A DECISION ANALYTIC FRAMEWORK FOR THE COSTS OF SUGAR-SWEETENED BEVERAGE CONSUMPTION

BY

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THESIS

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ABSTRACT

This thesis provides a decision analytic framework for calculating the medical costs associated with the decision to consume sugar-sweetened beverages. The model uses (i) records of mortality data, (ii) previously identified lifetime risks of diabetes, (iii) data on relative risks associated with sugar-sweetened beverage consumption, and (iv) the reported costs of diabetes medical treatment to determine the increase in expected costs that result from the consumption decision. Additionally the model can be used to analyze any decision that increases one's relative risk of diabetes.

The results indicate that sugar-sweetened beverage consumption is considerably more costly for younger individuals than for older individuals. Moreover, the frequency of beverage consumption also has a significant impact on expected medical costs. These results have wide ranging implications for such areas as health insurance, national health spending, and public health awareness campaigns.

ACKNOWLEDGMENTS

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1. BACKGROUND AND MOTIVATION

1.1 INTRODUCTION

Diabetes affects 25.8 million Americans, over 8% of the population, with almost 2 million new diagnoses in 2010 [1]. These numbers are sobering given the fact that diabetes is the leading cause of blindness, non-traumatic lower limb amputation, and kidney failure and that diabetes is the seventh leading cause of death in the U.S. [1].

Lifestyle choices are pivotal in the prevention and management of diabetes. Research has shown that the majority of type-2 diabetes cases could have been prevented through different lifestyle choices [2]. While clear recommendations exist on diets to minimize the risk of diabetes [3], the cost of these decisions as quantified in terms of their effects on increased expected lifetime medical expenditures has not been described. A framework for determining the cost of lifestyle decisions related to diabetes would allow for insights into a wide range of problems, including planning public health awareness campaigns. This chapter describes a model that enables just such an analysis with the goal of helping individuals better understand the impact of their lifestyle decisions.

The development of a model for lifestyle decisions in diabetes follows in the footsteps of other models that have quantified preferences for life and health states. Howard created the concept of a micromort, a one-in-a-million chance of death, and describes the price to pay for accepting or avoiding a given number of micromorts [4]. Several authors have used quality-adjusted-life-years (QALY's) to develop consumption planning models that incorporate preferences for health [5, 6, 7]. Others have used QALY's for medical decision making purposes, although the model has been criticized for oversimplifying preferences and failing to incorporate potentially important factors [8]. Hazen incorporates preferences for lifetime milestones that may be independent of length of life to advance the QALY model [9].

The cumulative impact of lifestyle decisions is tremendous. Keeney conducts an analysis of mortality data in the United States that shows that personal decisions are in fact the leading cause of death [10]. This frame underscores the importance of the present model describing the impact of beverage choices on the risk diabetes and the subsequent effects on medical costs. The focus on diabetes is motivated by the significant health impacts it poses, and on the fact that one's risk is strongly associated with lifestyle choices.

The following thesis analyzes personal decisions that affect one's chances of being diagnosed with diabetes. A framework is developed that enables the determination of values related to personal decision making and diabetes. The remainder of this chapter provides the requisite knowledge for understanding how the model is developed. Section 1.2 describes the Cox proportional hazards model. Section 1.3 explains how behaviors can be linked to increases in the relative risk of diabetes. Section 1.4 presents the baseline risk of diabetes. Section 1.5 describes mortality rates and how they are affected by diabetes. Section 1.6 presents the financial costs associated with diabetes. Finally, section 1.7 describes the research questions that are addressed by this thesis.

1.2 COX PROPORTIONAL HAZARDS MODEL

The Cox proportional hazards model has been well studied in statistics and survival studies. It is a useful tool that enables analysis of risks without requiring knowledge of the underlying hazard function [11, 12]. It is particularly useful in determining modified mortality probabilities given relative risks.

In examining the effects of covariates, the values of the covariates, $\boldsymbol{z}$, are known, but their effects are unknown parameters $\boldsymbol{\beta}$. Let the underlying, baseline hazard function be denoted $\lambda_0(t)$. To describe the effects of z, Cox uses the model

$$\lambda(\mathrm{t}; \mathbf{z}) = \exp\,(\mathbf{z}\boldsymbol{\beta})\lambda_0(t)$$

where the underlying hazard function need not be known [11]. Given this model, the relative risk, R, of the value of one particular covariate to another can be determined by the ratio of the hazard associated with each as

$$R = \frac{\exp\,(\boldsymbol{z_1}\boldsymbol{\beta})\lambda_0(t)}{\exp\,(\mathbf{z_2}\boldsymbol{\beta})\lambda_0(t)}$$

This formulation yields

$$R = \exp\,((\boldsymbol{z_1} - \boldsymbol{z_2})\boldsymbol{\beta}).$$

In the case where $\mathbf{z}$ is a single indicator variable with the values 0 and 1, the result is a constant hazard ratio,

$$R = \exp\,(\boldsymbol{\beta}).$$

The importance of the Cox proportional hazards model to the current problem formulation is in the fact that relative risks are multiplied by a baseline hazard function to determine hazard as a function of a covariate. The following section will describe research relative risks and diabetes. The relative risk model presented will determine the relative risks that are multiplied by baseline risks to determine a decision maker's risk of diabetes.

1.3 RELATIVE RISKS OF DIABETES

Following the Cox proportional hazards model, the relative risk of diabetes for particular covariates can be determined. Previous research has found increased relative risks for such covariates as body weight, smoking, family history, and diet [13, 14, 15]. Note that not all risk factors for diabetes may be under one's control, such as family history. For the purposes of developing a model to evaluate the value of personal decisions, any of the covariates that are under an individual's control may be chosen for analysis.

The consumption of sugar-sweetened beverages is one such personal decision that has been well studied in relation to its impact on the relative risk of diabetes mellitus. Several studies across different races, ethnicities, and gender have all found that consumption of sugar-sweetened beverages is positively correlated with a diagnosis of diabetes [16, 17, 18]. Thus, while many behaviors affect one's risk of diabetes and could be modeled, this framework focuses on the decision to consume sugar-sweetened beverages due to the existence of research on the impact of these specific decisions on relative risk as well as the prevalence of sugar-sweetened beverages in society. The methodology developed herein presents a general framework that can be used to explore the effects of other lifestyle decisions as well.

It is worthwhile to note that some of the research regarding sugar-sweetened beverages has been criticized for having too narrow a scope given that numerous behaviors affect the relative risk of diabetes [19]. The usefulness of the present personal decision making model as a framework for analyzing lifestyle decisions beyond those of beverage consumption must again be highlighted.

In order to quantify the effect of a decision on lifetime prospects due to diabetes, it is first necessary to derive the relationship between the decision in question and its effect on the relative risk of diabetes. Such a relationship would need to satisfy certain assumptions. The general properties assumed by the present model are explained below.

1. *The absence of a risk inducing behavior results in no increase in relative risk.* This assumption implies that the minimum relative risk is 1 if only those behaviors that increase risk are considered.
2. *The effect of a risk inducing dietary behavior is observed over time.* This assumption implies that an individual's diet over a period of time is the best indicator of risk. This assumption is consistent with dietary research [20].
3. *For a given time period, increased frequency of a risk inducing behavior is associated with increased risk, up to a maximum level.* This assumption implies that the rate at which a risk-inducing behavior is performed is important, up to a maximum point at which saturation of the effect occurs.
4. *For a given frequency, the effect of a risk inducing dietary behavior is proportional with time, up to a maximum level.* This assumption implies that a maximum level of increased risk exists. This assumption ensures that the probability of a negative outcome never reaches 1.

