

A PRIMER ON BAYESIAN COST-EFFECTIVENESS METHODS FOR HEALTH  
PSYCHOLOGISTS

by

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A Primer on Bayesian Cost-Effectiveness Methods for Health Psychologists  
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Master of Arts  
George Mason University, 2013

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## **DEDICATION**

This is dedicated to my incredibly supportive family and wonderful husband, without whom I would not be who I am today.

## ACKNOWLEDGEMENTS

I would like to thank my family, friends, and mentors, who have been instrumental in making this possible. From a young age, my family has given me a truly deep appreciation for learning and then provided me with the emotional and financial support that has allowed me to pursue this degree. My husband, Kristopher Wold, has given me an amazing amount of support during this process, helping with everything from reading drafts, listening to ideas (and if I'm being honest some frustrations), and helping me take breaks when needed. The members of my lab and cohort have made my education at George Mason University a wonderful experience by creating an atmosphere of intellectual rigor, collegial support, and fun. My mentors Dr. McKnight and Dr. Kashdan have provided me with invaluable support and guidance during all of my graduate education, and particularly during the dissertation process. Their respect for and emphasis on sound statistical and methodological practice helped shape my dissertation topic. I also appreciate their acceptance and support of my non-traditional research interests and dissertation topic. Lastly, I'd like to thank the third member of my committee, Dr. Mehlenbeck for her support and input on my dissertation and, more broadly, for her encouragement and mentoring of my clinical and research interests in pediatric psychology.

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## LIST OF ABBREVIATIONS

Cost-Effectiveness Acceptability Curve .....	CEAC
Disability-Adjusted Life Year.....	DALY
Incremental Cost-Effectiveness Ratio.....	ICER
Quality-Adjusted Life Expectancy .....	QALE
Quality-Adjusted Life Year .....	QALY

## **ABSTRACT**

### **A PRIMER ON BAYESIAN COST-EFFECTIVENESS METHODS FOR HEALTH PSYCHOLOGISTS**

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Recent changes to healthcare reimbursement and funding will likely make cost considerations more relevant for health psychologists. Cost-effectiveness analyses are one tool for providing evidence of financial feasibility, which is typically underutilized by health psychologists, usually due to lack of training and experience in this area. This dissertation seeks to address this need by providing an overview of cost-effectiveness analyses, focusing on Bayesian methods, using a school-based lifestyle intervention targeting childhood obesity as an example. My hope is that health psychologists can use this dissertation as a starting point for incorporating cost-effectiveness analyses into their intervention research.

## INTRODUCTION

In recent years, changes to healthcare payment have made costs a more serious consideration for psychologists working in healthcare systems. With the advent of the Patient Protection and Affordable Care Act, there has been increased emphasis on providing low-cost, high-quality services (Orszag, & Emanuel, 2010). Services that are unable to provide this evidence may face lower reimbursement under new models of care, particularly under single-payer systems (Drotar, 2012; McGrady, 2014). In order to meet the demands of this new financial system, it is paramount that psychologists practicing in healthcare provide evidence, not just of efficacy, but also of cost-effectiveness. While there is a call within the field for an increased emphasis on the financial aspects of our work (e.g. Harris, Wagner, & Dukhovny, 2016; Rozenky, & Janicke, 2012), psychologists receive little training in how to design these studies and conduct these analyses (Rozenky, 2013). This dissertation is intended to function as a primer on cost-effectiveness analyses for psychologists, with a particular emphasis on Bayesian methods which are becoming increasingly common in healthcare cost-effectiveness analyses. To demonstrate these analyses, I will focus on a school-based lifestyle intervention addressing childhood obesity. Obesity, particularly among children, represents an area of major concern for policy-makers because of its impact on health and healthcare costs

(Reilly, & Kelly, 2011; Trasande, 2010) and will likely be relevant to many psychologists working in healthcare settings.

There is a growing recognition in the field regarding the need for more cost-effectiveness research and other cost considerations of psychological interventions in healthcare settings (Goodhart, 2010; Harris et al., 2016; Wilson, 2015). Effective dissemination of these interventions, as well as achieving adequate funding, is contingent on making the case to policy-makers that they are a sound financial investment (Glasgow, & Emmons, 2007). Often, studies demonstrating the efficacy of an intervention are dissociated from the contextual factors that dictate implementation in real world clinical settings. Cost is one such factor. While an efficacy study may be supported by a grant or other external funding, interventions done in real healthcare settings need to either generate revenue to offset the pay for the psychologist or demonstrate sufficient effectiveness or future cost savings to warrant reimbursement or other financial support. Researchers recognize the need for cost-effectiveness research to provide this evidence (Nicassio, Meyerowitz, Kerns, 2004).

Despite these recent calls to action, cost-effectiveness analyses are not particularly commonplace in health psychology intervention research. In a review of 119 studies examining health behavior change interventions, only a minority (24%; 17 studies) reported any cost information (Glasgow, Klesges, Dzwalkowski, Bull, & Estabrooks, 2004). Without this crucial information, cost-effectiveness cannot be determined. Prior to that finding, Kaplan and Groessl (2002) found 19 studies documenting cost-effectiveness of behavioral health interventions, but expressed

concerns that only 2 studies adhered to the standards of high-quality cost-effectiveness research established by the Panel of Cost-Effectiveness in Health and Medicine (Gold, Siegel, Russell, & Weinstein, 2006). Methodological weaknesses of the studies reviewed included failing to account for important relevant costs and focusing solely on cost-offset as the measure of effectiveness, to the exclusion of improvements in health and quality of life. Thus, few studies report any costs and those that do conduct costs-effectiveness analyses fail to provide sufficient cost and health outcome information to make them useful.

Reviews in specific areas of health psychology also demonstrate the paucity of cost-effectiveness research. A review of integrating psychologists into cancer care (Gordon, Beesley, & Scuffham, 2011) found few economic evaluations in this area. Only 5 studies were found, and these exhibited a variety of methodological weaknesses including not reporting cost-effectiveness ratios and not considering uncertainty in the estimates of cost-effectiveness. In a recent review specific to pediatric psychology, researchers only found 15 studies published between 1979 and 2015 that examined the cost implications of pediatric psychology interventions (McGrady, & Hommel, 2016). Of these studies, only 5 reported incremental cost-effectiveness ratios, which are considered part of best practice for reporting cost-effectiveness research. The authors conclude that while the current evidence is promising, this type of research needs to be more frequent in future evaluations of pediatric psychology interventions (McGrady, & Hommel, 2016).

Lack of training in conducting cost-effectiveness analyses is regularly cited as one of the barriers to gathering more cost-effectiveness evidence for health psychology

interventions (Palermo et al., 2014; Tovian, 2004). Rozensky (2013) suggests that students should be actively encouraged to add cost data collection to their clinical research and that cost analyses should be part of the research curriculum. The *Journal of Pediatric Psychology* has recently sought to address this concern by supporting a special issue focusing on cost/economic considerations relevant to pediatric psychology research. Additionally, a recent article by McGrady (2014) provides an excellent overview of cost-effectiveness analyses and a practical example. This dissertation seeks to expand current efforts to make cost-effectiveness analyses more accessible to health psychologists. In particular, by presenting a primer on applying Bayesian methods to cost-effectiveness analyses (which were not covered by McGrady, 2014), this dissertation will help psychologists better account for uncertainty and variability around cost-effectiveness estimates. Researchers recognize the importance of considering uncertainty (Yates, 2015), and to my knowledge, no study has estimated the cost-effectiveness of a health psychology intervention using Bayesian methods.

### **Overview of Cost-Effectiveness Methodology**

Before presenting an example, I would like to provide some general information about cost-effectiveness methodology. This general overview will provide context for the specific example I discuss later. In this overview, I will discuss different types of cost-effectiveness analyses and their definitions in order to provide the reader with knowledge of relevant terms. I will discuss the importance of selecting a financial perspective, as it can have profound impacts on which costs are considered. Lastly, I will review Bayesian methods in general as well as two specific methods for presenting cost-effectiveness

results, incremental cost-effectiveness ratios (ICERs) and cost-effectiveness acceptability curves (CEACs), which I will use in my example.

### **Types of Analyses**

There are several distinct types of financial analyses that can fall under the broad definition of “cost-effectiveness” (Kaplan, & Groessl, 2002). In this section, I clarify the two most common types, cost-effectiveness and cost-utility analyses, which will be the focus of this article. In its more specific definition, cost-effectiveness refers to an analysis that compares clinical effectiveness to the costs of an intervention. Clinical effectiveness can be measured in a variety of ways including number of depression free days, changes in BMI, or number of hospitalizations. Depending on the scope of the analyses, effectiveness can also incorporate cost savings brought about by the intervention.

Cost-utility analyses represent a subset of cost-effectiveness analyses focusing on a specific outcome, quality-adjusted life years (QALYs) saved. QALYs represent years of life weighted by the quality of those years (often based on any dysfunction or disability due to specific diseases/health states), also called utility weights (Sassi, 2006). Within the QALY framework, each year lived is weighted ranging from 0 = death to 1 = perfect health. An intervention can “save” QALYs by increasing life expectancy, improving quality of life, or a combination of both. Decision-makers tend to prefer cost-utility analyses because they can be used to compare across studies with different proximal outcomes (Weinstein, Siegel, Gold, Kamlet, & Russell, 1996). Translating these outcomes into a common metric facilitates comparisons regarding the impact per financial invest and allows comparisons with generally accepted standards for cost-

effectiveness (i.e. \$50,000 per QALY saved (Grosse, 2008)). QALYs saved can be measured directly as a study outcome using standard Health-Related Quality of Life (HRQoL) measures such as the EQ-5D (EuroQol Group, 1990) or the Health Utilities Index (Feeny et al.,2002). These measures typically ask individuals to rate their level of dysfunction or disability as it relates to different facets of health (i.e. vision, mobility, pain). Ratings are associated with a utility weight for each facet of health, all of which are averaged together to calculate a single value/weight for HRQoL. QALYs can also be calculated indirectly using published literature linking specific health states with HRQoL deficits. When QALYs saved are measured over a long period of time, researchers can use quality-adjusted life expectancy (QALE) as a measure of effectiveness. QALE is a measure of future life expectancy, when every year has been weighted by the expected quality of life for that year. If a researcher has an estimate for the QALE of individuals in a treatment group and those in a no intervention control group, then the difference in QALE between the two groups provides a measure of QALYs saved by the intervention.

