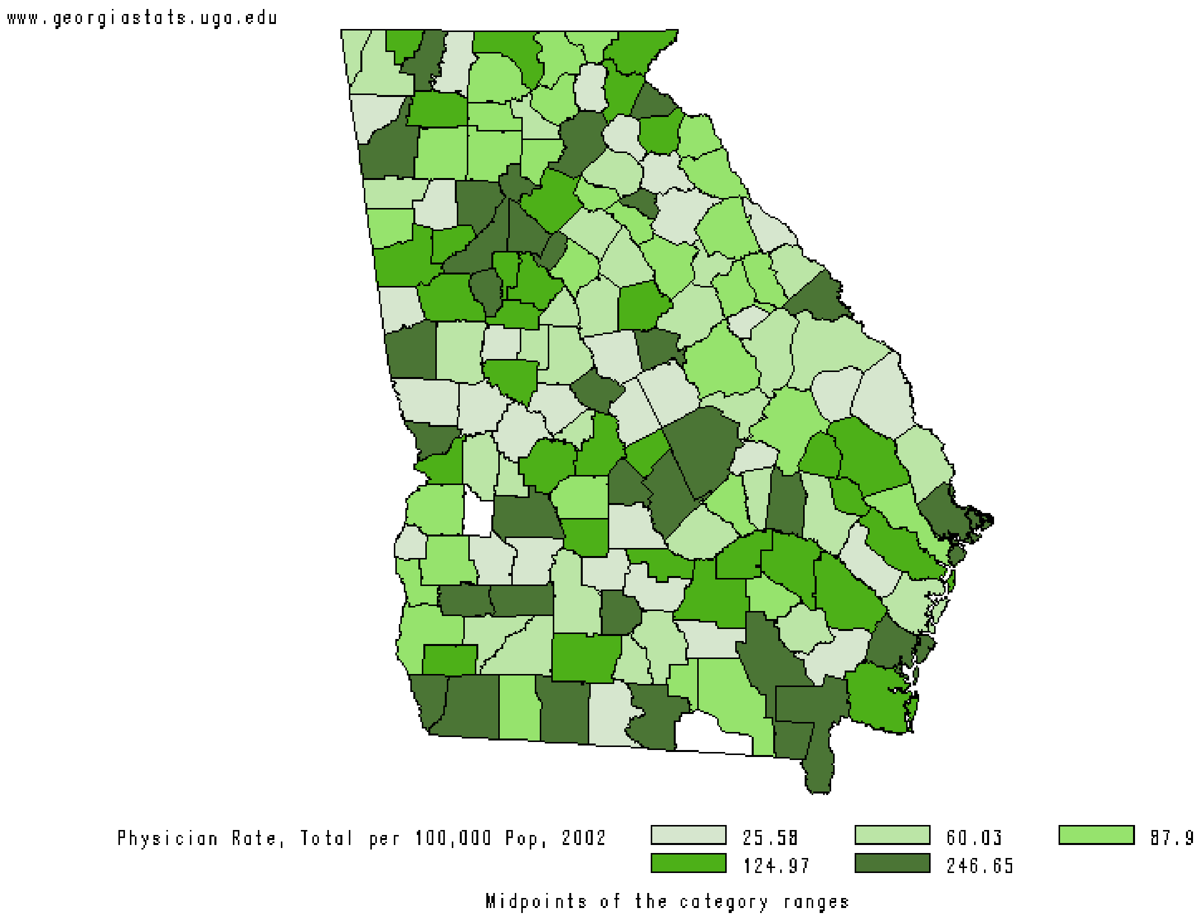

Figure B.14: Georgia Counties' Physicians per 100,000 Population

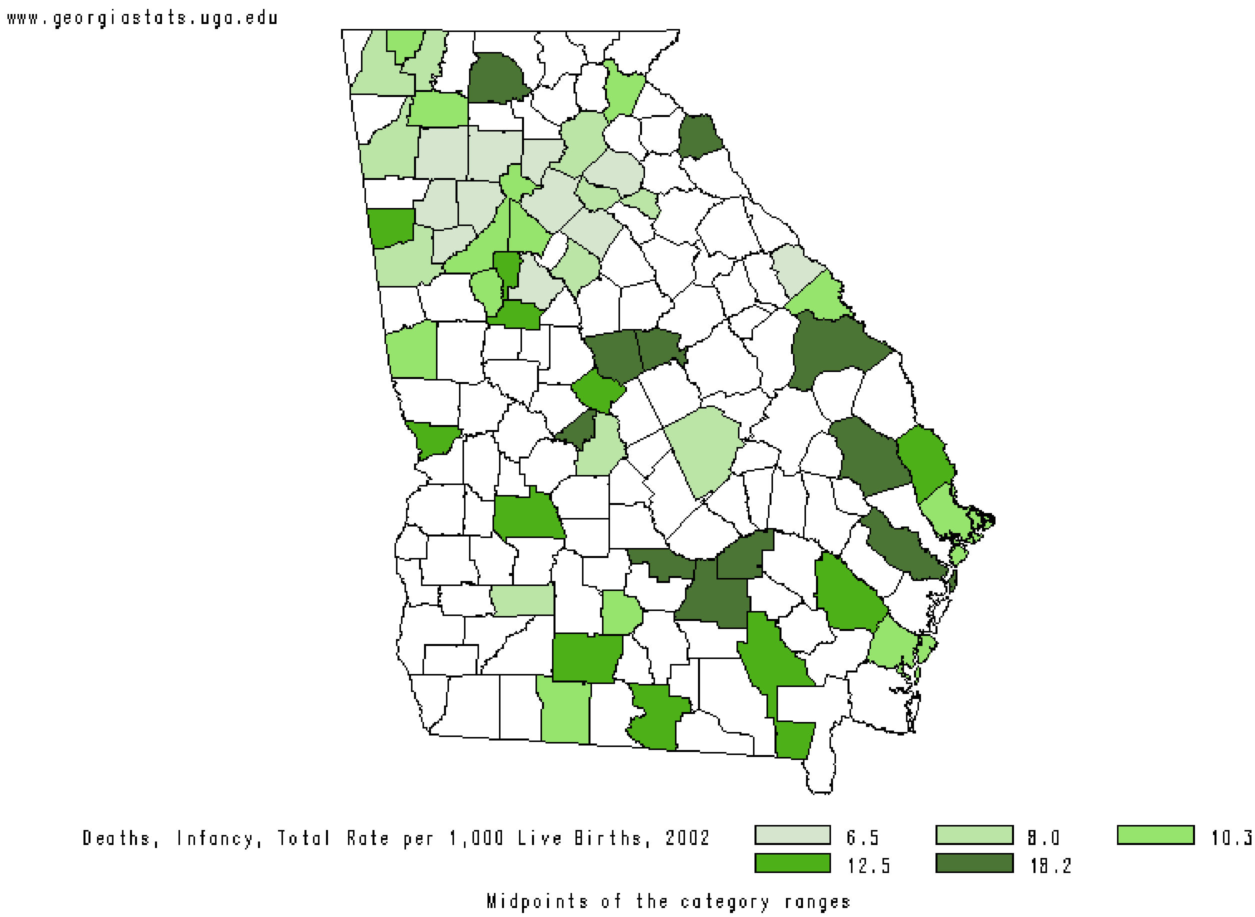

Figure B.15: Infant Mortality for Georgia Counties

B.2 Text of NHANES Questions

This section includes the text of questions from the NHANES survey used to predict local estimates of health conditions. Included before each question is the code number used by NHANES.

ALCOHOL ABUSE:
(ALQ150) Was there ever a time or times in your life when you drank 5 or more drinks of any kind of alcoholic beverage almost every day?
1 = Yes
2 = No
7 = Refused
9 = Don't Know

DRUG USAGE:
(DUQ100) Have you ever used cocaine, including crack or freebase, or other street drugs? Do not include marijuana.
1 = Yes
2 = No
7 = Refused
9 = Don't Know

MENTAL HEALTH:
(MCQ120B) During the past 12 months have you seen or talked to a mental health professional such as a psychologist, psychiatrist, psychiatric nurse or clinical social worker about your health?
1 = Yes
2 = No
7 = Refused
9 = Don't Know

LIKELIHOOD OF USING A CLINIC:
(HUQ0303) Is there a place that you usually go when you are sick or you need advice about your health?
1 = Yes
2 = There is no place
3 = There is more than one place
7 = Refused
9 = Don't know

(HUQ040) What kind of place do you go to most often: is it a clinic, doctor's office, emergency room, or some other place?
1 = Clinic or health center
2 = Doctor's office or HMO
3 = Hospital emergency room
4 = Hospital outpatient department
5 = Some other place
7 = Refused

9 = Don't know

INSURANCE TYPE:
(HID010) Are you covered by health insurance or some other kind of health care plan?
(HID030A)Are you covered by private insurance?
(HID030B) Are you covered by Medicare?
(HID030C) Are you covered by Medicaid/CHIP?
(HID030D) Are you covered by other government insurance?
(HID030E) Are you covered by any single service plan? Include those that pay for only one type of service (e.g. nursing home care, dental care, vision care, etc.)
1 = Yes
2 = No
7 = Refused
9 = Don't Know

The following questions were used for comparison with BRFSS data.