The development of the relative risk model is based on the above assumptions as well as interpolation from published data. Plotting the relative risks (and their respective 95% confidence intervals) found by Schulze, et al. against the midpoint of the associated consumption range of sugar-sweetened beverages, a strong linear relationship is observed as presented in Figure 1.1. The data covers an eight year time span of follow-up.

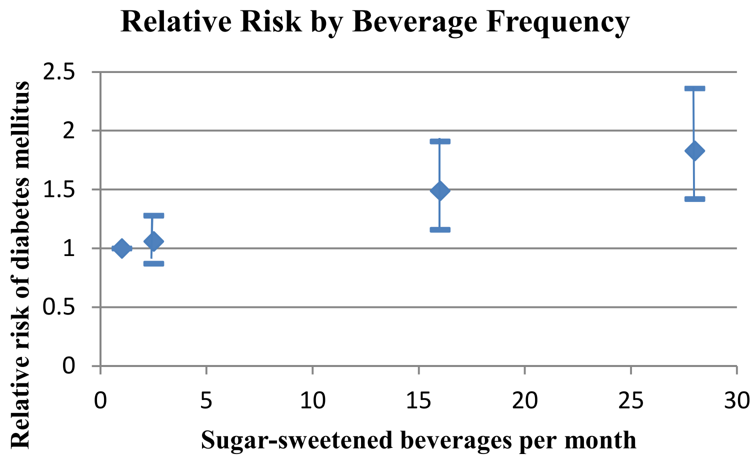

Figure 1.1. Observed relationships between relative risk of diabetes and frequency of sugar-sweetened beverage consumption, plotted with 95% confidence intervals.

Following the assumptions about the nature of risk-inducing behavior and the observed linear relationship between consumption frequency and increased relative risk, the following relative risk model is proposed. The relationship between relative risk and monthly consumption frequency is linear for all consumption time periods. When no sugar-sweetened beverages are consumed (0 years of consumption), a constant relative risk of 1 is present. For ten years of consumption, the relative risk for a given monthly consumption frequency follows the upper bound found in the research. The slope of the line relating relative risk to monthly consumption frequency increases proportionally, up to the ten year slope at which point no further increase in relative risk is observed. A decrease in consumption for a year likewise reduces the slope, down to a minimum of 0. This model is illustrated in Figure 1.2.

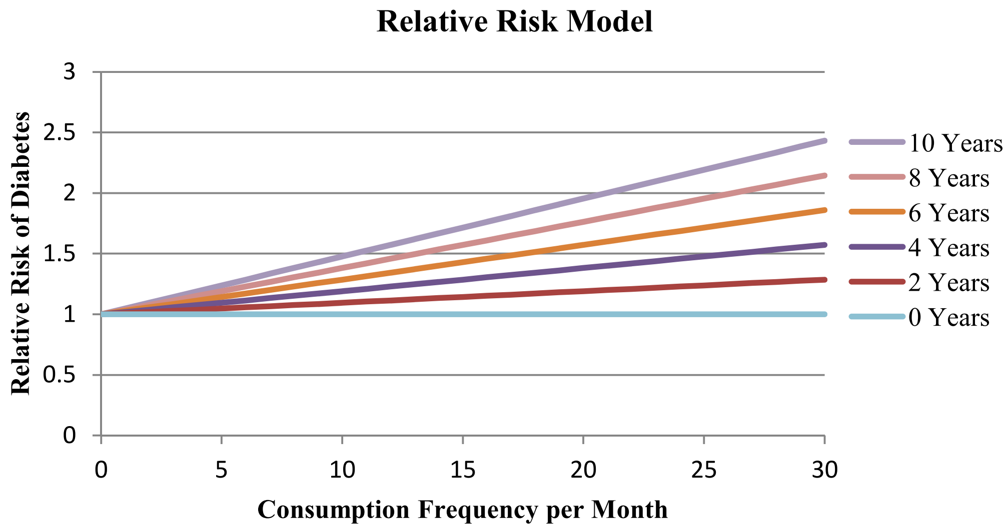

Figure 1.2. The relative risk model relating sugar-sweetened beverage consumption over time to increased relative risk of diabetes.

The development of a model relating relative risks to personal decisions is necessary for the subsequent quantification of changes in lifetime prospects. The development of the model valuing personal decisions is not dependent on a single relative risk model. While the approach presented here adheres to plausible assumptions and relationships derived from published research, the experiments to determine its validity have not been done. Further research is required in this area. If adjustments to the relative risk model are found necessary, they can be easily incorporated into the personal decision model.

1.4 BASELINE RISK OF DIABETES

In order to apply the relative risks derived above to a decision model, the underlying hazard function must be known. The hazard function that is used throughout is drawn from risks calculated by Narayan et al. [21]. The risks are derived from a Markov model multiple sources of U.S. data. Figure 1.3 below illustrates the cumulative lifetime risk of diabetes mellitus for male and females, all races. Note that the risk of diabetes levels off after age 80. Thus, in the personal decision valuation model, the maximum age considered is 80 years.

The risk of diabetes for an individual is determined as the product of the absolute risk and the relative risk according to the Cox proportional hazards model.

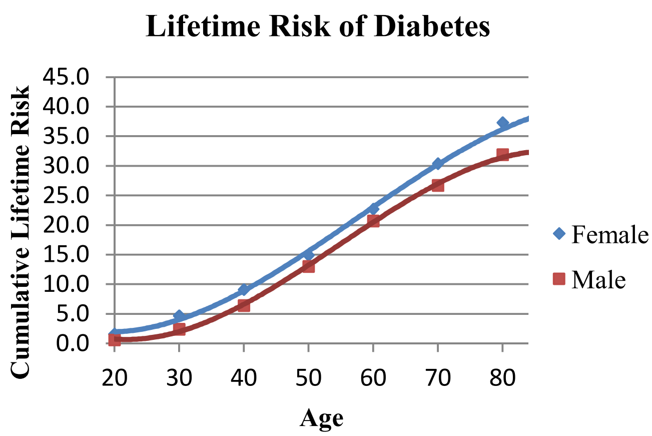

Figure 1.3. The Cumulative lifetime risk of diabetes mellitus by gender.

1.5 MORTALITY AND DIABETES

Diabetes increases an individual's risk of death and is reported as the seventh leading cause of death in the U.S. [1]. Researchers have found that diabetes raises the risk of mortality by cancer by factor of 1.25 and increases the risk of mortality by vascular causes by a factor of 2.3 [22]. Other researchers have found that diabetes increases an individual's risk of death from any cause by as much as a factor of 2.5 [23]. The Centers for Disease Control and Prevention report that the mortality rate for individuals with diabetes is approximately twice that of individuals without diabetes [1]. This value is used in the lifestyle decision valuation model.

Calculating the costs of lifestyle decisions will require the probability of dying in a given year conditional on the individual being alive at the beginning of that year. These probabilities are known as age-specific mortality rates. Their baseline values in the U.S. can be obtained from the U.S. Department of Health and Human Services [24]. However, because the mortality rates reported include mortality of individuals with diabetes, simply multiplying the probability of dying in a given year by a factor of 2 will lead to an over estimation of mortality rates for individuals with diabetes. Some calculations are necessary.