Disability-adjusted life years (DALYs) are another concept, developed out of the QALYs framework, that can be used in cost-utility analyses as a measure of disease burden. DALYs are based in disability weights associated with different diseases and range from 0 = no disability to 1 = death/total disability. The premise behind DALYs is that a disease causes disability by preventing individuals from “living life to the fullest” (i.e. decreases in mobility prevents someone from participating in enjoyable hobbies). The specific detriment a disease has to quality of life is then quantified on a scale of 0 to 1, and defined as a disability weight. To determine the worth of a year lived with a

specific disease, you would subtract the disability weight associated with the disease from one. For example, to determine the worth of a year lived with a disease with a disability weight of 0.25, you take the value of a year lived in perfect health (1.0) and subtract the disability weight of the disease (0.25). This calculation produces a value of 0.75, indicating that the year lived with this disease is only worth three quarters of a year without the disease. These disability weights are typically universal standards derived from expert opinion while the utility weights associated with QALYs are typically generated by surveying individuals (Sassi, 2006). Decisions about whether to focus on QALYs or DALYs saved depends on a variety of factors including 1) available evidence; 2) whether the focus is on specific diseases or general health states; and 3) whether the intervention is more likely to impact morbidity or mortality.

### **Perspective**

Cost selection is an integral component of cost-effectiveness analyses, and a study's financial perspective shapes what costs will be considered as well as how the results should be interpreted. The administrative and societal perspectives are two important terms to be familiar with. An administrative perspective usually only focuses on the costs of administering an intervention and dealing with any potential side effects (i.e. the costs accrued by a hospital or insurance company). This perspective may be selected when the decision-maker has a specific interest in the financial ramifications of a program in a specific context. The societal perspective incorporates a broader set of costs. If an intervention is designed to prevent a future disorder, the medical costs averted by this prevention can be considered. Additionally, prevention or treatment of a disorder that

usually results in reduced workplace productivity can save money in the long-term, producing cost savings. Indirect costs of the treatment can also be considered. For example, a patient may need to take time off from work or pay for transportation for a treatment. When results are being used to inform broad policy decisions, the societal perspective is generally recommended because it considers the widest range of potential costs (Weinstein et al., 1996). The ability to account for different costs may be limited based on what is measured in a study or what information is available in the literature. Published guidelines (Gold et al., 1996) can guide the selection of costs, and it is important to be clear about what costs will/will not be considered in any given analyses.

### **Incremental Cost-Effectiveness Ratios**

Cost-effectiveness results are commonly presented in the form of a ratio. These ratios are simply relative costs divided by relative effectiveness. By saying they are relative, I mean that both costs and effectiveness must be compared to something else (an alternative treatment, no treatment, etc.); hence, these two parts of the ratio are relative differences. If a new intervention costs US\$10 and the typical treatment costs US\$2 then the relative cost is US\$8 because the new intervention is the focus of the analysis. Conversely, if the costs swapped (new intervention costs US\$2 and typical treatment costs US\$10), the relative cost would be US\$8 saved or -US\$8. A similar logic gets applied to the effectiveness or denominator in the ratio. Effectiveness is a measure that communicates the relative difference between some focal intervention and a comparison condition. Measuring the differences between these two outcomes requires either primary, secondary, or archival data but the cost-effectiveness ratio must include some

form of effectiveness between two treatments - just as I outlined above for costs. For example, the measure of effectiveness for an intervention for individuals with diabetes could be decreases in hospitalizations. If individuals receiving the new treatment have, on average, 2 hospitalizations annually, while individuals receiving typical treatment have 8, then the relative effectiveness is a decrease of 6 hospitalizations per year.

Since the cost-effectiveness ratio is a relative estimate, often, health care economists refer to the ratio as an incremental cost-effectiveness ratio (ICER; Muennig, 2008). The incremental simply implies that the cost-effectiveness estimate is relative to some other standard of care, no treatment, or treatment as usual. ICERs are calculated by dividing the difference in cost between an intervention and control (or alternative intervention) by the difference in effectiveness between an intervention and control - as described above (see Equation 1).

**Equation 1. ICER**

$$ICER = \frac{C_{new\ tx} - C_{comparison}}{E_{new\ tx} - E_{comparison}}$$

Cost-utility analyses, the second type of analysis discussed above, utilize the same ICER, but effectiveness must involve the impact on QALYs or DALYs. The difference in effectiveness in a cost-utility analyses is referred to as QALYs or DALYs saved. To illustrate this calculation, let us assume that a new intervention costs US\$10 ( $C_{new\ tx}$ ) and the typical treatment costs US\$2 ( $C_{comparison}$ ). Individuals receiving the new intervention have a quality-adjusted life expectancy (QALE) of 55 years ( $E_{new\ tx}$ ) while individuals

receiving typical treatment have a QALE of 50 years ( $E_{\text{comparison}}$ ). These values are entered in the equation as illustrated below, indicating the new intervention costs \$1.60 per QALY saved relative to typical treatment:

$$ICER = \frac{\$10 - \$2}{55 - 50} = \frac{\$8}{5 \text{ QALYs saved}} = \$1.60 \text{ per QALY saved (Eq.1)}$$

### **Bayesian Methods**

Up to this point, I've referred to ICERs as simple ratios. While an analysis may produce a specific ICER value, this single or "point" estimate is imperfect and has some degree of uncertainty around it. This uncertainty can come from a variety of sources such as differential responses to the intervention by individual patients. Simply calculating a ratio without providing a measure of confidence or uncertainty may be misleading to policy-makers or clinicians (Briggs et al., 2012). Bayesian methods are increasingly recognized as a useful tool for accounting for uncertainty and will be the focus of the methods described in this dissertation (Armero, Carcia-Donato, & Lopez-Quilez, 2010; Briggs, 1999, 2000; Spiegelhalter, & Best, 2002).

Central to Bayesian data analysis is an understanding of how we make decisions concerning data and our beliefs about them, which represents a fundamental difference between Bayesian and frequentist statistics. In frequentist statistics, decisions are made regarding the likelihood that a specified "null hypothesis" is true, given the data collected, which is viewed as a random sample from a larger population. If the likelihood of the null hypothesis is low enough (typically less than 5%), the null hypothesis is rejected, providing indirect support for the actual hypothesis of interest (i.e. that the value of variable X is less than 50). Within Bayesian statistics, the likelihood of a hypothesis of

interest being true can be directly estimated, using Bayes Rule. Bayes Rule combines the current state of evidence or beliefs about the variable of interest (the *prior*) with empirical data (the *data*) to generate the *posterior* likelihood about the variable, which can be directly used to draw conclusions. Bayesian methods can be used to generate posterior distributions around all cost-effectiveness model parameters (i.e. intervention costs) which reflect uncertainty or variability in these values. Instead of using the point estimates of parameter values for cost-effectiveness analyses, the distributions of all relevant parameters are used, generating a distribution of ICER values.

Additionally, Bayesian methods require all assumptions and uncertainty to be explicitly stated, providing transparency to the research process. This process is similar to that of a meta-analysis, where the study selection process and study weighting is made clear and accessible to the reader. Using Bayesian methods, the reader can make more informed decisions about how to interpret the results based on how well they agree with the assumptions about uncertainty.

### **Cost-Effectiveness Acceptability Curves**

Bayesian methods also are uniquely suited for generating cost-effectiveness acceptability curves (CEACs), a newer method of describing cost-effectiveness values which is considered part of best practice for presenting cost-effectiveness findings (Briggs et al., 2012; Fenwick, O'Brien, & Briggs, 2004). Because these methods account for uncertainty in the final estimates of cost and effectiveness, they produce a distribution of ICER values, as opposed to a single point estimate, which is used to generate the CEAC. On the graph of a CEAC, probabilities are mapped onto the y-axis, while values

of the ICER are mapped on the x-axis. The values that fall along the curve represent the proportion of the ICER distribution that is at or below (i.e. less costly than) any given ICER value. The CEAC allows a decision-maker to determine the likelihood that the intervention is cost-effective at various thresholds.

### **Justification for the Current Study: Cost-Effectiveness of School-Based Lifestyle Intervention**

In this paper, I intend to demonstrate Bayesian methods for cost-effectiveness analysis using a school-based lifestyle intervention as a simple example. First, I will provide some context as to why this type of intervention, which addresses diet and physical activity in the hope of reducing childhood adiposity, is particularly pertinent and in need of cost-effectiveness evidence. Between 1980 and 2010, the prevalence of obesity has nearly tripled among American children (ages 6 - 11, increased from 6.5% to 18.0%) and adolescents (ages 12 - 19, increased from 5.0% to 18.4%; Fryar, Carroll, & Ogden, 2012). Many public health policy-makers consider this drastic increase to be an epidemic and worry about the implications for life expectancy, quality of life, and medical costs. While the immediate consequences of childhood obesity may be small, the cumulative effects over the lifespan are substantial. Childhood obesity typically persists into adulthood (Singh, Mulder, Twisk, Mechelen, & Chinapaw, 2008), causing premature mortality, usually due to the development of cardiometabolic diseases such as heart disease, diabetes, and hypertension (Reilly, & Kelly, 2011). With this increased risk of chronic diseases comes increased costs. One study estimated that US children who were 12 years old in 2005 will accrue over 4 billion in medical expenses attributable to obesity across their lifespans (Trasande, 2010).

Given these concerns, a major public health priority is to investigate potential interventions for addressing childhood obesity (Institute of Medicine, 2009). Since managing obesity usually involves behavioral change, or a lifestyle intervention, psychologists are often involved in developing and implementing this work (i.e. Borner et al., 2016). Additionally, lifestyle interventions targeting childhood obesity can take a variety of different forms including school- or community-based programs or individual programs through medical centers. These different forms require different levels of financial investment, underscoring the need for cost-effectiveness studies to determine where best to invest funding. The school setting offers the potential for particularly low-cost interventions, which influenced my decision to select a school-based lifestyle intervention (HEALTHY Study Program, 2010) as the example in this primer. Prior research indicates that school-based lifestyle interventions (targeting diet and physical activity) can be very cost-effective (Project Health - \$4,305 per QALY saved for female students, Wang et al., 2003; CATCH - \$900 per QALY saved, Brown et al., 2007). As new interventions are developed, it is important to continue evaluating cost-effectiveness, and comparing it to previously studied interventions, to justify the financial investment in these programs. Neither the cost-effectiveness of the HEALTHY Study program, nor its impact on health-related quality of life across the lifespan has been estimated. As a result, I chose to use this data and other supporting data for this primer on Bayesian cost-effectiveness methods. Next, given the richness of the data that Bayesian methods provide above and beyond other methods of cost-effectiveness analysis, I provide details

about how to conduct a cost-effectiveness analysis using contemporary Bayesian tools and procedures.