DIABETES:
(NHANES - DIQ010) Other than during pregnancy, have you ever been told by a doctor or health professional that you have diabetes or sugar diabetes?
1= Yes
2= No
3= Borderline
7= Refused
9= Don't know

(BRFSS) Have you ever been told by a doctor that you have diabetes?
1 = Yes
2 = Yes, but female told only during pregnancy
3 = No
7 = Don't know/Not sure
9 = Refused

ASTHMA:
(MCQ010) Has a doctor or other health professional ever told you that you have asthma?
1 = Yes
2 = No
7 = Refused
9 = Don't Know

(BRFSS) Did a doctor ever tell you that you had asthma?
1 = Yes
2 = No
9 = Refused
7 = Don't Know

(BRFSS) Do you have any kind of health care coverage?
1 = Yes

2 = No
9 = Refused
7 = Don't Know

B.3 Data Tables

Table B.18: Logistic Regression Results Predicting Uninsured Persons: Sample Size = 9,404

Variable	Beta Coeff	SE Beta	p-value
Intercept	-6.27	0.71	0.0000
AGE			
=<18 years	4.03	0.63	0.0000
=18 - 35	4.77	0.65	0.0000
=35 - 65	3.95	0.65	0.0000
GENDER = male	-0.35	0.40	0.3907[1]
INCOME = below poverty level	2.01	1.19	0.1121
RACE			
=black	2.65	0.73	0.0025
=Hispanic/latino	2.35	1.32	0.0961
AGE, GENDER			
=<18, male	0.20	0.36	0.5904
=18 - 35, male	0.95	0.39	0.0294
=35 - 65, male	0.43	0.46	0.3644
AGE, INCOME			
=<18, below	-1.22	1.30	0.3624
=18 - 35, below	-1.25	1.23	0.3253
=35,65, below	-0.32	1.29	0.8048
AGE, RACE			
=<18, black	-2.79	0.66	0.0007
=<18, Hispanic/latino	-1.66	1.22	0.1925
=18 - 35, black	-2.58	0.63	0.0010
=18 - 35, Hispanic/latino	-1.41	1.30	0.2947
=35 - 65, black	-2.02	0.63	0.0059
=35 - 65, Hispanic/latino	-1.37	1.18	0.2670
INCOME, RACE			
=Below, black	-0.67	0.22	0.0081
=Below, Hispanic/latino	0.04	0.30	0.8830

Table B.19: Logistic Regression Results Predicting Persons with Private Insurance: Sample Size = 9,404

Variable	Beta Coeff	SE Beta	p-value
Intercept	0.35	0.06	0.0000
AGE			
=<18	1.10	0.23	0.0002
=18 - 35	0.66	0.15	0.0005
=35 - 65	1.41	0.18	0.0000
INCOME = below poverty	-1.12	0.30	0.0019
RACE			
=black	-0.98	0.28	0.0033
=Hispanic/latino	-0.89	0.31	0.0125
AGE, INCOME			
=<18, below	-1.40	0.46	0.0075
=18 - 35, below	-0.46	0.23	0.0591
=35 - 65, below	-1.48	0.45	0.0045
AGE, RACE			
=<18, black	-0.15	0.35	0.6777
=<18, Hispanic/latino	-0.07	0.40	0.8714
=18 - 35, black	0.47	0.28	0.1090
=18 - 35, Hispanic/latino	-0.09	0.35	0.8033
=35 - 65, black	0.39	0.35	0.2757
=35 - 65, Hispanic/latino	-0.00	0.35	0.9925

Table B.20: Logistic Regression Results Predicting Publicly Insured Persons: Sample Size = 9,404

Variable	Beta Coeff	SE Beta	p-value
Intercept	2.44	0.22	0.0000
AGE			
=<18	-4.63	0.27	0.0000
=18 - 35	-5.58	0.31	0.0000
=35 - 65	-4.98	0.31	0.0000
GENDER = male	-0.03	0.15	0.8583
INCOME = below poverty level	-0.21	0.41	0.6166
RACE			
=black	-0.25	0.32	0.4324
=Hispanic/latino	0.29	0.64	0.6559
AGE, GENDER			
=< 18, male	0.10	0.16	0.5641
=18 - 35, male	-0.73	0.20	0.0027
=35 - 65, male	0.00	0.18	0.9845
AGE, INCOME			
=<18 , below	2.96	0.47	0.0000
=18 - 35, below	2.72	0.52	0.0001
=35 - 65, below	2.30	0.43	0.0001
AGE, RACE			
=<18, black	1.77	0.33	0.0001
=<18, Hispanic/latino	0.71	0.65	0.2932
=18 - 35, black	1.64	0.44	0.0022
=18 - 35, Hispanic/latino	0.45	0.85	0.6028
=35 - 65, black	0.82	0.36	0.0379
=35 - 65, Hispanic/latino	0.30	0.53	0.5740
INCOME, RACE			
=below, black	-0.45	0.28	0.1295
=below, Hispanic/latino	-1.44	0.49	0.0096