Let us consider a single year of mortality data. In this year, the total number of individuals of age a who die is given by δ_a. This total number of deaths is the sum of the number of deaths of individuals of age a with diabetes, $\delta_{D,a}$, and those without diabetes, $\delta_{\bar{D},a}$.

$$\delta_a = \delta_{D,a} + \delta_{\bar{D},a}$$

Letting $N_{D,a}$and $N_{\bar{D},a}$ represent the total number of individuals alive at the beginning of the year with and without diabetes, respectively, and considering that the probability of dying at age a, q_a, is the number of respective deaths divided by the total individuals alive at the beginning of the year, we arrive at the following equation.

$$q_a = \frac{\delta_{D,a} + \delta_{\bar{D},a}}{N_{D,a} + N_{\bar{D},a}}$$

Given also a relationship between the mortality rate of individuals with and without diabetes, the relative risk at age a denoted by R_a, the following equation can be written.

$$\frac{\delta_{D,a}}{N_{D,a}} = R_a \frac{\delta_{\bar{D},a}}{N_{\bar{D},a}}$$

The values q_a, $N_{D,a}$, $N_{\bar{D},a}$, and R_a are all available in the literature. The only remaining quantities to solve for are $\delta_{D,a}$ and $\delta_{\bar{D},a}$, which can then be used to calculate the probability of dying at age *a* for those with and without diabetes according to the following equations.

$$q_{D,a} = \frac{\delta_{D,a}}{N_{D,a}} = \frac{(N_{D,a} + N_{\bar{D},a})R_a q_a}{N_{\bar{D},a} + R_a N_{D,a}}$$

$$q_{\bar{D},a} = \frac{\delta_{\bar{D},a}}{N_{\bar{D},a}} = \frac{(N_{D,a} + N_{\bar{D},a})q_a}{N_{\bar{D},a} + R_a N_D}$$

The difference in mortality between individuals of a given age with and without diabetes will play an important role when determining the value over lifetime prospects that differ in length of life.

1.6 LIFE TABLE CALCULATIONS

In addition to the age-specific mortality rates discussed in the previous chapter, it is important to know the probability of an individual dying in all future years conditional on current age. These probabilities are for a given age, and do not update for each year the individual survives. As such, they sum to one and will be used to calculate expected medical costs once an individual is diagnosed with diabetes.

The age-specific mortality rates already calculated are used to determine the probability of dying at all future ages. Let these values be denoted in terms of the variable *x* where *q(x)* is the age specific-mortality at age *x*. The survival function, *S(x)*, gives the fraction of individuals in the cohort who are alive at age x, and is calculated as

$$S(x) = \exp\left(-\int_0^x q(x)dx\right)$$

The failure function is the cumulative fraction of individuals who have not survived to age x and can be defined in terms of $S(x)$ as

$$F(x) = 1 - S(x)$$

The failure function is a cumulative probability distribution. The probability of dying in all future years is the probability density function determined from $F(x)$ and is

$$f(x) = q(x)\exp\left(-\int_0^x q(x)dx\right)$$

Because the failure function begins at age 0 but the decision makers that will be considered here are all at least 25 years old, the distributions must be rescales so that the probabilities sum to one.

1.7 MEDICAL COST OF DIABETES

The lifestyle decision valuation model considers the effects of decision making on direct medical costs. The overall cost of diabetes is estimated to have reached at least $174 billion in 2007 [25]. This figure includes both increased medical expenditures ($116 B) and lost productivity ($58 B), with the average increase in direct medical costs attributable to diabetes being $6,649 per year [25]. This figure is estimated for uncomplicated cases of diabetes. When medical complications develop as a result of diabetes, this annual figure rises.

The framework presented in this thesis makes some simplifications concerning the analysis of medical costs. Given a diagnosis of diabetes, the annual direct medical costs are treated as deterministic instead of probabilistic. Uncertainty still remains in the models, however, as a result of the uncertainties surrounding a diagnosis of diabetes.

The actual medical costs incurred may differ from those estimated in the literature, leading to sources of error. It is possible that individuals do not seek recommended care following a diagnosis. In this case, it is likely that the individual will seek care once his or her condition deteriorates to a sufficient degree, at which point the medical costs may be greater.

It is also possible that an individual will develop medical complications related to diabetes that greatly increase annual costs. Because the model does not take into account the increasing probability of developing complications over time, it likely presents an underestimation of the medical costs incurred.

Additional costs are present in the form of lost wages, productivity, or costs that are not directly medical in nature. Again, the model will necessarily present an underestimation of the true costs associated with diabetes. This trend is important to consider when drawing insights from the model analysis.

1.8 RESEARCH QUESTIONS

Through the development of a framework to analyze the value of personal decision making, this thesis will address two central research questions.

1. What additional expected medical costs are associated with the personal decision to consume sugar-sweetened beverages? How are these costs affected by different frequencies of consumption?
2. What effect does risk aversion have on the certainty equivalent of medical costs associated with sugar-sweetened beverage consumption?

The following chapter presents a normative framework for answering these questions. The subsequent chapters present the model, its analysis, and discussion.

2. THE DECISION TREE MODEL

2.1 INTRODUCTION

Personal decision making has a tremendous impact on life outcomes, including the probability of being diagnosed with diabetes [2]. The role of personal decision making in the prevention of diabetes, a condition with serious health implications, motivates the development of a normative decision making model describing the value of these decisions in terms of effects on expected lifetime medical costs.

A diagnosis of diabetes has many effects on an individual's life prospects. This model focuses on the effects on lifetime medical costs because it enables insightful analysis on the cost of drinking sugar-sweetened beverages. Such insights are useful in many applications, such as planning public health awareness campaigns or in better understanding the growth in health care spending in the U.S.

The personal decision making model described in this chapter is based on the decision to consume sugar-sweetened beverages but also provides a framework for analyzing any decision that affects one's risk of diabetes. Thus the model is not limited to sugar-sweetened beverage decisions. Any choice or behavior that increases one's relative risk of developing diabetes can be analyzed once the degree to which the decision increases one's risk is specified.

This chapter describes the structure of the framework proposed for determining the effect of deciding to consume sugar-sweetened beverages on lifetime medical costs. The chapter is structured as follows. Section 2.2 describes the important distinctions in the model and their respective uncertainties. Section 2.3 explains the decision tree. Section 2.4 describes the calculations necessary based on the given decision tree. Section 2.5 discusses implications of some of the assumptions that are made.

2.2 DISTINCTIONS AND UNCERTAINTIES

In calculating the expected lifetime medical costs associated with the decision to consume sugar-sweetened beverages, several distinctions and their respective probabilities are important. The important distinctions are, for a given year, whether the individual is alive, and if he is alive, whether he has been diagnosed with diabetes. Let the event that the decision maker is alive in year j be denoted as A_j, and the event that the decision maker is not alive in year j denoted by $\overline{A_j}$. Furthermore, let the event that the decision maker is diagnosed with diabetes in year j be denoted by D_j, and the event the decision maker is not diagnosed with diabetes in year j denoted by $\overline{D_j}$. Note that both D_j and $\overline{D_j}$ are conditional on the decision maker being alive in year j.

The uncertainties associated with the events A_j and D_j are also important. Given that the decision maker was alive in year j, the probability of A_{j+1}, the event that the decision maker is alive in year $j+1$, is denoted by p_{j+1}. Conversely, the probability of its complement, $\overline{A_j}$, is given by $1-p_{j+1}$, conditional on the decision maker being alive in year j. The values of p_{j+1} for each age are derived from the *National Vital Statistics Reports* [24] and the mortality calculations derived in Section 1.5. These values are also known as the age-specific risks of death. Because the decision maker has not been diagnosed with diabetes, these probabilities are those calculated for an individual without diabetes.

The uncertainties associated with D_j are conditional on the event that the decision maker has not previously been diagnosed with diabetes and that the decision maker is alive in year j.