## METHODS

### Participants

Data regarding the intervention's impact on obesity comes from the HEALTHY study dataset (Healthy Study Group, 2010), a block-randomized school-based intervention trial conducted between 2005 and 2009. Data was obtained through the NIDDK Repository following approval from the George Mason University IRB. During primary data collection, schools were randomized to either the intervention (outlined below) or a no intervention control. Children at the intervention schools participated in the intervention for 3 years (6<sup>th</sup> – 8<sup>th</sup> grade).

In total, 5571 6th grade students were enrolled in the 21 intervention schools, and 5587 were enrolled in the 21 no intervention control schools. The final sample, from which data was analyzed, consisted of 2307 students from the intervention schools and 2296 students from the no intervention control schools. A majority of students who were excluded did not provide consent (2266 among intervention schools and 2319 among no intervention control schools). Other reasons for exclusion included providing invalid data (i.e. if they were pregnant or wearing a cast during data collection), withdrawing from the study, and changing schools. Students were also excluded from analyses if they were diagnosed with diabetes or had a physical condition that prohibited them from participating in PE classes. Demographic information on students in the intervention and

no intervention groups is presented in Table 1. In general, students in both groups were of a similar age and gender distribution, and had a similar prevalence of obesity at baseline.

**Table 1. Demographics for HEALTHY Study Participants**

Intervention Schools		No Intervention Control Schools	
N	2307	N	2296
Age – mean(SD)	11.3 (0.5)	Age – mean(SD)	11.3 (0.6)
Male sex (%)	47.4	Male sex (%)	47.1
Race or ethnic group (%)		Race or ethnic group (%)	
Hispanic	54.8	Hispanic	53.5
Black	20.3	Black	15.7
White	17.1	White	21.6
Other	7.8	Other	9.2
Obesity (%)	30.1	Obesity (%)	30.4

### **HEALTHY Study Intervention Overview**

This study involves secondary data analysis of the HEALTHY study intervention (Healthy Study Group, 2010), a school-based lifestyle intervention. While specifically described as an intervention to reduce risk factors for type II diabetes, the primary outcomes of the study were measures of adiposity (i.e. obesity and overweight) and the program is similar to other interventions targeting childhood obesity. I focus on the program’s impact on obesity broadly because these changes will influence the risk not just for type II diabetes, but a host of other diseases as well including heart disease and hypertension. The HEALTHY study program addresses 4 integrated components (nutrition; physical activity; behavioral knowledge and skills; communications and social marketing) within the school context. I provide descriptions of each of these components,

as well as the relevant costs considered for the cost-effectiveness analysis. Interested readers ought to consult the HEALTHY study publications and public protocol for more details (<http://www.healthystudy.org/studypublications.htm>; DeBar et al., 2009; Gillis et al., 2009; Health Study Group, 2008, 2010; McMurray et al., 2009; Venditti et al., 2009).

### **Component 1: Nutrition.**

The main goal of the nutrition component was to improve the nutritional quality of food and beverages the students obtained while at school. This change in the school food environment included meals provided before, during, and after school as well as through snack bars and vending machines. In general, nutritional changes included: 1) reducing fat content; 2) offering more fruits and vegetables; 3) offering lower-calorie snack options; 4) eliminating sugary drink options; and 5) increasing fiber intake. Each of the 7 centers (which coordinated the data collection and implementation at 3 intervention and 3 control schools) employed a research dietician who worked with the food service staff at each intervention school to support these changes. The research dietician also conducted learning activities in the cafeteria each semester to explain the rationale behind the changes and help motivate students toward healthy eating.

Employment of the research dietician represented a main cost of the nutrition component. A project manager for the original study was consulted regarding costs, but could not remember the typical salary for the research dieticians. The median annual salary for a dietician in 2007 (the mid-point of the study) was obtained through the Bureau of Labor Statistics. This salary (\$49,010) was used to estimate the salary for the research dieticians in this study. Each school was also provided with \$3000 per year to

help offset the costs of altering the food they offered. At each school, each food service manager and staff member was compensated \$100 per year to attend trainings. Finally, each school was given \$250 per year to enhance the presentation of food, including attractive serving dishes, trays, and signage. For more information on the nutritional component see the article by Gillis and colleagues (2009).

**Component 2: Physical Activity.**

The main goal of the physical activity component was to increase the amount of moderate-to-vigorous physical activity (MVPA) occurring during PE class. PE teachers were provided with recommended teaching units (each consisting of 8 - 15 lessons) that involved different sports/activities. For more information, see the article by McMurray and colleagues (2009).

Pilot studies of the physical activity component indicated that lack of equipment often decreased MVPA since many students were waiting for the opportunity to participate in a given activity; therefore each intervention school was provided with \$15,000 across the three years of the study to counteract this occurrence. Each center also hired a physical activity coordinator (PAC) to help train PE teachers and support the intervention. Consultation with a project manager for the original center indicated that their PAC was paid \$36,000 - \$40,000 annually. The midpoint of this range (\$38,000) was used as the estimate of the PAC salary across centers for the cost analyses. The study also provided each school with a PE teacher assistant to support PE activities. This salary was estimated at \$21,850, the median annual salary for a teacher assistant in 2007 (U.S. Department of Labor, 2007). PE teachers also received \$300 per year to compensate them

for attending 12 hours of training. Consulting with the project manager indicated that there was no record of the number of PE teachers per school. A process evaluation of the HEALTHY study (Schneider et al., 2009) was used to estimate the number of PE teachers at 4 per school.

### **Component 3: Behavioral Knowledge and Skills.**

The behavioral component involved peer learning, behavioral skills development, and family outreach to support the lifestyle changes in physical activity and nutrition encouraged by other components. Classroom teachers conducted FLASH (Fun Learning Activities for Student Health) modules once per week which taught students about health behaviors. FLASH activities usually included self-monitoring, goal-setting, and the opportunity for students to work in small groups (facilitating peer learning). Family outreach was achieved by sending home newsletters which reiterated the information and tools learned through FLASH to help families implement them at home. Students also received materials during school-break periods that were used by the entire family to meet a behavior change “challenge”. For more information, see the article by Venditti and colleagues (2009).

One of the main costs of the behavioral knowledge and skills component was the health promotion coordinator and three HEALTHY assistants hired by each center to train and support teachers in the implementation of this component. The salary for the health promotion coordinator was estimated at \$42,920 (the median annual salary for a health educator in 2007; U.S. Department of Labor, 2007) and the salary for the HEALTHY assistants was estimated at \$35,870 each (the median annual salary for a

research assistant in 2007; U.S. Department of Labor, 2007). Additionally, teachers were reimbursed \$125 per year to attend 5 hours of training. As with PE Teachers, data wasn't available on the number of classroom teachers involved in the HEALTHY study implementation at each school. Again the process evaluation of the HEALTHY study (Schneider et al., 2009) was used to estimate this number at 5 classroom teachers per school. I also estimated the per student cost of the printed material required to implement the behavioral knowledge and skills component. Reviewing the study materials indicated that each child would get approximately 461 of printed material across the study period. At \$0.085 per page, this cost was \$39.19 per child. The total cost for printed materials for the 2307 students across all intervention study schools was \$90,411.33.

#### **Component 4: Communications and Social Marketing.**

The main goal of the communications and social marketing component was to use these tools to increase motivation and engagement among students to implement the changes encouraged by the other components. Each semester had a specific theme and tagline which was portrayed through several school media messages including school banners, posters (created by both study staff and students), and messages delivered during PE class, near the cafeteria line, and through public service announcements. Students were recruited to spread the positive messages about healthy living. All students at the interventions schools also received "theme enhancers" (i.e. t-shirts and water bottles with the HEALTHY logo) to support motivation and buy-in. The cost of these incentives was estimated at \$15 per student. The total cost for incentives for the 2307 students across all

intervention study schools was \$34,605. For more information on the communication and social marketing component see the article by DeBar and colleagues (2009).

## **Measures**

While a variety of physical outcome measures were collected for students, in the interest of keeping my example simple, I focus on the prevalence of obesity. Height and weight were collected by trained staff using standard, calibrated equipment, and used to generate Body-Mass Index (BMI) scores. Given that children in the study were at various stages of physical development, BMI score and waist circumference were compared to growth charts to determine each child's percentile compared to same-age and same-sex peers. I used the CDC definition of childhood obesity (BMI  $\geq$  95th percentile) to classify students as obese or not obese. I chose to focus on obesity as opposed to overweight because obesity tends to have a more profound impact on health (i.e. Muennig, Lubetkin, Jia, & Franks, 2006). I also chose to calculate the cost-effectiveness separately for male and female students because the intervention's impact on obesity was different for males and females. For females, the impact was small yet significant (OR = 0.72,  $p < 0.05$ ,  $d = 0.18$ ), but there wasn't a significant impact for males (OR = 0.92,  $p = 0.539$ ,  $d = 0.05$ ). While other demographic variables (i.e. race/ethnicity) are likely relevant to obesity and its health impact, I chose to focus only on gender to simplify my model and make it more useful as an introductory primer. I also utilized published research on the HEALTHY Study intervention (i.e. DeBar et al., 2009; Gillis et al., 2009; Health Study Group, 2008, 2010; McMurray et al., 2009; Venditti et al., 2009) as the primary source of intervention costs.

## **Model Selection, Design, and Calculations**

In essence, I need to estimate four elements to conduct a cost-effectiveness or cost-utility analysis: 1) cost of the intervention; 2) cost of no intervention; 3) effectiveness of the intervention; 4) effectiveness of no intervention. There are a multitude of options for how to define these four elements, and they can be informed by many different sources. The researcher should make the decision-making process explicit to his/her reader, which I will do in the following sections. Before beginning, I would like to note that I intentionally chose to keep the model fairly simple and with fewer steps since this is a primer on Bayesian cost-effectiveness methods and not a definitive, empirical study on the cost-effectiveness for the HEALTHY Study program.