Table B.21: Logistic Regression Results Predicting Clinic Usage: Sample Size = 9,404

Variable	Beta Coeff	SE Beta	p-value
Intercept	-1.27	0.37	0.0038
AGE			
=<18	-0.20	0.23	0.3858
=18 - 35	-0.08	0.32	0.8139
=35 - 65	0.16	0.16	0.3295
GENDER = male	-0.18	0.05	0.0016
INCOME = below poverty level	-0.23	0.23	0.3234
RACE			
=black	-0.54	0.40	0.1967
=Hispanic/latino	0.10	0.46	0.8297
INSURANCE			
=PRIVATE	-0.10	0.17	0.5394
=PUBLIC	0.29	0.15	0.0756
AGE, INCOME			
=<18, below	0.62	0.17	0.0028
=18 - 35, below	0.85	0.25	0.0040
=35 - 65, below	0.48	0.31	0.1377
AGE, RACE			
=< 18, black	0.74	0.31	0.0320
=< 18, Hispanic/latino	0.47	0.44	0.3007
=18 - 35, black	0.35	0.37	0.3665
=18 - 35, Hispanic/latino	-0.16	0.46	0.7306
=35 - 65, black	-0.07	0.29	0.8047
=35 - 65, Hispanic/latino	-0.31	0.43	0.4790

Table B.22: Logistic Regression Results Predicting Mental Health Service Users: Sample Size = 8,117

Variable	Beta Coeff	SE Beta	p-value
Intercept	-2.55	0.21	0.0000
AGE			
=<18	0.24	0.28	0.4016
=18 - 35	0.33	0.23	0.1667
=35 - 65	0.52	0.25	0.0560
GENDER = male	-1.16	0.32	0.0026
INCOME = below poverty level	0.62	0.15	0.0010
RACE			
=black	-0.54	0.21	0.0204
=Hispanic/latino	-0.46	0.20	0.0326
AGE, GENDER			
=<18, male	1.62	0.34	0.0003
=18 - 35, male	0.71	0.36	0.0651
=35 - 65, male	0.88	0.39	0.0397

Table B.23: Logistic Regression Results Predicting Alcohol Abuse Service Users: Sample Size = 3,661

Variable	Beta Coeff	SE Beta	p-value
Intercept	-2.94	0.15	0.0000
GENDER = male	1.79	0.14	0.0000
INCOME = below	1.23	0.29	0.0008
GENDER, INCOME = male, below	-1.26	0.36	0.0032

Table B.24: Logistic Regression Results Predicting Drug Abuse Service Users: Sample Size = 2,782

Variable	Beta Coeff	SE Beta	p-value
Intercept	-1.48	0.12	0.0000
AGE = 18 - 35	0.04	0.14	0.7796
GENDER = male	0.48	0.11	0.0004
INCOME = below	0.49	0.17	0.0138
RACE			
=black	-0.04	0.15	0.7817
=Hispanic/latino	-0.48	0.20	0.0321
AGE, RACE			
= 18 - 35, black	-1.56	0.48	0.0053
=18 - 35, Hispanic/latino	0.61	0.23	0.0170
INCOME, RACE			
= below, black	-0.11	0.40	0.7916
= below, Hispanic/latino	-0.93	0.34	0.0143