Given these events, the probability of being diagnosed with diabetes in year j is denoted d_j, and its complement, the probability of not being diagnosed with diabetes in year j is denoted $\overline{d_j}$. These values are drawn from the risks calculated in literature [21] and are modified according to the relative risk model discussed in Chapter 1. Recall that the relative risk of diabetes increases with sugar-sweetened beverage consumption [16, 17, 18]. This increase in risk causes the differentiation between the decision alternatives over sugar-sweetened beverage consumption.

It is worthwhile to note that the decision maker is assumed to be an individual who has not had a prior diagnosis of diabetes or of pre-diabetes. The probabilities developed herein follow this assumption. It is assumed that any individual who is diagnosed with diabetes follows the advice of his or her physician.

2.3 DECISION TREE

Decision trees are useful tools for graphically displaying the uncertainties, events, and possible outcomes of a given decision situation and are used here to illustrate the framework developed.

The model calculates the value of personal decisions based on the expected medical costs associated with that decision. Thus, only the negative consequences of each decision alternative are considered. As such, in this formulation, the decision not to consume sugar-sweetened beverages dominates the decision to consume them because the satisfaction and enjoyment of consumption are not included on the decision tree. Both the decision to consume and not to consume must be included, however, in order to determine the increase in costs due to a given decision alternative. The expected medical costs associated with each alternative are calculated, and the value of a particular decision alternative is the difference in costs between that alternative and the alternative with the minimum cost.

The decision tree is framed as a choice of whether or not to consume sugar-sweetened beverages at a given frequency for the remainder of one's life. Figure 2.1a illustrates all the possible alternatives faced by a decision maker, where *n* represents the frequency of sugar-sweetened beverage consumption per month.

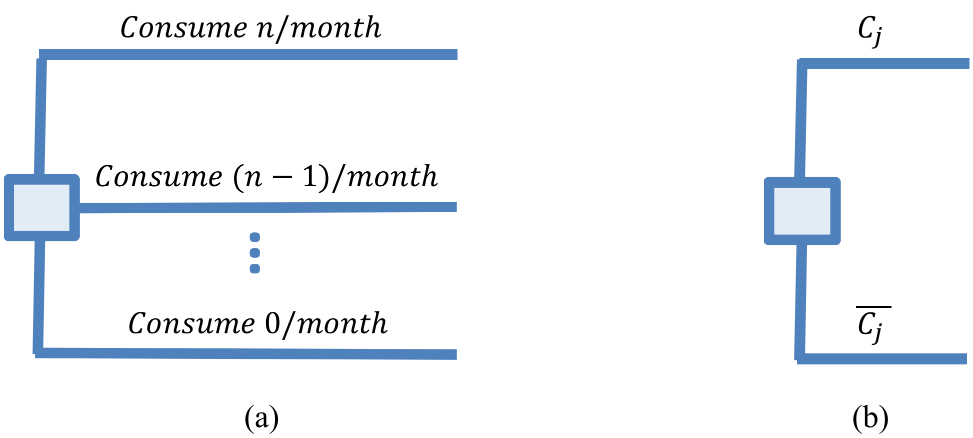

Figure 2.1. The decision alternatives.
(a) Considering consumption frequency.
(b) Simplification to two alternatives.

Alternatively, the decision tree can be simplified by only considering two alternatives at a time, to begin consumption of sugar-sweetened beverages at a given frequency at age *j*, denoted by C_j, or not to consume sugar-sweetened beverages for the remainder of one's life, denoted by $\overline{C_j}$. This simplification is illustrated in Figure 2.1b.

Given these alternatives, and the previously described distinctions and uncertainties, the full decision tree is derived using a sequential approach from age *j* through age 80. The decision maker chooses to begin consumption or not in year *j*. In the first year, the relative risk of diabetes is unaffected. At the start of year *j+1*, the decision maker is either still alive or not. Given that the decision maker is alive, he can either be diagnosed with diabetes or not. If after choosing alternative *C*, he is diagnosed with diabetes at age *j+1*, he faces expected medical costs, $E_C(M_{j+1})$, over his future life prospects. If he is not diagnosed, he progresses to year *j+2* where he again faces uncertainties over being alive or not and over being diagnosed with diabetes or not. Figure 2.2 illustrates the full decision tree, and Table 2.1 provides a summary of the notation for reference.

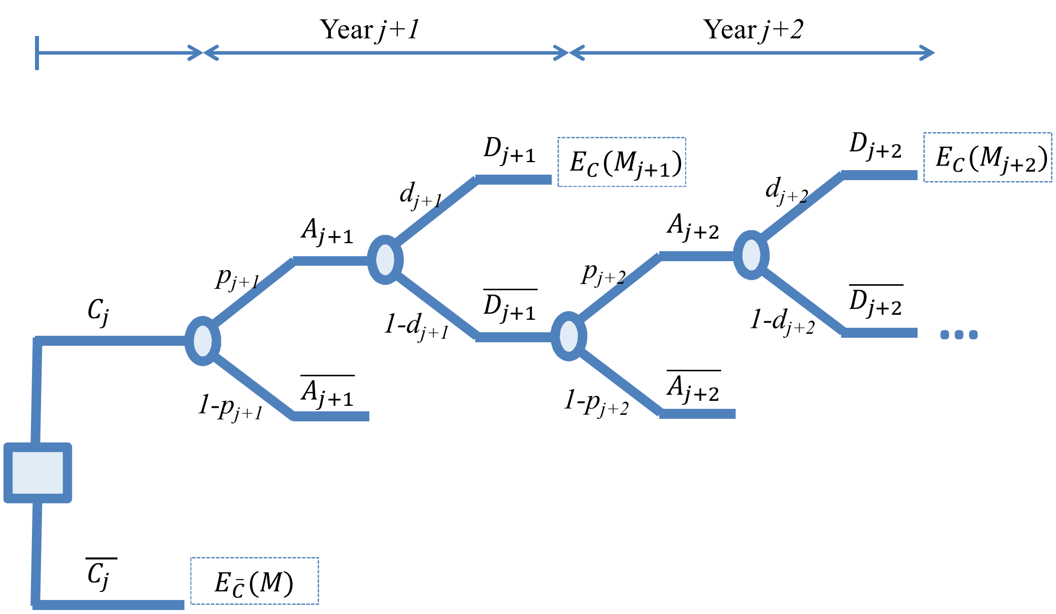

Figure 2.2. The decision tree illustrating the sequential uncertainties and events associated with the decision to consume sugar-sweetened beverages or not.

The sequential approach to the decision tree only continues through age 80 because the absolute risk of diabetes approaches zero at this age [21]. Once age 80 has been reached, the decision maker either has been diagnosed with diabetes or not and lives the remainder of his life in either of these two states. The remainder of life is considered through age 99. At this point, the probability of living longer than this is truncated in the probabilities considered.

$\boldsymbol{C_j}$	The alternative to begin a given frequency of consumption of sugar-sweetened beverages from age j onward
$\boldsymbol{\bar{C}_j}$	The alternative to not consume sugar-sweetened beverages from age j onward
$\boldsymbol{A_j}$	The event that the decision maker is alive in year j, given that he was alive in year j-1
$\boldsymbol{\overline{A_j}}$	The event that the decision maker is not alive in year j, given that he was alive in year j-1
$\boldsymbol{p_j}$	The probability that the decision maker is alive in year j, given that he was alive in year j-1
$\boldsymbol{D_j}$	The event that the decision maker is diagnosed with diabetes in year j, given that he is alive in year j and has not previously been diagnosed
$\boldsymbol{\overline{D_j}}$	The event that the decision maker is not diagnosed with diabetes in year j, given that he is alive in year j and has not previously been diagnosed
$\boldsymbol{d_j}$	The probability that the decision maker is diagnosed with diabetes in year j, given that he is alive in year j and has not previously been diagnosed
$\boldsymbol{E_C(M_j)}$	The expected lifetime medical costs associated with choosing alternative C and being diagnosed with diabetes at age j
$\boldsymbol{E_{\bar{C}}(M)}$	The expected lifetime medical costs due to diabetes associated with choosing alternative $\bar{C}$

Table 2.1. The notation used in the decision tree.