### **Effectiveness**

Based on the HEALTHY study data, I calculated the likelihood that students were obese at the end of the study with the intervention and without the intervention. The likelihood of being obese following the intervention was derived directly from the data (0.220 for females and 0.274 for males). For example, among female students in the intervention schools, 267 were obese after the intervention out of a total sample of 1213 female students, which corresponds to a proportion of 0.220 (P1). In order to determine the likelihood of obesity with no intervention, I calculated the change in obesity prevalence across the study period for students in the no intervention schools. For example, the prevalence of obesity for female students who did not receive the intervention decreased from 26.8% to 24.8%, a change of two percentage points. I can't use 24.8% as the prevalence of obesity with no intervention since the intervention and control groups had slightly different levels of baseline obesity prevalence. Instead, I

estimated what the prevalence would be if the intervention group experience the same change seen in the no intervention group. Thus if female students in the intervention group (with a baseline obesity prevalence of 26.4%) did not receive the intervention, I would expect their obesity prevalence to decrease by two percentage points (the change with no intervention), ending the study with an obesity prevalence of 24.4% (or a proportion of 0.244; P2). This method of determining the study outcomes under the no intervention condition was taken from other, similar cost-effectiveness research (i.e. Wang et al., 2003). These relevant probabilities, as well as their uncertainty, are presented in Table 2.

Because I expect the implications of a lifestyle intervention in early adolescence to extend across the lifespan, it is useful to model the effects of the intervention over time - an extrapolation beyond the HEALTHY data but available utilizing other databases explained below. Specifically I used longitudinal research by Wang and colleagues (2008) to predict the likelihood of obesity (defined as BMI at or above 30 kg/m<sup>2</sup>) in middle age (37/38 years old) based on weight status in adolescence (16/17). This time frame matches fairly well with the ages of children at the end of the HEALTHY study (approximately 14 years old), thus allowing me to predict the progression of children in the HEALTHY study into adulthood. For example, Wang and colleagues (2008) found that of the 16 female participants who were obese in adolescence, 15 remained obese in middle age which corresponds to a 93.8% likelihood of being obese at age 40 if obese in adolescence (P3). These relevant probabilities, as well as their uncertainty, are presented in Table 2. I would like to note that Wang and colleagues' (2008) study end point was

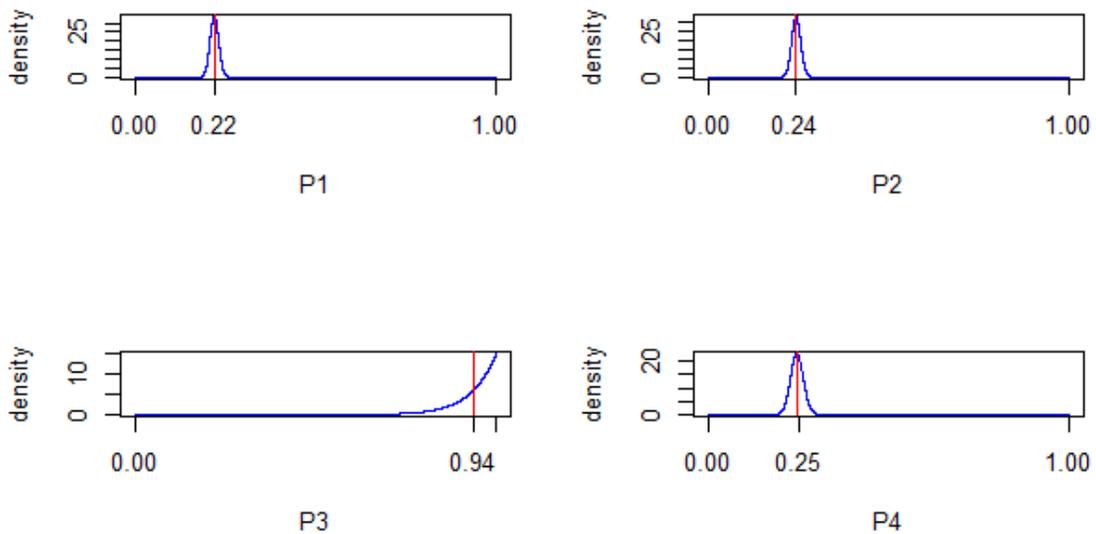
37/38 years old, but I used 40 years of age in the description of my model. I made this decision because the life-expectancy estimates I used (Peeters et al., 2003) are from age 40 and the research estimating obesity at age 37/38 is the closest estimate I could find.

**Table 2. Point Estimates, Priors, and Sources for Obesity Probabilities**

Variable	Estimate	Prior (Uncertainty)	Source
<b>Females</b>			
Probability of being obese at the end of the study, intervention (P1)	0.220	Beta(267,946)	HEALTHY Study data
Probability of being obese at the end of the study, no intervention (P2)	0.244	Beta(296,917)	HEALTHY Study data
Probability of being obese at age 40 if obese in adolescence (P3)	0.938	Beta(15,1)	Wang et al., 2008
Probability of being obese at age 40 if not obese in adolescence (P4)	0.246	Beta(150,459)	Wang et al., 2008
<b>Males</b>			
Probability of being obese at the end of the study, intervention (P1)	0.274	Beta(300,794)	HEALTHY Study data
Probability of being obese at the end of the study, no intervention (P2)	0.281	Beta(307,787)	HEALTHY Study data
Probability of being obese at age 40 if obese in adolescence (P3)	0.828	Beta(24,5)	Wang et al., 2008
Probability of being obese at age 40 if not obese in adolescence (P4)	0.238	Beta(156,499)	Wang et al., 2008

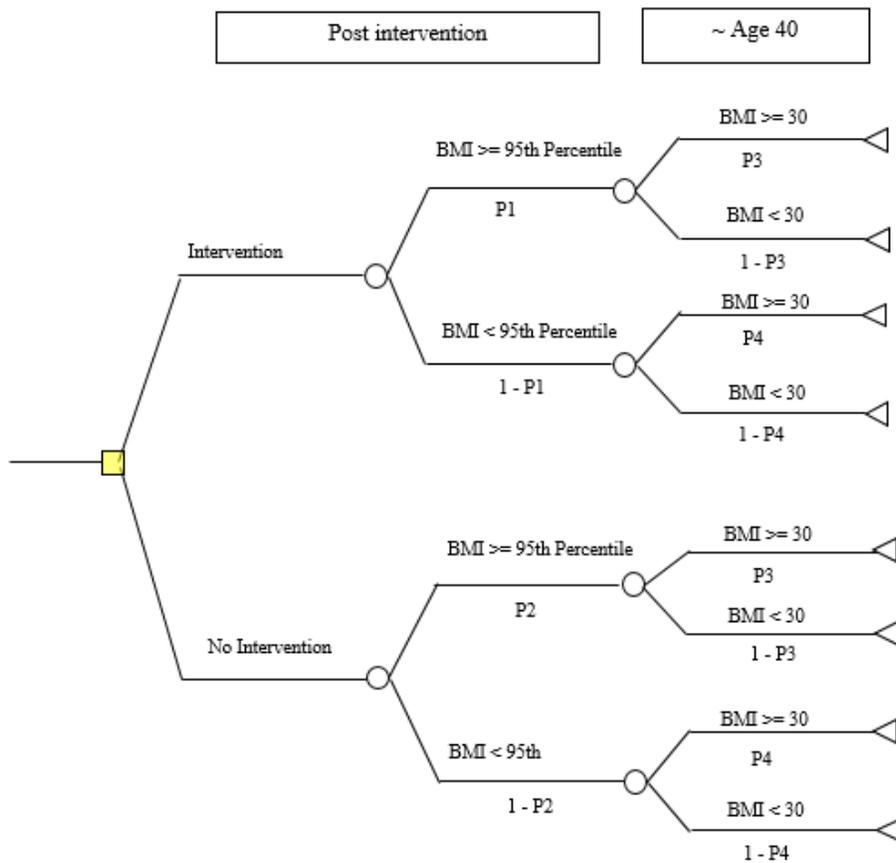
The relevance of the prior/uncertainties listed in Table 2 will be discussed in the following sections. At this point, I include a graphic that visually demonstrates this

uncertainty. Figure 1 presents the uncertainty around values P1, P2, P3, and P4 for female students (the first four lines in Table 2). The red line in each graph represents the point estimate while the blue line reflects the expected distribution of possible values around each point estimate.



**Figure 1. Probability Density Functions for Relevant Probabilities for Female Participants**

One useful way of depicting this progression of obesity into adulthood is with a decision tree (Kim & Goldie, 2008), which is depicted in Figure 2. The square to the far left represents the intervention decision (intervention vs. no intervention). The round circles represent chance nodes, i.e. the probabilities of various events, which I have defined using the HEALTHY study data and Wang and colleagues' (2008) research.



**Figure 2. Decision Tree Depicting Obesity Progression over Time**

From the parameters in Table 2, I calculated the probability of being obese at age 40 under both the intervention (PO.1) and no intervention (PO.0) conditions. The formulas for this calculation are presented below (Eq. 2 and 3). Under the intervention condition, to account for those who remain obese from adolescence into adulthood, I multiplied the likelihood of being obese at the end of the study (P1) by the likelihood being obese at age 40 if obese during adolescence (P3). To account for those who become obese by age 40 who were not obese in adolescence, I multiplied the likelihood of being not obese at the end of the study (1 - P1) by the likelihood of being obese at age 40 if not

obese during adolescence (P4). Adding these two proportions together gives me the overall likelihood of being obese at age 40 in the intervention condition. The same rules apply for calculations regarding the no intervention condition, just using the correct post-intervention likelihood of obesity (P2 instead of P1). Equations for these calculations are presented below (Equations 2 and 3).

**Equation 2. Probably of Obesity at Age 40, Intervention Group (PO.1)**

$$\mathbf{Probability\ of\ obesity\ at\ age\ 40\ (PO.1) = P1 * P3 + (1 - P1) * P4}$$

**Equation 3. Probability of Obesity at Age 40, No Intervention Group (PO.0)**

$$\mathbf{Probability\ of\ obesity\ at\ age\ 40\ (PO.0) = P2 * P3 + (1 - P2) * P4}$$

To demonstrate these calculations, I will insert the point estimate values for female students from Table 2. To calculate the probability of obesity at age 40 following the intervention (PO.1), I multiplied the likelihood of being obese after the intervention (0.220; P1) by the likelihood of being obese at age 40 if obese during adolescence (0.938; P3). I then added this value to the product of the likelihood of not being obese at the end of the intervention (0.780; 1 – P1) and the likelihood of being obese at age 40 and not obese during adolescence (0.246; P4). The sum of these two products is 0.398, which is the likelihood of being obese at age 40 following the intervention. Below is Equation 2 with these values inserted:

Probability of obesity at age 40 (PO.1) =  $0.220 \times 0.938 + 0.780 \times 0.246 = 0.398$  (Eq. 2)

As mentioned previously, the preferred outcome of a cost-effectiveness analysis is QALYs saved (thereby making it a cost-utility analysis). In order to estimate the QALYs saved by the intervention, I estimated quality-adjusted life expectancy (QALE) for individuals in the intervention and no intervention groups. Using research conducted by Peeters and colleagues (2003) and Jia and Lubetkin (2010), I estimated the QALE, from age 40, for individuals in various weight groups (normal weight, overweight, and obese). For example, the QALE for an obese female from age 40 is 31.20, which means that after age 40, an obese women will typically live 31.2 quality-adjusted life years (QALYs). As expected, the QALE of an obese female from age 40 (31.20 QALYs) is less than that of a woman of a normal weight (38.96 QALYS), since obesity impacts both life expectancy and quality of life. This information, along with the uncertainty of these estimates, is presented in Table 3. I also include information on the life expectancy of obese individuals in Table 3, which will be used for cost analyses.