Table B.25: Prevalence Estimates for U.S. Census Demographic Categories

GENDER	POVERTY	RACE	AGE	NO INSURANCE	PRIVATE INS.	GOV'T. INS.	ALCOHOL ABUSE	DRUG ABUSE	MENTAL HEALTH	CLINIC NO INS.	CLINIC GOV'T.	CLINIC PRIVATE
Male	Above	Black	< 18	0.07	0.58	0.34	N/A	N/A	0.08	0.19	0.24	0.18
Male	Above	Black	[18,35)	0.30	0.62	0.07	0.16	0.07	0.04	0.15	0.19	0.14
Male	Above	Black	[35,65)	0.17	0.76	0.07	0.32	0.26	0.05	0.13	0.17	0.12
Male	Above	Black	≥ 65	0.02	0.34	0.64	0.26	0.26	0.01	0.12	0.15	0.11
Male	Above	Hisp.[2]	< 18	0.15	0.60	0.23	N/A	N/A	0.09	0.25	0.31	0.24
Male	Above	Hisp.	[18,35)	0.51	0.49	0.00	0.18	0.30	0.04	0.17	0.21	0.16
Male	Above	Hisp.	[35,65)	0.22	0.69	0.09	0.30	0.19	0.06	0.18	0.23	0.17
Male	Above	Hisp.	≥ 65	0.01	0.33	0.66	0.24	0.19	0.02	0.21	0.26	0.19
Male	Above	White	< 18	0.08	0.81	0.10	N/A	N/A	0.14	0.16	0.20	0.15
Male	Above	White	[18,35)	0.29	0.74	0.00	0.28	0.28	0.06	0.18	0.22	0.16
Male	Above	White	[35,65)	0.10	0.85	0.05	0.23	0.27	0.09	0.22	0.27	0.20
Male	Above	White	≥ 65	0.00	0.59	0.41	0.19	0.27	0.02	0.19	0.24	0.18
Male	Below	Black	< 18	0.08	0.10	0.82	N/A	N/A	0.15	0.26	0.32	0.24
Male	Below	Black	[18,35)	0.32	0.26	0.37	0.16	0.10	0.07	0.25	0.31	0.23
Male	Below	Black	[35,65)	0.36	0.20	0.39	0.32	0.34	0.10	0.16	0.20	0.15
Male	Below	Black	≥ 65	0.07	0.16	0.78	0.26	0.34	0.03	0.10	0.13	0.09
Male	Below	Hisp.	< 18	0.30	0.15	0.52	N/A	N/A	0.16	0.33	0.40	0.31
Male	Below	Hisp.	[18,35)	0.70	0.22	0.08	0.19	0.22	0.08	0.27	0.34	0.26
Male	Below	Hisp.	[35,65)	0.62	0.19	0.19	0.30	0.13	0.10	0.22	0.28	0.21
Male	Below	Hisp.	≥ 65	0.10	0.19	0.71	0.24	0.13	0.03	0.17	0.22	0.16
Male	Below	White	< 18	0.17	0.23	0.60	N/A	N/A	0.23	0.22	0.27	0.20
Male	Below	White	[18,35)	0.47	0.33	0.20	0.28	0.38	0.11	0.29	0.35	0.27
Male	Below	White	[35,65)	0.37	0.27	0.36	0.23	0.38	0.16	0.26	0.32	0.24
Male	Below	White	≥ 65	0.01	0.30	0.69	0.19	0.38	0.04	0.16	0.20	0.14
Female	Above	Black	< 18	0.08	0.58	0.34	N/A	N/A	0.05	0.22	0.27	0.20
Female	Above	Black	[18,35)	0.19	0.62	0.15	0.03	0.05	0.06	0.18	0.22	0.16
Female	Above	Black	[35,65)	0.16	0.76	0.08	0.07	0.18	0.07	0.15	0.19	0.14
Female	Above	Black	≥ 65	0.03	0.34	0.63	0.05	0.18	0.04	0.14	0.18	0.13
Female	Above	Hisp.	< 18	0.18	0.60	0.22	N/A	N/A	0.06	0.29	0.35	0.27
Female	Above	Hisp.	[18,35)	0.36	0.49	0.09	0.04	0.21	0.06	0.20	0.25	0.18
Female	Above	Hisp.	[35,65)	0.21	0.69	0.10	0.06	0.12	0.08	0.21	0.26	0.19
Female	Above	Hisp.	≥ 65	0.02	0.33	0.65	0.05	0.12	0.05	0.24	0.29	0.22
Female	Above	White	< 18	0.10	0.81	0.09	N/A	N/A	0.09	0.19	0.24	0.17
Female	Above	White	[18,35)	0.18	0.74	0.04	0.06	0.19	0.10	0.21	0.26	0.19
Female	Above	White	[35,65)	0.09	0.85	0.06	0.05	0.19	0.12	0.25	0.31	0.23
Female	Above	White	≥ 65	0.00	0.59	0.41	0.04	0.19	0.07	0.22	0.27	0.20
Female	Below	Black	< 18	0.09	0.10	0.80	N/A	N/A	0.10	0.29	0.36	0.27
Female	Below	Black	[18,35)	0.21	0.26	0.54	0.10	0.07	0.11	0.28	0.35	0.27
Female	Below	Black	[35,65)	0.34	0.20	0.44	0.21	0.24	0.12	0.19	0.24	0.17
Female	Below	Black	≥ 65	0.09	0.16	0.75	0.17	0.24	0.08	0.12	0.15	0.11
Female	Below	Hisp.	< 18	0.33	0.15	0.52	N/A	N/A	0.10	0.38	0.45	0.35
Female	Below	Hisp.	[18,35)	0.56	0.22	0.22	0.11	0.15	0.11	0.31	0.38	0.29
Female	Below	Hisp.	[35,65)	0.60	0.19	0.21	0.19	0.08	0.13	0.26	0.31	0.24
Female	Below	Hisp.	≥ 65	0.13	0.19	0.67	0.15	0.08	0.08	0.20	0.25	0.18
Female	Below	White	< 18	0.19	0.23	0.58	N/A	N/A	0.16	0.25	0.31	0.24
Female	Below	White	[18,35)	0.32	0.33	0.34	0.18	0.28	0.17	0.33	0.39	0.30
Female	Below	White	[35,65)	0.35	0.27	0.38	0.15	0.27	0.20	0.30	0.36	0.28
Female	Below	White	≥ 65	0.01	0.30	0.69	0.12	0.27	0.13	0.18	0.23	0.17