2.4 CALCULATIONS

The calculations determine the expected lifetime medical costs due to diabetes as mediated by a choice of behavior, such as drinking a sugar-sweetened beverage, are performed in stages. First, given a diagnosis of diabetes at age *k*, the expected medical costs for the future life prospect are calculated. Second, the probability of being diagnosed with diabetes at age *k* is calculated. Given these values, the overall expected lifetime medical costs attributable to the choice of behavior are determined.

Given the diagnosis of diabetes at age *k*, the expected future lifetime medical costs due to diabetes are calculated as illustrated in Figure 2.3. The lifetime medical costs incurred by diabetes depend on the age at which diabetes is diagnosed as well as on the age of death. Annual medical costs due to diabetes are assumed to be deterministic and constant, with an annual value of \$6,649 [25]. Given the age of diagnosis, k, and the age of death, i, the lifetime medical costs due to diabetes are denoted as $Cost_{k,i}$ and calculated as

$$6649(i-k)$$

The probability of dying in a future year i, where $i > k$, conditional on the decision maker being alive and diagnosed with diabetes in year k, is denoted by q_i where $\sum_i^{99} q_i = 1$. These probabilities are calculated based on mortality data from the *National Vital Statistics Reports* [24], the mortality calculations derived in Section 1.5, and the life table calculations described in Appendix B. Note that these probabilities are based on the mortality for an individual with diabetes, and that these mortality rates are double those for individuals without diabetes [1]. Given the additional medical costs associated with death at each age, the expected future lifetime medical costs due to diabetes are calculated as

$$\sum_{i=k}^{99} q_i Cost_{k,i}$$

These expected lifetime medical costs associated with choosing alternative C and being diagnosed with diabetes at age k are denoted $E_C(M_k)$.

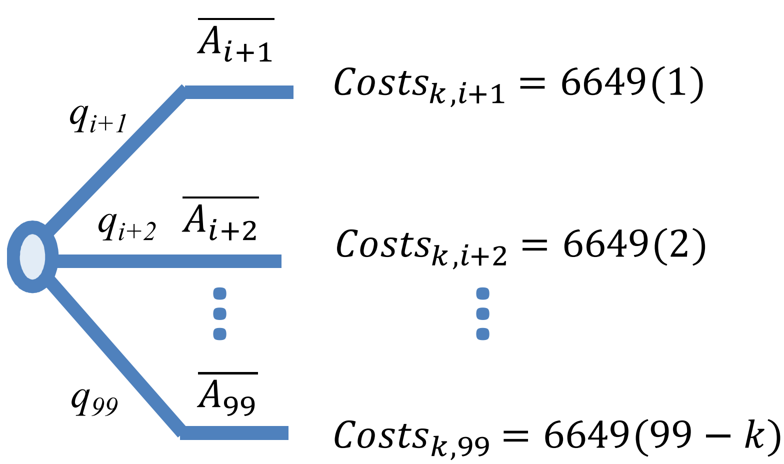

Figure 2.3. Calculating expected lifetime medical costs due to diabetes with diagnosis at age k.

The probability of being diagnosed with diabetes at age k is next determined. The probability of being diagnosed, conditional on the decision maker being alive and on not having been previously diagnosed, is determined as the product of the baseline risk of diabetes and the relative risk based on the individual's decision as described in Chapter 1. To determine the unconditional probability of being diagnosed at age k, $p(D_k)$, the following equation is used

$$p(D_k|A_k,\overline{D_{k-1}})p(A_k|A_{k-1})p(A_{k-1})p(\overline{D_{k-1}})$$

The probability of A_{k-1} and $\overline{D_{k-1}}$ is calculated as

$$\prod_{c=j}^{k-1} p(A_c)p(\overline{D_c})$$

where j is the age at which the individual makes a decision to consume sugar-sweetened beverages or not. These probabilities are calculated recursively, beginning with the fact that the decision maker is alive in year j, so that $p(A_j) = 1$, and also that the decision maker does not have diabetes in year j, so that $p(\overline{D_j}) = 1$.

Once the values of $p(D_k)$ are determined, the expected lifetime medical costs due to diabetes are the summation of the product of these probabilities by their respective expectations, $E_C(M_k)$. If no diagnosis of diabetes is made, then the additional medical costs due to diabetes are zero.

Finally, the expected lifetime medical costs due to the decision to consume sugar-sweetened beverages is calculated as the difference of the expected costs when the decision maker chooses to consume the beverages and when the decision maker chooses to abstain from consumption. The increase in cost is mediated by the increase in the relative risk of diabetes associated with the behavior. It is important to note that this model calculates the costs associated with a choice of behavior, not the expected lifetime medical costs due to diabetes.

2.5 DISCUSSION

The simplifying assumptions used in calculating the expected medical costs will have certain implications on the results. Because the additional medical costs due to complications of diabetes are not considered, the costs derived by this model will likely be underestimated. These costs provide useful lower bounds on costs. Additionally, sensitivity analysis to the average annual cost provides additional insight.

The model presented in this chapter enables insightful analysis into the cost associated with the personal decision to consume sugar-sweetened beverages. The framework is also widely applicable for any decision that impacts one's risk of developing diabetes.

The insights that may be derived include the impact of age at which one begins consuming sugar-sweetened beverages on the expected lifetime cost of the decision. The effect of relative risk and average annual medical costs due to diabetes can also be examined. Chapter 3 presents these analyses as well as other insights.

3. MEDICAL COSTS OF LIFESTYLE DECISIONS

3.1 INTRODUCTION

The cost of diabetes to society is estimated to have reached $117 billion in 2007 with increased direct medical costs of $116 billion [25]. The role of lifestyle decisions in the development of diabetes motivates the development of a model to determine the increase in expected lifetime medical costs associated with individual lifestyle decisions. Chapter 2 describes this model as applied to decisions on whether to consume sugar-sweetened beverages at a given frequency for the remainder of one's life. This problem formulation allows a variety of insightful analyses into the cost of personal decision making, and specifically, the cost of consuming sugar-sweetened beverages.

The distinction between the cost of diabetes and the cost of decision making is important. This model calculates the added expected cost as a result of lifestyle decision making. The values presented are not the total expected medical costs of diabetes for an individual.

Several parameters affect the expected lifetime costs associated with lifestyle decision making. For example, the age at which an individual decides either to begin consuming sugar-sweetened beverages or to abstain from consumption for the remainder of her life affects the number of years over which risks are increased. The frequency of sugar-sweetened beverage consumption also affects one's relative diabetes risk and thus expected costs. This chapter examines the effect of these parameters.

Model assumptions also affect the calculations, and the values of all inputs may not always be precisely known. Sensitivity analysis highlights how these factors influence expected medical costs.

This chapter presents the analysis of the model and answers several questions. Section 3.2 describes the increases in expected medical costs and how they are affected by both the decision maker's age and the frequency of consumption that is chosen. Section 3.3 examines the effect of relative risk. Section 3.4 explores the impact of changes in the average annual medical costs due to diabetes.