**Table 3. Point Estimates, Priors, and Sources for Quality-Adjusted Life Expectancy and Life Expectancy By Weight Status**

Variable	Estimate (in years)	Prior	Source
<b>Females</b>			
Quality-Adjusted Life Expectancy at age 40, Obese (QALE.obese)	31.20	Normal(31.20, 0.010)	Jia, & Lubetkin, 2010; Peeters et al., 2003
Quality-Adjusted Life Expectancy at age 40, Overweight (QALE.overweight)	36.39	Normal(36.39, 0.009)	Jia, & Lubetkin, 2010; Peeters et al., 2003

Quality-Adjusted Life Expectancy at age 40, Normal Weight (QALE.normal)	38.96	Normal(38.96, 0.009)	Jia, & Lubetkin, 2010; Peeters et al., 2003
Life Expectancy at age 40, Obese (LE.obese)	39.19	Normal(39.19, 0.006)	Peeters et al., 2003
<hr/>			
Males			
Quality-Adjusted Life Expectancy at age 40, Obese (QALE.obese)	29.99	Normal(29.99, 0.009)	Jia, & Lubetkin, 2010; Peeters et al., 2003
Quality-Adjusted Life Expectancy at age 40, Overweight (QALE.overweight)	34.29	Normal(34.29, 0.009)	Jia, & Lubetkin, 2010; Peeters et al., 2003
Quality-Adjusted Life Expectancy at age 40, Normal Weight (QALE.normal)	36.67	Normal(36.67, 0.008)	Jia, & Lubetkin, 2010; Peeters et al., 2003
Life Expectancy at age 40, Obese (LE.obese)	37.54	Normal(37.54, 0.005)	Peeters et al., 2003

Because Peeters and colleagues (2003) calculated life expectancy for individuals who were normal weight, overweight, and obese, I needed to account for the proportion of individuals who are normal weight vs. overweight. Since I did not model the impact of the intervention on the proportion of normal weight versus overweight, I assumed that the ratio of overweight to normal weight individuals is equal in both the intervention and no intervention groups. Current data indicate that of individuals who are not obese, 47% are of a normal weight and 53% are overweight (National Center for Health Statistics, 2015) which are the proportions I used in my calculations. To estimate the average QALE for individuals in the intervention (QALE.1) and no intervention groups (QALE.0), I multiplied the QALE of individuals at each weight status (QALE.obese,

QALE.overweight, QALE.normal) by the proportion of individuals at that weight status, then added these three products together (see formulas below, Equations 4 and 5).

**Equation 4. Quality-Adjusted Life Expectancy, Intervention Group (QALE.1)**

$$QALE.1 = PO.1 * QALE.obese + ((1 - PO.1) * 0.53) * QALE.overweight + ((1 - PO.1) * 0.47) * QALE.normal$$

**Equation 5. Quality-Adjusted Life Expectancy, No Intervention Group (QALE.0)**

$$QALE.0 = PO.0 * QALE.obese + ((1 - PO.1) * 0.53) * QALE.overweight + ((1 - PO.1) * 0.47) * QALE.normal$$

To demonstrate these calculations, I will insert the point estimate values for female students into Equation 4. Most of these values come from Table 3, and the likelihood of being obese at age 40 following the intervention (PO.1) was calculated earlier in the text as 0.398. First I multiplied the likelihood of being obese at age 40 following the intervention (0.398; PO.1) by the quality-adjusted life expectancy from age 40 of an obese female (31.20; QALE.obese) which equals 12.42. Then I determined the likelihood of not being obese at age 40 following the intervention as 1 – 0.398 (PO.1) which equals 0.602. Of that group, I assumed that 0.53 are overweight, which when multiplied by 0.602 equals 0.319 (the likelihood of being overweight at age 40 following the intervention). I multiplied that value (0.319) by the quality-adjusted life expectancy from age 40 of an overweight female (36.39; QALE.overweight) which equals 11.61. To

determine the likelihood of being a normal weight at age 40 following the intervention, I multiplied the likelihood of not being obese at age 40 following the intervention (0.602) by 0.47, the proportion those not obese who are of a normal weight, which equals 0.283. I then multiplied this value by the quality-adjusted life expectancy from age 40 of a normal weight female (38.96; QALE.normal) which equals 11.02. Adding these three products (12.42, 11.61, and 11.02) together equals 35.05, which is the estimated quality-adjusted life expectancy of females, from age 40, following the intervention (QALE.1). Below, these numbers are inserted into Equation 4:

$$\begin{aligned} \text{QALE.1} &= 0.398*31.20 + ((1-0.398)*0.53)* 36.39 + ((1-0.398)*0.47)* 38.96 \text{ (Eq.4)} \\ &= 35.05 \end{aligned}$$

The relative effectiveness of the intervention can therefore be calculated as the average QALE from age 40 in the intervention group (QALE.1) minus the average QALE from age 40 in the no intervention group (QALE.0).

Selecting the effectiveness measure for a cost-effectiveness analysis should be a deliberate decision-making process for the researcher, and any assumptions/limitations in the process should be adequately explained to the research consumer. In this section, I discuss some assumptions I made, as well as how other researchers can alter my model to avoid making these assumptions. For example, because the source for QALE I used provided estimates at three different weight statuses (normal, overweight, and obese), I needed to account for each of these weight statuses in my calculation; however, I only modeled the impact of the intervention on obesity. Therefore, I made an assumption about the proportion of overweight to normal weight among these who were not obese. A

more complex model could have modeled the impact of the intervention on all three weight statuses, thus providing a more precise estimate of the impact of the intervention on QALE. Additionally, I choose to model the general effects of obesity on QALE for simplicity, but a more complex model could depict the association of obesity with a variety of disease states (cardiovascular disease, type 2 diabetes, etc.). These specific disease states could provide more precise estimates of the impact of obesity on QALE, which represents a limitation of my model. Measures of central adiposity (i.e. waist circumference) may be better predictors of disease risk than weight status (i.e. Huxley, Mendis, Zheleznyakov, Reddy, & Chan, 2010); however, research measuring trajectories of waist circumference overtime are not available so I was unable to use this variable in my model. I also could have used DALYs saved as opposed to QALYs. One main factor in choosing QALYs is that the established disability weights used to calculate DALYs are for specific diseases (i.e. type 2 diabetes, cancer) as opposed to general risk factors like obesity. Using DALYs would be more appropriate in a more complex model that considers the impact of obesity on various disease states as opposed to its general impact on life expectancy and quality of life. Lastly, I am only estimating the effects of the intervention after age 40. Again, this choice was made in part to simplify the model, but it does correspond with other models used to estimate the cost-effectiveness of school-based lifestyle interventions (i.e. Brown et al., 2007; Wang et al., 2003), so there is a precedent for this decision.

## Costs

Lastly I need to consider the costs. One cost I included is that of the intervention. I attempted to include all costs relevant to the implementation of the intervention. Published research on the HEALTHY Study intervention (i.e. DeBar et al., 2009; Gillis et al., 2009; Health Study Group, 2008, 2010; McMurray et al., 2009; Venditti et al., 2009) provided the primary source of cost data. Additionally, I consulted with a former project manager from the HEALTHY Study to gather cost information that was not available in these documents (i.e. salary of the dietician). When I could not determine salaries from either of these sources I estimated them based on information from the Bureau of Labor Statistics (2007). Three different levels of cost were considered. The intervention was coordinated by different centers, each of which hired a Dietician (\$49,010), PE Specialist (\$38,000), Health Promotion Coordination (\$42,920), and three HEALTHY assistants (\$35,870 each) to support the implementation of the intervention. Additionally, there were school level costs including \$5,000 for new PE equipment, \$3,000 to offer more healthy food options, and payment for teacher training. Lastly, there were individual student costs which included printed handouts and prizes (water bottles, T-shirts). I converted all of the center and school level costs to student costs based on the number of schools per center and students per school. Information on all relevant intervention costs is presented in Table 4.

**Table 4. Intervention Costs for the HEALTHY Study Program**

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Center Level Costs - Yearly	School Level Costs - Yearly	Student Level Costs - Entire Program
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Dietician Salary	\$49,010	PE Equipment	\$5,000	Printed handouts	\$39.19
PE Specialist	\$38,000	PE Assistant Salary	\$21,850	Branded “theme enhancers”	\$15
Health Promotion Coordinator	\$42,920	PE Teacher Training	\$1,200		
Healthy Assistants	\$35,870 x 3	Classroom Teacher Training	\$625		
		Support for food changes	\$3,000		
		Training for food service manager and workers	\$800		
		Cafeteria Enhancements	\$250		
Total Costs, Entire Program, All Students					
Center Level Costs		School Level Costs		Student Level Costs	
\$4,988,340		\$98,175		\$125,016.33	
Average Cost Per Student					
\$3,110.11					

When discussing economic analyses, opportunity costs should be considered.

Opportunity costs encompass what one misses out on by choosing one alternative over

another. For example, a child might have several choices of after-school activities. If the child chooses sports over an academic club, her/she may miss out on academic gains, which is the opportunity cost. Despite their importance, opportunity costs are difficult to measure. With the HEALTHY Study program, opportunity costs are somewhat limited because the intervention takes place during the school day, which is a required activity; however, since some of the intervention takes place during class time, theoretically, less time devoted to academic work could represent an opportunity cost for students at the intervention schools. Given the constraints of current research knowledge and the data collected, I chose to not model potential opportunity costs. Research also suggests that the academic opportunity costs of the HEALTHY study program are minimal since intervention and control schools did not differ on passing rates for state reading and mathematics tests (Hernandez et al., 2014), supporting my decision to exclude these costs.