B.4 Supplementary Results

Table B.26: Model County Selections by Assumptions - Counties are Ordered from North to South

County	10% Highest Population Density	10% Lowest Population Density	10% Least Number of Uninsured	Current CHC Locations	Base Model Choices	60-mile Model	0-mile Model	Budget 88million	Budget 22Million	Weighted Model (0.9, 1.1)	Weighted Model (0.8,1.2)	Weighted Model (0.7, 1.3)	Weighted Model (0.6,1.4)	Weighted Model (0.5, 1.5)	Minimum 25% Rural Model
Dade	2[3]	1	3	X											
Chattooga	2	2	2												
Walker	1	1	1		X			X		X					X
Floyd	1	3	1		X		X	X							X
Haralson	2	2	2												
Polk	2	4	2												
Catoosa	1	1	1												
Heard	3	2	3												
Carroll	1	3	1	X	X			X		X					X
Quitman	4	1	4												
Troup	1	2	1												
Clay	4	2	4												
Whitfield	1	4	1					X							
Muscogee	1	3	1	X	X		X	X	X	X	X	X	X	X	X
Early	4	2	3												
Gordon	2	3	1										X		
Harris	3	1	2												X
Seminole	3	3	4												
Paulding	1	2	1					X			X	X	X	X	
Bartow	1	2	1					X				X	X	X	
Stewart	4	2	4			X									
Chattahoochee	2	4	4												
Murray	2	4	2							X					
Coweta	1	2	1		X			X		X	X				X
Randolph	4	3	4												
Miller	4	1	4												
Douglas	1	2	1					X		X	X	X		X	
Calhoun	4	3	4												
Meriwether	3	1	2			X									
Decatur	3	3	2												
Cobb	1	4	1				X	X							
Webster	4	3	4			X									
Talbot	4	3	4			X									X
Macon	4	4	4												X
Fayette	1	1	1		X		X	X		X	X	X	X	X	X
Cherokee	1	2	1				X	X			X	X	X	X	
Gilmer	3	3	2												
Pickens	2	1	2					X							
Terrell	3	3	3			X									
Fulton	1	4	1	X			X	X				X	X	X	
Baker	4	4	4			X									X
Pike	2	1	3					X							
Clayton	1	4	1		X		X	X		X	X	X	X	X	
Schley	4	3	4												
Upson	2	1	2			X									
Fannin	3	1	3												
Spalding	1	2	1		X			X	X	X	X	X	X	X	X
DeKalb	1	4	1	X			X	X							
Grady	3	4	2												
Taylor	4	3	4												
Sumter	2	4	2	X											
Henry	1	1	1		X		X	X		X	X	X	X	X	X
Lee	2	1	2												
Mitchell	3	3	2												
Dougherty	1	3	1	X	X	X	X	X	X	X	X				X
Lamar	2	1	3	X	X										
Dawson	2	1	3					X							
Forsyth	1	2	1	X			X	X					X	X	
Gwinnett	1	4	1				X	X							
McDuffie	3	4	3			X									
Rockdale	1	2	1					X		X	X	X	X	X	X
Union	3	1	3												

[3]For these three columns, 1 = top quartile, 2 = 2nd quartile, 3 = 3rd quartile, 4 = bottom quartile

Table B.26 (Cont.)