3.2 EXPECTED MEDICAL COSTS

The increase in expected medical costs due to sugar-sweetened beverage consumption is affected by both the age of the decision maker and the frequency of consumption that is chosen. These results are intuitive. By beginning sugar-sweetened beverage consumption at a later age, more years have passed without an increased risk. With fewer years of increased risk, and fewer expected years of life remaining over which to incur expenditures, the costs are reduced. The effect of the frequency of sugar-sweetened beverage consumption follows from the relationship between changes in consumption level and changes in relative risk. This change in risk for diabetes mediates changes in expected medical expenditures. Note also that other factors such as age and race affect one's baseline risk of diabetes and mortality risks, and thus the expected cost of lifestyle decisions. This section presents the expected lifetime medical costs due to sugar-sweetened beverage consumption specifically for females, all races.

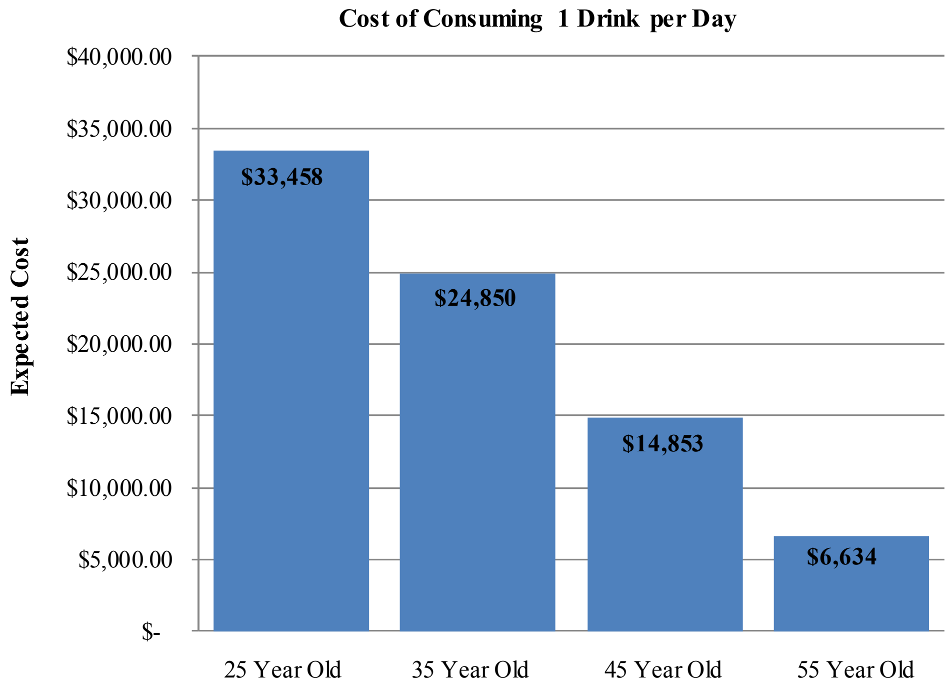

Figure 3.1. The cost of choosing to consume 1 sugar-sweetened beverage per day, by age.

The cost of beginning consumption of one sugar-sweetened beverage per day, as measured by increased lifetime medical expenditures, is $33,458 for a 25 year old female, $24,850 for a 35 year old female, $14,853 for a 45 year old female, and $6,634 for a 55 year old female. Figure 2.1 illustrates these differences. A 25 year old who postpones consumption of one drink per day until she is 35 years old saves $8,608 in expected medical expenditures. Delaying consumption until she is 55 years old saves $26,825 in expected cost. These results indicate that the cost of sugar-sweetened beverage consumption by young individuals is significantly greater than that of consumption by older individuals, and suggest that delaying consumption of sugar-sweetened beverages can yield significant savings in expected costs.

An individual may also choose to begin sugar-sweetened beverage consumption at a lower frequency than one per day which will result in a lower relative risk according to the relative risk model discussed in Chapter 1. The effect of consumption frequency depends on the age of the individual. These results are presented in Figure 3.2. For a 25 year old, the difference in expected medical costs between consuming one drink per day and consuming five per month is $27,413. For a 55 year old, the same difference in consumption level gives a cost difference of only $5,494, approximately one-fifth the savings of the 25 year old. These results suggest that consuming sugar-sweetened beverages in moderation can yield considerable savings in expected lifetime medical costs, but that these savings are significantly greater for younger individuals.

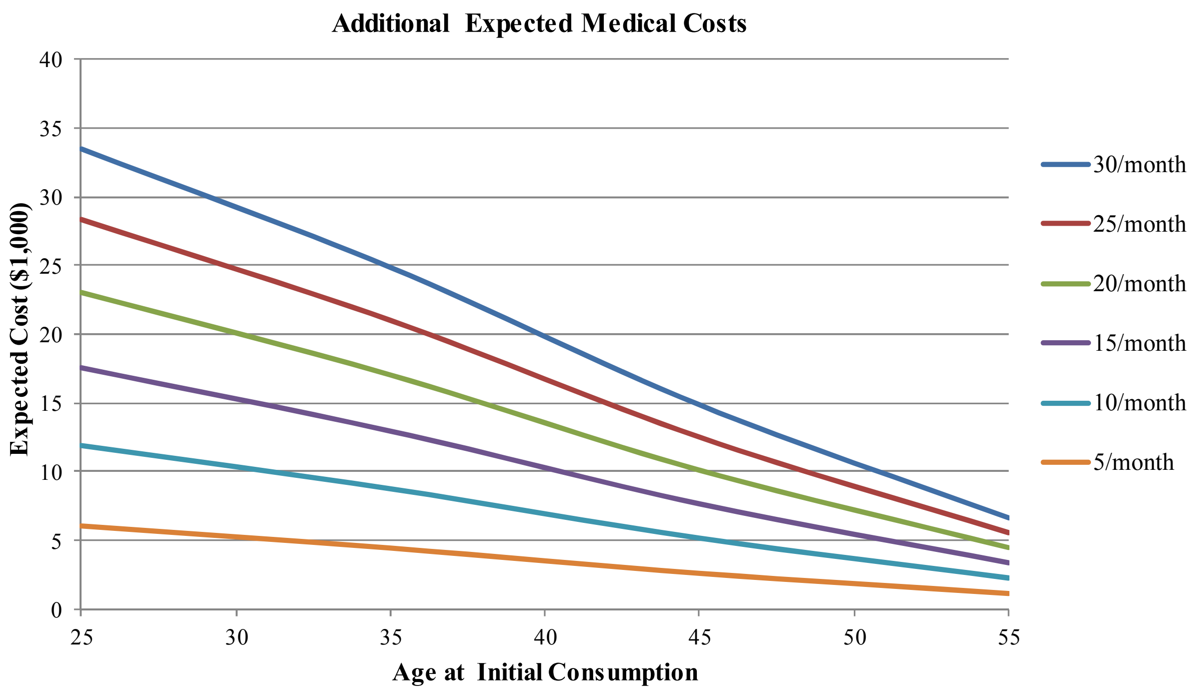

Figure 3.2. Increased expected medical costs by age and frequency of sugar-sweetened beverage consumption.

The effect on age is not linear. This is a result of the nonlinearity of the baseline hazard function for diabetes as illustrated in Figure 1.3, as well as a result of the increasing relative risk for a time period after beginning consumption, up to the saturation point.

3.3 SENSITIVITY TO RELATIVE RISK

An important input to calculating the cost of lifestyle decisions is the relative risk associated with these decisions. Previous research has investigated the relative risks associated with consuming sugar-sweetened beverages [16, 17, 18]. These results form the basis of the relative risk model presented in Chapter 1 and used in this analysis. Some of the research on the effects of sugar-sweetened beverages has come under criticism, particularly from the beverage industry [19]. In addition, some assumptions have been made in the relative risk model. As such, it is important to understand how changes in the relative risk used in the model affect the calculated expected costs.