When taking a societal perspective for an economic analysis, a researcher can also consider future medical costs that may be averted. Evidence suggests that obese individuals do accrue more medical costs than non-obese individuals (Finkelstein, Trogon, Cohen, and Dietz, 2009). Again, decisions must be made regarding what medical costs to consider. To keep costs fairly simple since this is a primer, I found a general estimate for the yearly medical costs attributable to obesity (Finkelstein, et al., 2009). This estimate came from the Medical Expenditure Panel Survey and the National Health Expenditure Accounts, which includes spending for inpatient hospitalizations, non-inpatient doctor's visits (outpatient, office-based, etc.), and medications. I chose to

exclude indirect costs associated with obesity that include missed work and decreased productivity. This type cost has not been as well researched and I was unable to find a per person estimate of this cost attributed to obesity. The medical costs attributed to obesity as well as the average per student intervention cost are presented in Table 5.

**Table 5. Point Estimates, Priors, and Sources for Medical Costs of Obesity and Intervention Costs**

Variable	Estimate	Prior	Source
Yearly medical costs attributable to obesity (COST.M)	\$1,429	Normal(1429, 0.00004)	Finkelstein et al., 2009
Per person intervention cost (COST.I)	\$3,110.11	Normal(1841.17, 0.000001)	HEALTHY Study data; researcher's estimation

In my estimates of cost-savings over time, I chose to account for the time value of money and inflation. Because the value of money changes over time, it is common in economic analyses to account for these changes so that future costs/cost savings can be converted to present value. Since most of the estimated costs savings in this study occur far in the future, I chose to make these adjustments. Regarding the time value of money, there is an economic principle that money is worth more to an individual immediately as compared to some point in the future. Money has earning power via compounding interest, investment appreciation, and other mechanisms that make today's dollar worth more to a person than a dollar earned in the future. I applied the traditional annual discount rate (3%; Weinstein, et al., 1996) to estimate how much future cost savings are worth to someone in the present. Additionally, I considered the potential for health care

prices to increase over time. If healthcare costs increase over time, then the yearly medical cost attributable to obesity will also increase. Again, in order to get an accurate depiction of how much future cost savings are worth to someone in the present, this inflation in healthcare costs should be accounted for. I used an annual increase rate of 5.8%, a recent estimate from the Centers for Medicare and Medicaid Services (2015). By combining these two rates, (a 3% annual discount rate and the 5.8% annual increase rate for rising healthcare costs), I had a yearly increase of 2.8% for healthcare costs. I discuss below how this yearly increase in healthcare costs will be used to calculate the average per person costs for both the intervention and no intervention groups.

For each group, I estimated the medical costs after age 40 by multiplying the life expectancy, past age 40, of an obese person (LE.obese) by the medical costs per year of obesity (COST.M). To convert these future costs to present value, I divided the medical costs of obesity by  $1 - 0.028$  (the yearly increase in medical costs calculated above) raised to the number of years since the end of the study that the costs are expected to be accrued (26 + the life expectancy of an obese individual past 40 (LE.obese)). I used 26 because that is the average number of years from the end of the study to when participants are 40 years old. This value represents the expected medical costs after age 40 of an obese person adjusted to “present value” (i.e. at the time the study ended). To generate the expected future costs for both the intervention and no intervention groups, I multiple this value by the likelihood of being obese at age 40 in the intervention and no intervention groups (PO.1 and PO.0 respectively). Lastly, I added the per person intervention cost

(COSTS.I) to the costs of the intervention group. These formulas are presented below (Equations 6 and 7):

**Equation 6. Costs, Intervention Group**

$$\mathbf{Costs, Intervention = COST.I + \frac{COST.M * LE.obese}{(1 - 0.028)^{26+LE.obese}} * PO.1}$$

**Equation 7. Costs, No Intervention Group**

$$\mathbf{Costs, No Intervention = \frac{COST.M * LE.obese}{1(-0.028)^{26+LE.obese}} * PO.0}$$

To demonstrate these calculations, I will insert the point estimate values for female students into Equation 6. To calculate the per person, unadjusted medical costs after age 40, I multiplied the average yearly cost of obesity (\$1,429; Table 5) by the average life expectancy after age 40 of an obese women (39.19; Table 3) which equals \$56,002.51. To adjust these future costs to present day value, they are divided by 1-0.028 raised to the power of 65.19 (the years since the end of the study; 26 + 39.19), which equals \$356,651.20. This value is then multiplied by the likelihood of being obese at age 40 following the intervention (0.398; PO.1) which was calculated earlier in the text. This equals \$141,947.20 which is the estimated future medical costs attributable to obesity among females in the intervention group. This value is then added to the per person intervention costs (\$3,110.11; Table 5) which equals \$145,057.31, the estimated total

costs for females in the intervention group. These values are inserted into Equation 6 below:

$$\text{Costs, Intervention} = \$3,110.11 + \frac{\$1,429 * 39.19}{(1 - 0.028)^{26 + 39.19}} * 0.398 = \$145,057.31 \text{ (Eq. 6)}$$

## **Analyses**

Bayesian methods are relevant to my analyses when I consider the need to account for uncertainty in all the parameter estimates discussed thus far. Given that each parameter is derived from a sample of individuals within a population, there is some level of uncertainty around the true (“population”) value of each parameter. In other words, if the parameter was calculated using different samples, there would be variability in the parameter values. As discussed previously, variability in the parameter values contributes to variability in cost-effectiveness estimates (i.e. the ICER), which needs to be represented. Bayesian methods are uniquely suited to accurately represent this uncertainty because they allow us to define distributions around each individual parameter (prior distributions) which are then propagated throughout the entire model, and all of the calculations mentioned above. The resulting distributions of cost and effectiveness estimates are therefore a direct representation of the uncertainty in parameter estimates.

These prior distributions can be specified in a variety of ways (expert opinion, subjective beliefs, or empirical data). I derived my priors empirically (from either the HEALTHY data or published research), which is generally recommended when conducting cost-effectiveness analyses (Briggs 1999, 2000). For example, Finkelstein and colleagues (2009) provided the estimate of yearly medical costs attributable to obesity

(\$1,429) as well as the standard deviation (\$156). This information allows me to specify that medical costs attributable to obesity have a normal distribution with a mean of \$1,429 and precision of 0.000041 (precision is equal to 1 divided by the standard deviation squared, and is the measure of dispersion used in the software I will use). I used this method to specify the prior distributions for all of the continuous variables (QALE, LE, and costs).

For all of the probability variables (see Table 2), which are bounded by 0 and 1, I used beta priors. Beta priors are typically used to model uncertainty around proportions because they are also bounded by 0 and 1. I will use the probability of being obese at the end of the study for females in the intervention group to demonstrate this. At the end of the study, among females in the intervention group, 267 were obese while 946 were not. We can understand this data as a series of 1s and 0s with 1 indicating an individual is obese and 0 indicating that she is not obese. In other words, I have 267 1s and 946 0s. A beta prior is defined by shape constants A and B with A being equal to the number of 1s (i.e. the number of females who are obese at the end of the study in the intervention group), while B is equal to the number of 0s (i.e. the number of females who are not obese at the end of the study in the intervention group). A beta prior with  $A = 267$  and  $B = 946$  (shorthand is  $\text{beta}(267, 946)$ ) provides a distribution around a mean 0.220, which corresponds to the proportion of females who are obese at the end of the intervention.

Once I specified the point estimates and distributions of all of my parameters, I used the R2jags package (Su, & Yajima, 2015) in R along with JAGS (Just Another Gibbs Sampler; Version 4.1.0; Plummer, 2016) to generate my final samples (i.e. the

“posterior” distribution). These programs use Markov Chain Monte Carlo methods to draw random, simulated samples from the prior distributions, which gives us an expected distribution of values for each parameter. I specified 1500 for the number of samples, which corresponds with other cost-effectiveness examples run using R2jags and JAGS (Baio, 2013). We can think of this as theoretically running the experiment and model 1,500 times.

After this stage of the analysis, I had 1,500 samples of parameter estimates. From each of these samples, using the equations above, I generated an estimate of the costs and effectiveness (QALE) of both the intervention and no intervention groups. This data was represented as a matrix with four columns (effectiveness of the intervention, effectiveness of no intervention, cost of the intervention, and cost of no intervention) and 1,500 rows, each corresponding to a simulated sample. Data in this format was analyzed using the BCEA package in R (Baio, Berardi, & Heath, 2016) to generate a point estimate for the ICER, a distribution of ICER values, and the CEAC.

## RESULTS

### Posterior Distributions

I will first present descriptive statistics (mean and standard deviation) for the posterior distributions of all of the parameters of interest (Table 6). These statistics are based on the 1500 Markov Chain Monte Carlo samples.

**Table 6. Posterior Means and Standard Deviation for Relevant Model Parameters**

Variable	Mean	Standard Deviation
<b>Females</b>		
Probability of being obese at the end of the study, intervention (P1)	0.221	0.008
Probability of being obese at the end of the study, no intervention (P2)	0.244	0.009
Probability of being obese at age 40 if obese in adolescence (P3)	0.938	0.041
Probability of being obese at age 40 if not obese in adolescence (P4)	0.247	0.012
Quality-Adjusted Life Expectancy at age 40, Obese (QALE.obese)	31.25	9.84
Quality-Adjusted Life Expectancy at age 40, Overweight (QALE.overweight)	36.05	10.43
Quality-Adjusted Life Expectancy at age 40, Normal Weight (QALE.normal)	38.85	10.78
Life Expectancy at age 40, Obese (LE.obese)	39.66	13.42
<b>Males</b>		
Probability of being obese at the end of the study, intervention (P1)	0.274	0.010
Probability of being obese at the end of the study, no intervention (P2)	0.280	0.010

Probability of being obese at age 40 if obese in adolescence (P3)	0.828	0.048
Probability of being obese at age 40 if not obese in adolescence (P4)	0.238	0.012
Quality-Adjusted Life Expectancy at age 40, Obese (QALE.obese)	30.05	10.22
Quality-Adjusted Life Expectancy at age 40, Overweight (QALE.overweight)	34.65	10.37
Quality-Adjusted Life Expectancy at age 40, Normal Weight (QALE.normal)	36.46	11.25
Life Expectancy at age 40, Obese (LE.obese)	37.07	14.08
<hr/>		
Costs		
<hr/>		
Yearly medical costs attributable to obesity (COST.M)	\$1,440.19	\$156.60
Per person intervention cost (COST.I)	\$3,100.77	\$908.40
<hr/>		

### **Cost-Effectiveness – Females**

Among female participants, the ICER point estimate for the intervention indicated that it “dominated” no intervention, meaning that the intervention was less costly and more effective than no intervention. In other words, due to cost savings by preventing adult obesity, the intervention saved QALYs and reduced healthcare costs compared to no intervention. I won’t interpret the specific ICER point estimate because it doesn’t have any inherent meaning when one condition dominates. Compared to no intervention, on average, the intervention saved 0.100 QALYs and saved \$4,240.32 per person. Figure 3 shows the distribution of ICER values on a cost-effectiveness plane.