County	10% Highest Population Density	10% Lowest Population Density	10% Least Number of Uninsured	Current CHC Locations	Base Model Choices	60-mile Model	0-mile Model	Budget 88million	Budget 22Million	Weighted Model (0.9, 1.1)	Weighted Model (0.8,1.2)	Weighted Model (0.7, 1.3)	Weighted Model (0.6,1.4)	Weighted Model (0.5, 1.5)	Minimum 25% Rural Model
Lumpkin	2	3	2												
Crawford	3	2	3												
Butts	2	2	3		X			X	X	X				X	X
Thomas	2	2	2												
Monroe	3	1	2			X									
Newton	1	2	1		X			X	X		X	X	X		X
Hall	1	4	1				X	X							
Worth	3	2	2												
Peach	1	4	2		X			X	X						X
Dooly	3	3	3			X									
Colquitt	2	4	1												
Crisp	2	3	2												
Towns	2	1	4												
White	2	1	3												
Walton	1	1	1		X			X		X	X	X	X	X	X
Barrow	1	2	1					X				X	X	X	
Jasper	3	1	3												
Bibb	1	2	1		X		X	X	X	X	X	X	X	X	X
Houston	1	2	1				X			X	X	X	X	X	
Turner	3	3	4												
Brooks	3	3	3												
Jackson	2	2	2					X							
Jones	2	1	2		X			X							
Habersham	2	3	2												
Tift	1	4	2												
Banks	2	3	3		X			X							
Morgan	3	1	3												
Pulaski	3	3	4												
Wilcox	4	2	4												
Oconee	1	1	2												
Rabun	3	1	3												
Cook	2	3	3												
Twiggs	3	3	4												
Clarke	1	4	1					X							
Putnam	3	2	3			X									
Bleckley	3	1	3												
Stephens	1	1	2												
Irwin	3	2	4	X											
Lowndes	1	4	1				X								
Ben Hill	2	4	3												
Baldwin	1	3	2												
Wilkinson	4	2	4			X									
Berrien	3	3	3												
McIntosh	2	2	2												
Franklin	2	1	3												
Dodge	3	2	3												
Greene	3	3	3	X		X									
Oglethorpe	3	1	3			X									
Lanier	3	3	4												
Hancock	4	3	4			X						X			X
Hart	2	1	2			X									
Echols	4	4	4												
Laurens	3	2	1												
Telfair	4	2	4												
Taliaferro	4	3	4			X									
Elbert	2	2	2												
Atkinson	4	4	4												
Coffee	2	4	2												
Washington	3	2	3			X									
Wheeler	4	4	4												X
Wilkes	4	1	4			X									
Clinch	4	3	4												
Warren	4	3	4	X		X									
Johnson	3	1	4	X											
Jeff Davis	3	4	3												
Glascock	4	1	4												X
Treutlen	3	4	4												
Montgomery	3	3	4												
Madison	2	1	2	X											
Bacon	3	4	3												
Lincoln	3	1	4												
Jefferson	3	2	3												

Table B.26 (Cont.)

County	10% Highest Population Density	10% Lowest Population Density	10% Least Number of Uninsured	Current CHC Locations	Base Model Choices	60-mile Model	0-mile Model	Budget 88million	Budget 22Million	Weighted Model (0.9, 1.1)	Weighted Model (0.8,1.2)	Weighted Model (0.7, 1.3)	Weighted Model (0.6,1.4)	Weighted Model (0.5, 1.5)	Minimum 25% Rural Model
Ware	3	2	2	X											
Toombs	2	4	2												
Appling	3	4	3												
Emanuel	3	4	2	X											
Pierce	3	3	3												
Columbia	1	1	1		X		X	X	X	X	X	X	X		X
Candler	3	4	4												
Charlton	4	2	4							X					
Tattnall	3	4	3												
Richmond	1	4	1		X		X	X	X	X	X		X	X	
Burke	4	3	2												
Brantley	3	2	3												
Jenkins	4	3	4												
Wayne	3	2	2												
Evans	2	4	3												
Bulloch	2	4	1												
Long	4	4	3												
Camden	2	4	2												
Screven	4	2	3												
Liberty	2	4	1												
Glynn	1	1	1												
Bryan	3	1	2					X							
Marion	4	2	3												
Effingham	2	1	2												
Chatham	1	3	1		X		X	X	X		X	X		X	X

APPENDIX C

SUPPLEMENTARY MATERIAL FOR MARKOV CHAINS AND CHRONIC DISEASE

C.1 Proofs of analytic results

We wish to compare the number of people expected to be in the disease state when we use an average value for the transition from risk to disease compared to when we use several transition values specific to how long the person has been in the risk state. We can make the disease state an absorbing state, without loss of generality, since we are concerned with the probability of going from the risk state to the disease state. Additionally, if we assume that all of the population at the beginning of the study is in one of the risk states, then we can look at the transition probabilities that involve the risk and disease states only, thus simplifying the proofs below.

In the following, we assume that time spent in the risk state increases the probability of disease, as would be true in our lung cancer example. However, the opposite of the claims below are also true when the time spent in the risk state decreases the probability. To begin, we compare one "average" risk state with two "split" risk states, as shown in the diagram above. It should be clear that if these results are true for the two-risk-state case, they will extend to multiple risk states.

Let:

R_1 = state risk 1, or the number of people in state risk 1,

R_2 = state risk 2+, or the number of people in state risk 2+,

R = the average risk state, or the number of people in the average risk state,

$D =$ the disease state, or the number of people in the disease state,

$x =$ the perceived probability of transition from average risk state to disease.