As the relative risk of diabetes increases, so do the expected lifetime medical costs. The effect is dependent on age as illustrated in Figure 3.3. If the relative risk is 1, meaning that the risk is not increased over the baseline hazard, then the expected medical costs are zero. The expected costs for all ages begin at this point. As the relative risk increases, however, the effect is greater for younger individuals. The difference in medical costs between age groups is more exaggerated as the relative risk increases.

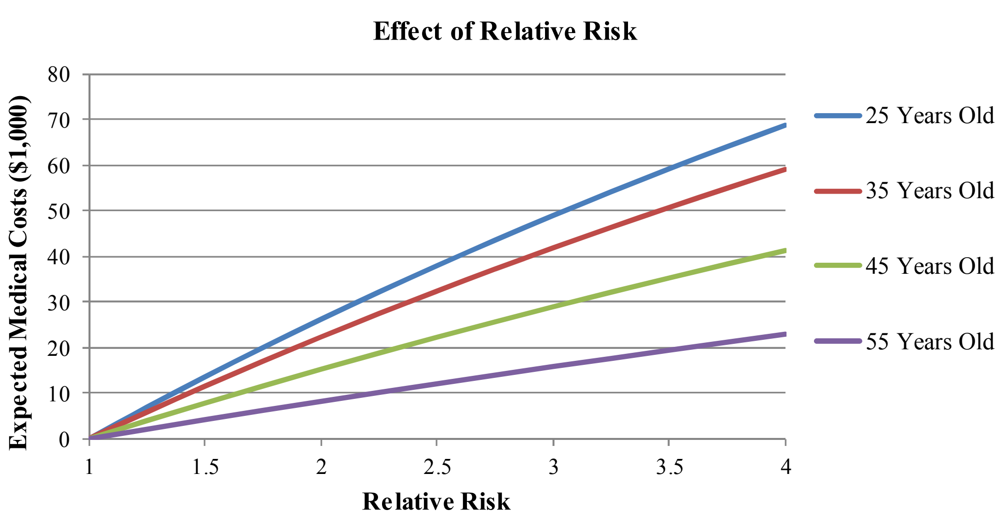

Figure 3.3. The effect of relative risk on expected medical costs, by age.

The expected medical costs are increased even for small increases in the relative risk. For a relative risk of 1.25, the additional expected medical costs are $6,897 for a 25 year old, $5,850 for a 35 year old, $3,957 for a 45 year old, and $2,099 for a 55 year old. Thus, even if the relative risks associated with sugar-sweetened beverages are lower than those reported in the literature, the expected lifetime medical costs due to sugar-sweetened beverage consumption are still sizable.

The effect of relative risk on expected lifetime medical costs is nonlinear. As the relative risk increases, the increase in expected medical costs is not as great. This relationship can be observed by plotting the slope of the increased costs against the relative risks as illustrated in Figure 3.4. Overestimating the relative risk will impact the expected costs calculated, but as the overestimation increases, its effect will decrease.

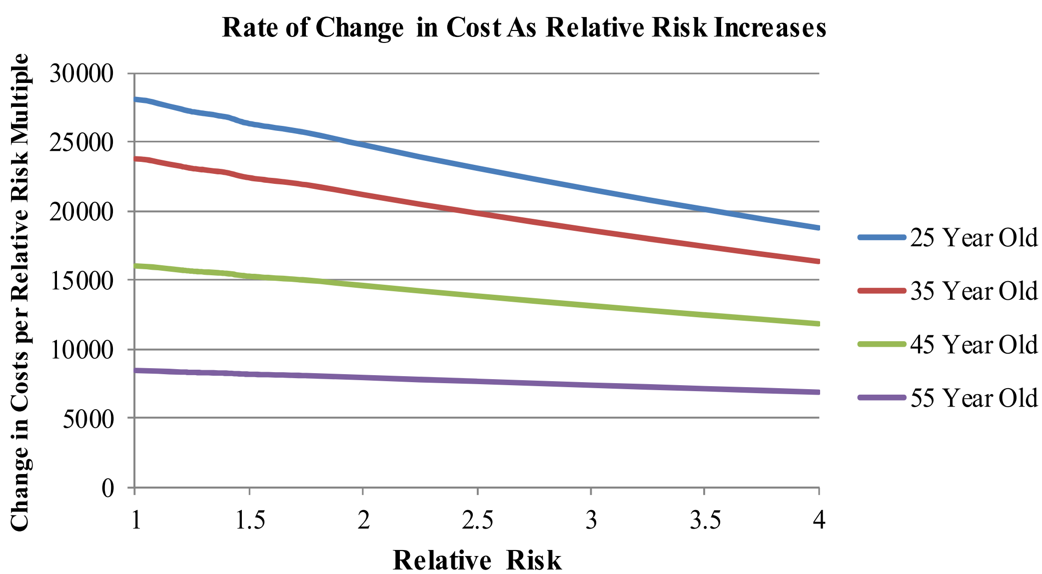

Figure 3.4. The rate of change in costs induced by changes in the relative risk.

Examining the results of the lifestyle decision model purely in terms of the relative risk associated with a particular behavior or risk covariate illustrates the usefulness of the model in calculating expected costs beyond those due to sugar-sweetened beverage consumption. Other factors that increase one's risk of diabetes that this model may be useful in analyzing include exercise level, body weight, and smoking.

3.4 SENSITIVITY TO ANNUAL MEDICAL COSTS

The additional expected medical expenditures calculated are based on the average annual cost of diabetes without complications. These costs are treated as deterministic once an individual is diagnosed. In reality, these medical costs may be variable, and will likely increase over time as complications develop due to diabetes. These complications include amputation, blindness, renal failure, cardiovascular disease, peripheral vascular disease, and neurological symptoms. Because none of these complications are taken into account, the calculated expected medical costs likely underestimate the true cost associated with lifestyle decisions.

The effect of greater annual medical costs on the additional medical costs due to drinking one sugar-sweetened beverage per day is illustrated in Figure 3.5.

If the annual medical costs attributable to diabetes increase from $6,649 to $10,000, then the cost of consuming a sugar-sweetened beverage per day increases to $50,321 for a 25 year old, $37,374 for a 35 year old, $22,339 for a 45 year old, and $9,977 for a 55 year old.

The effect of increasing the annual medical costs in this model is linear due to the assumption that costs are deterministic following a diagnosis of diabetes. The increased costs are multiplied by the same probabilities of life prospects when calculating the expected value. Thus it is possible to determine the increase in expected medical costs for each dollar that annual medical costs due to diabetes increases. These results are displayed in Figure 3.6. For a 25 year old, each dollar of annual spending on medical costs for diabetes increases expected costs by over 5 times when consuming a sugar sweetened beverage each day. For a 55 year old, each dollar increase in annual medical costs increases expected medical costs by just under a dollar.