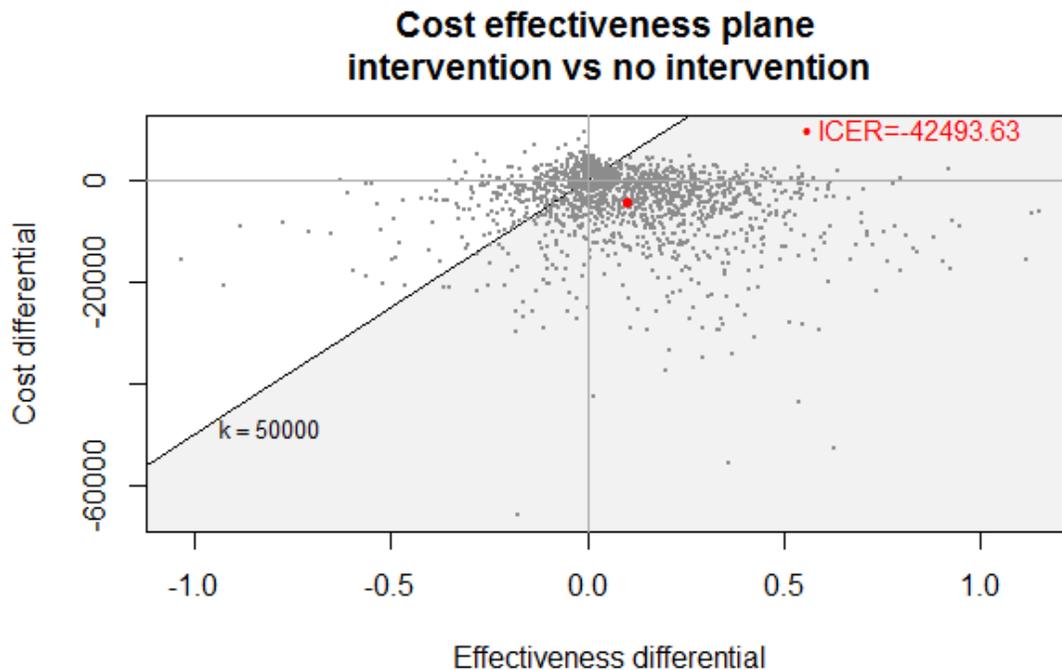


Figure 3. Cost-Effectiveness Plane Depicting ICER Values, Females

The ICER point estimate falls in the bottom right quadrant, which indicates that the intervention is less costly and more effective than no intervention (i.e. it dominated no intervention). Additionally, nearly half (47.7%) of simulated ICER values also fall in this quadrant. Another 22.9% of the ICER values fall in the bottom left quadrant, indicating that the intervention was less costly, but also less effective than no intervention. These ICER values are meaningful and can be compared to cost-effectiveness thresholds. The black diagonal line represents the \$50,000 per QALY saved threshold, and all of the ICER values to the right/below that line (in the shaded area) represent the intervention being cost-effective at this threshold. A small proportion (9.7%) of simulated values fall in the top left quadrant, indicating that no intervention dominates the intervention (i.e. it

is less costly and more effective). Lastly, 19.7% of the ICER values fall in the top right quadrant which indicates that the intervention is more effective and more costly than no intervention. Those values that fall to the right of/below the black diagonal line have ICER values less than \$50,000 per QALY saved. Overall, 73.6% of the simulated samples fall to the right of/below this line, indicating the likelihood that the intervention will be cost-effective at \$50,000 per QALY saved. The Cost-Effectiveness Acceptability Curve, Figure 4, presents this likelihood over a range of values.

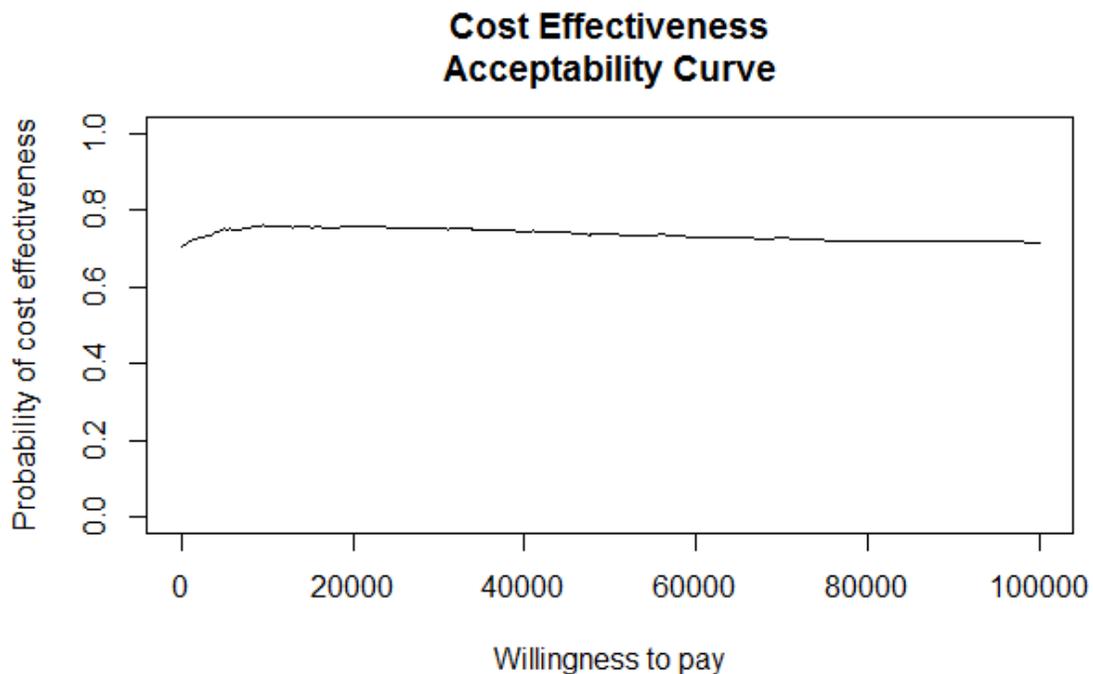


Figure 4. Cost-Effectiveness Acceptability Curve, Females

At a willingness to pay of zero, the intervention would only be cost-effective if it was cost saving, which includes all values in the bottom left and right quadrants (70.6%) of

Figure 3. As the willingness to pay increases, one can think of the black diagonal line starting at the x-axis and gradually rotating counter-clockwise. At each point, the probability of the intervention being cost-effective is equal to the proportion of the ICER values that fall to the right of/below this line. The probability that the intervention is cost-effective actually decreases slightly as the willingness to pay increases because there are more ICER values in the bottom left quadrant than in the top right. As the willingness to pay increases towards infinity, the likelihood of the intervention being cost-effective trends towards 67.4%, the proportion of ICER values in the top and bottom right quadrants. Overall, these results indicate that even a small intervention effect ( $d = 0.18$ ) can be fairly cost-effective (with reasonable confidence), when the intervention is made early and decreases a risk factor with strong ties to health costs and QALE.

### **Cost-Effectiveness – Males**

Among male participants, the ICER for the intervention was \$81,023.05 per QALY saved, which falls above the typical threshold of \$50,000 per QALY saved. Compared to no intervention, on average, the intervention saved 0.021 QALYs per person and cost \$1,728.88 per person, once future cost savings were taken into account. Figure 5 shows the distribution of ICER values on a cost-effectiveness plane.