Now let us suppose that the transition probabilities are as follows for the average case:

$$\begin{array}{c} \\ R \\ D \end{array} \begin{array}{c} \begin{array}{cc} R & D \end{array} \\ \begin{bmatrix} (1-x) & x \\ 0 & 1 \end{bmatrix} \end{array}$$

Using matrix multiplication, the probability of going from state R to D in two periods is:

$$2x - x^2. \tag{14}$$

Now let us suppose that the transition probabilities are as follows for the split case:

$$\begin{array}{c} \\ R_1 \\ R_2 \\ D \end{array} \begin{array}{c} \begin{array}{ccc} R_1 & R_2 & D \end{array} \\ \begin{bmatrix} 0 & 1-(x-\alpha) & x-\alpha \\ 0 & 1-(x+\beta) & x+\beta \\ 0 & 0 & 1 \end{bmatrix} \end{array}$$

where α and β are both positive numbers when the probability function is increasing. Using matrix multiplication, the probability of going from state R_1 to D in two periods is:

$$2x - x^2 - \alpha + \alpha x - \beta x + \alpha\beta + \beta \tag{15}$$

Proposition 4.1: **If $x \leq 1 + \frac{\alpha\beta}{\beta-\alpha}$ $\{x > 1 + \frac{\alpha\beta}{\beta-\alpha}\}$ and the population all begins in state risk 1, then the single transition probability obtained from the arithmetic mean of the actual transition probabilities always underestimates {overestimates} the number of people who end up in the disease state when**

compared to the calculation when risk states are taken into consideration. Furthermore, this is always true if the transition probability function is convex and increasing {concave and decreasing} as a function of the time spent in the risk state.

Proof: We are interested in determining when equation (15) is greater than equation (14). Mathematically, we want to know when:

$$-\alpha + \alpha x - \beta x + \alpha\beta + \beta > 0 \tag{16}$$

The inequality is true when:

$$1 + \frac{\alpha\beta}{\beta - \alpha} > x \tag{17}$$

If the function is convex and increasing, then $\beta \geq \alpha$, and both β and α are positive. However, since x is less than one, (17) is always true.

Note that in the concave, decreasing case the proof is the same except that α and β are both negative and $|\alpha| > |\beta|$. □

Proposition 4.2: **If $\frac{\beta}{2+\sqrt{3}} \leq \alpha < 3\beta$, and the population begins evenly split between states risk 1 and risk 2, then the single transition probability obtained from the arithmetic mean of the actual transition probabilities always underestimates the number of people who end up in the disease state when compared to the calculation when risk states are taken into consideration. Otherwise, it overestimates. Furthermore, the first case is true whenever the transition probability function is convex and increasing as a function of the time spent in the risk state, and the second case is true whenever it is concave and decreasing**

Proof: The number of people who start in state R_1 and progress to state D in two periods is:

$$R_1[(1-x-\alpha)(x+\beta)+x-\alpha] \tag{18}$$

The number of people who start in state R_2 and progress to state D in two periods is:

$$R_2[(1-x-\beta)(x+\beta)+x+\beta] \tag{19}$$

When this is algebraically simplified, scaled such that $R_1 + R_2 = 1$, and compared to the average model, we determine that the average model underestimates the number of people in the disease state when:

$$R_1\beta - R_1\beta x + R_1\alpha x + R_1\alpha\beta - R_1\alpha + 2R_2\beta - 2R_2\beta x - R_2\beta^2 > 0 \tag{20}$$

If $R_1 = R_2$ this simplifies to:

$$3\beta - 3\beta x + \alpha x + \alpha\beta - \alpha - \beta^2 > 0 \tag{21}$$

This is true when $\frac{\beta}{2+\sqrt{3}} \leq \alpha < 3\beta$, which is always true when the probability function is convex and increasing. □

Proposition 4.3: **If the transition probability function is increasing linearly, then the single transition probability obtained from the arithmetic mean of the actual transition probabilities always underestimates the number of people who end up in the disease state, independently of what proportion of the population began in risk 1 or risk 2.**

Proof: From equation 20 above, we need:

$$R_1\beta - R_1\beta x + R_1\alpha x + R_1\alpha\beta - R_1\alpha + 2R_2\beta - 2R_2\beta x - R_2\beta^2 > 0 \tag{22}$$

If $\alpha = \beta$, as in the linear case, this simplifies to:

$$R_1\beta^2 + 2R_2\beta - 2R_2\beta - 2R_2\beta x - R_2\beta^2 > 0 \tag{23}$$

which can be rewritten as:

$$1 + \frac{R_1\beta - R_2\beta}{2R_2} > x \tag{24}$$

If $R_1 > R_2$ then the left hand side is greater than one, and the equation is true.

If $R_1 < R_2$, then the left hand side is greater than $1 + \frac{-R_2\beta}{2R_2} = 1 - \frac{\beta}{2}$. But, since $x + \beta < 1$, then $x < 1 - \frac{\beta}{2}$. □

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