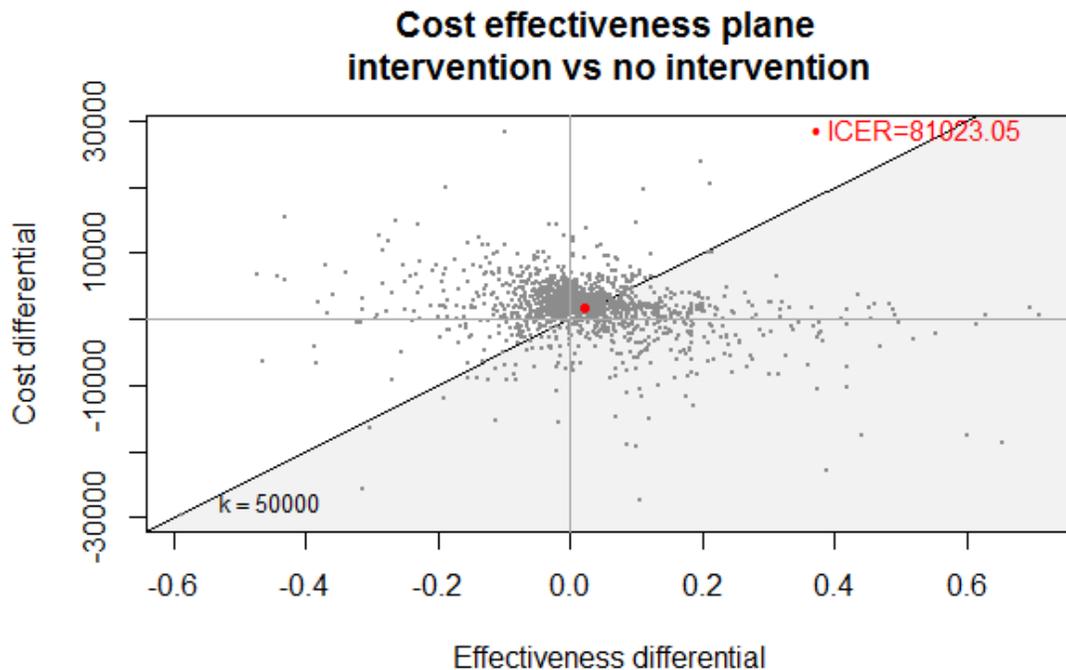
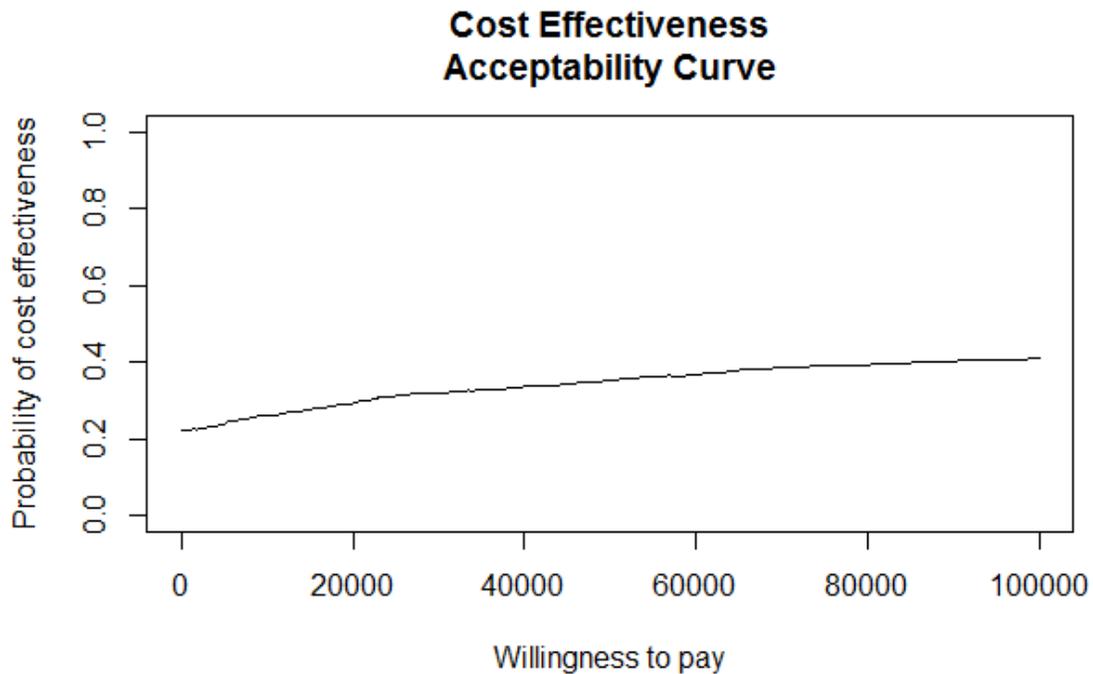


Figure 5. Cost-Effectiveness Plane Depicting ICER Values, Males

Across all ICER values, there was a 35.3% likelihood that the intervention would be cost-effective at the threshold of \$50,000 per QALY saved. In contrast to the female participants, the intervention only produced cost-savings for males in a minority of simulations with 14.7% of ICER values indicating that the intervention dominates no intervention and 7.5% of ICER values indicating that the intervention was less costly, but also less effective than no intervention. In addition, there was a 40.6% chance that the intervention was more costly, but also more effective than no intervention, and a 37.3% chance that no intervention dominated the intervention. The Cost-Effectiveness Acceptability Curve for males is depicted in Figure 6.



**Figure 6. Cost-Effectiveness Acceptability Curve, Males**

Overall, the likelihood that the intervention is cost-effective for males increases somewhat as the willingness to pay increases but generally remains below 50%. This is likely due to the fairly even spread of ICER values to the left and right of the y-axis, indicating considerable uncertainty around the ICER estimate. At a willingness to pay of \$0, the likelihood that the intervention is cost-effective is 22.2%. As the willingness to pay increases towards infinity, the likelihood that the intervention is cost-effective trends toward 55.3%.

Although the ICER estimate for the intervention for males was above the \$50,000 per QALY threshold, it isn't unreasonably high and there are situations where a policy-maker may be willing to pay \$81,023.05 per QALY saved; however, even if a policy-

maker was willing to pay more per QALY, the uncertainty around the ICER estimate indicates that there is very little confidence in the intervention being cost-effective for males. This finding is expected, given that the intervention's impact wasn't statistically significant for males. Without the context of uncertainty, the ICER value could be misleading.

## DISCUSSION

### Interpretation

The results of my example model indicate that on average, the HEALTHY Study program would result in reduced costs and increased quality-adjusted life expectancy for female students compared to no intervention. If policy-makers are willing to pay \$50,000 per QALY saved, there is a 73.6% chance that the intervention would be cost-effective for female students. For male students, the intervention would not be considered cost-effective on average, costing \$81,023.05 per QALY saved, and there was more uncertainty around this estimate compared to female students. For males, even if there was no limit to what policy-makers would pay per QALY saved, there was only a 55.3% chance that the intervention was cost-effective. These differences in the cost-effectiveness of the intervention between genders is expected since the intervention had a stronger impact on obesity for females. Additionally, there was a somewhat stronger link between childhood and adulthood obesity for females compared to males, indicating that the effects of the intervention were more strongly propagated through the model for females. This differential impact corresponds to prior research on school-based lifestyle interventions indicating stronger effects for females compared to males (Gortmaker et al., 1999). One potential explanation for this difference is that females receive more societal messages about weight, making them more aware of the importance of diet and physical

activity to losing weight and thus more responsive to the intervention (Stone, Baranowski, Sallis, & Cutler, 1995).

Since the main purpose of this dissertation is to provide a primer on cost-effectiveness analyses for health psychologists, and my model was kept intentionally simplistic to accomplish this goal, I will refrain from making clinical interpretations based on these results. Instead, I highlight the utility of using Bayesian methods and presenting my cost-effectiveness analyses as a distribution of ICER values and the CEAC. Instead of relying on point estimates for ICER values, Bayesian methods allow me to quantify the uncertainty and make statements regarding the likelihood of the intervention being cost-effective at various thresholds, given my data. This information is particularly important for policy-makers by providing them with the best, most complete data to inform decisions about funding programs or reimbursing clinical services.

The ability of these methods to provide more nuanced information to policy-makers is illustrated with a slightly more complex scenario. While not included in this primer, these methods can be used to make comparisons among multiple treatments. Imagine a scenario where two new treatments (A and B) may fall below the threshold of cost-effectiveness compared to treatment as usual. Compared to treatment B, treatment A has a smaller impact, but less variability in treatment outcome. Treatment A, therefore, has a larger ICER value than treatment B, but also less uncertainty around the ICER estimate, and thus a greater likelihood of being cost-effective at \$50,000/QALY saved. When relying on point estimates, treatment B would probably be favored because of the smaller ICER value, even though treatment A may be the better choice if we want to

maximize the likelihood of being cost-effective at a certain threshold. Questions of cost-effectiveness are necessarily complex, and Bayesian methods for cost-effectiveness analyses attend to this complexity and present it to policy-makers in a clear and accessible way.

Additionally, the ability of these methods to model clinical outcomes into the future makes them particularly appealing for health psychologists who want to advocate for reimbursement or financial investment in their services. Most behavioral interventions, particularly for children, do not pay for themselves in the short-term; however, psychologists can use these methods to demonstrate future cost-savings which can help justify a hospital's financial investment in these services in the present. This example demonstrates that while the HEALTHY intervention was fairly costly (~\$3,110.11 per student), for female students, the intervention has a fairly high likelihood of providing future cost-savings. In particular, this likelihood has been quantified, and can be used to advocate for the financial investment in the intervention.

### **Limitations**

Because of the nature of this dissertation as a primer for Bayesian methods, there are a variety of limitations as the model was kept deliberately simple. One of the biggest limitations is the assumption that the HEALTHY Study program has a lasting effect on an individual's weight status trajectory. In other words, I do not account for the possibility of relapse after the study period ends. The Bayesian methods I use address this concern somewhat by allowing for the possibility that the intervention isn't effective (as

is the case in some of the simulated samples); however, a more complex model could have included and directly estimated relapse rate, which would be an improvement.

Additionally, a more complex model could have examined the impact of obesity on the likelihood of developing a variety of specific diseases, which would likely provide a more precise estimate of the impact of the intervention on QALYs saved and future medical costs. I also only estimated the impact of the intervention on QALYs saved and medical costs after age 40. While there is precedence for this decision in the research literature (i.e. Wang et al., 2003), a more complex model could have estimated costs and effectiveness throughout adolescence and young adulthood as well, thus providing a more accurate estimate of the cost-effectiveness of this program. I was also limited in my choice of outcomes by the available literature tracking measures of adiposity over time. While measures of central adiposity (i.e. waist circumference) may be better predictors of disease risk than weight status based on BMI, I could not find research measuring trajectories of these variables from adolescence into adulthood and was unable to use these variables in my model. Lastly, I was unable to directly access information on several aspects related to the costs of the intervention (i.e. salary of the dietician, number of teachers/PE teachers who implemented the study per school) so these had to be estimated. This estimation likely increased the variability in the cost of the intervention entered into my model, which in turn increased the uncertainty in the ICER values. This limitation underscores the importance of collecting specific, individual-level cost data when implementing an intervention, to avoid introducing unnecessary uncertainty into the model. For all of these reasons, this dissertation should not be taken as a definitive

estimate of the cost-effectiveness of the HEALTHY Study program, but rather as an example and primer in how to apply Bayesian methods to cost-effectiveness analyses.

## **Conclusions**

This primer responds to calls from within the field of health psychology for more research supporting the cost-effectiveness of our interventions (i.e. Glasgow, & Emmons, 2007; Goodhart, 2010; Harris et al., 2016; Wilson, 2015). Changes to the healthcare financial system have already made this an important consideration, and if the United States shifts more to a single-party payer system, it will be even more pertinent. Within the field of medicine and pharmoeconomics, Bayesian methods are increasingly used to model uncertainty in cost-effectiveness analyses and provide more nuanced information about cost-effectiveness to better inform funding decisions (Briggs, 1999, 2000; Armero, Carcia-Donato, & Lopez-Quilez, 2007). By presenting an overview of Bayesian methods for accounting for and presenting uncertainty around cost-effectiveness estimates, this dissertation builds directly on an article by McGrady (2014) which provided an excellent overview of calculating ICERs and conducting univariate sensitivity analyses to consider uncertainty. I believe that this dissertation provides health psychologists interested in conducting cost-effectiveness analyses with the beginning tools needed to explore Bayesian methods. Given changes to healthcare systems and insurance reimbursement, using economic analyses to support the importance and relevance of health psychology interventions is likely to become increasingly important, and I hope this dissertation helps to prepare health psychologists for these changes.

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