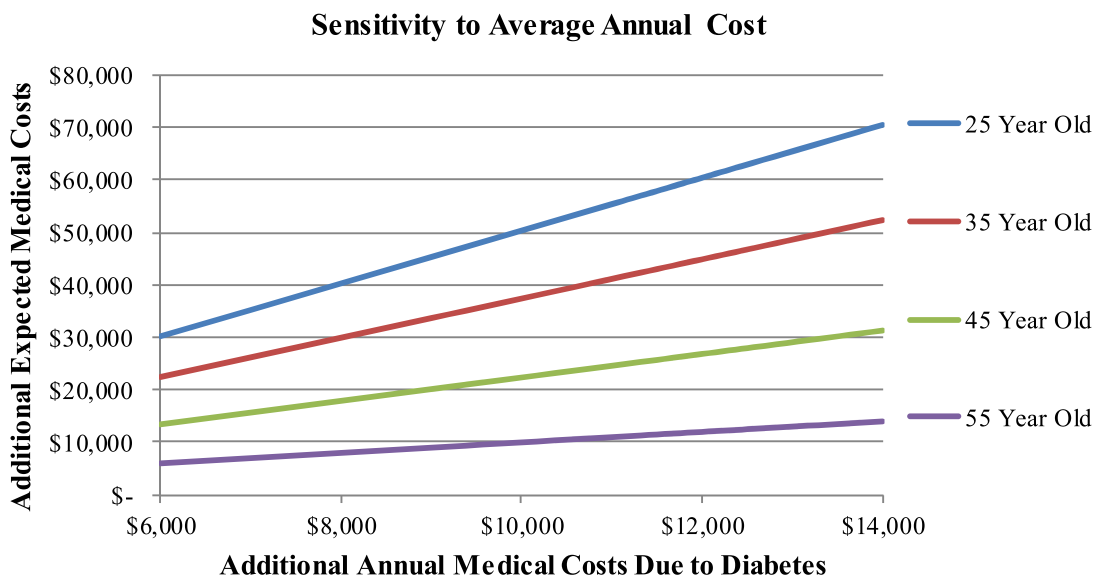

Figure 3.5. The effect of increased annual medical costs on medical expenditures due to drinking one sugar-sweetened beverage per day.

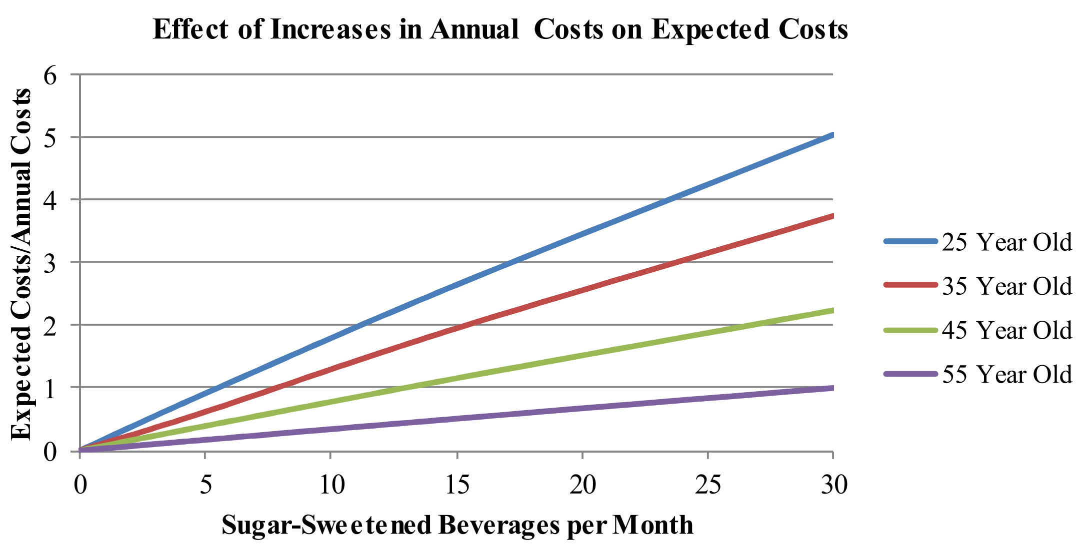

Figure 3.6. Increase in expected costs due to a dollar increase in annual medical costs as a function of sugar-sweetened beverage consumption and age.

4. IMPLICATIONS AND FUTURE WORK

4.1 IMPLICATIONS

The model developed herein has several implications in various fields including insurance, public health campaigns, and national health care spending. This section illustrates some of these implications in more detail.

4.1.1 Insurance

The previous work is of direct interest to insurance companies. The purpose of insurance is to protect individuals from risks that they face in the future. The insurance company needs to calculate the expected value of costs it will incur per individual insured. It is well known that certain behaviors such as smoking lead to increases in life insurance levels due to the increase in relative risk. This is why insurance companies analyze the effects of smoking on medical costs and charge a premium for smokers. Similarly, the analysis shows how the consumption of a sugar-sweetened beverage each day increases expected lifetime medical costs. For example, insurance companies can expect an increase in these costs equal to $33,000 for a 25 year old female.

The level of co-insurance offered is also of interest. The issue of moral hazard is well known in the medical insurance industry. Moral hazard exists for individuals when they do not face the consequences of behaviors that lead to increased costs, such as the case with health insurance where some of the consequences of unhealthy behaviors are transferred to the insurance company. For example, an individual knows whether or not he has decided to drink a sugar-sweetened beverage per day whereas the insurance company may not. As such, he may seek a higher level of insurance. To combat this, insurance companies often do not offer insurance at 100% of costs, requiring the individual to share the burden of costs. This practice is known as co-insurance and is used to reduce moral hazard. Insurance companies can use the cost of lifestyle decisions to guide policies on co-insurance.

4.1.2 National Health Care Spending

Spending on medical care in the U.S. has been increasing dramatically for decades, with spending in 2008 reaching $2.3 trillion [26]. Given these trends, it would be significant to know how much of that spending is a result of lifestyle decisions. The model and analysis presented in this thesis make such determinations possible.

To calculate the expected costs in the United States that are a result of individual decision making, it is necessary to know how many individuals are consuming sugar-sweetened beverages and at what frequency. Such research has been conducted using the National Health and Nutrition Examination Survey and found that on average, 63% of U.S. adults consume an average of 17 oz of sugar-sweetened beverages per day [27]. Using this statistic along with 2010 US census data [28], it is possible to multiply the number of residents in each age category by the percentage who consume a sugar-sweetened beverage each day and by the expected medical costs that result. For example, using ten-year age cohorts for the population, for ages 20-29, 30-39, 40-49, and 50-59, and the expected medical cost of the midpoint age of each group, one finds that the expected medical costs due to sugar-sweetened beverage consumption, over the 80 years it takes for the youngest individual in this group to reach age 100, are $2.1 trillion. This amount averages out to over $28 billion per year. Note that this calculation assumes each individual only begins consuming sugar-sweetened beverages at the current age and does not account for previous consumption. This calculation also only considers those adults who are between the ages of 20 and 59 and does not consider costs accrued by individuals who are currently under age 20 and will become adults in the next 80 years.

4.1.3 Public Health Awareness Campaigns

Public health awareness campaigns are used to educate the public about issues related to health that may be beneficial. Education about behaviors that are within the public's control can lead to improvement in health measures nationwide. Being able to calculate the expected medical costs associated with lifestyle behaviors enables better planning for public health awareness campaigns. For example, if it is known that the expected costs of a 25 year old beginning consumption of sugar-sweetened beverages is $33,458, then a campaign that costs less than $33,458 times the number of individuals who will stop their consumption as a result of the campaign will be cost effective.

4.2 FUTURE WORK

The model presented in this thesis calculates the expected medical costs that result from sugar-sweetened beverage consumption, and can also be used to calculate medical costs associated with any behavior that increases one's relative risk of diabetes. As shown in this chapter, this information is useful in a range of applications. The model, however, can be further expanded to take into account additional factors including the effect of lifestyle decisions from a personal decision making perspective.

Diabetes has a significant impact on the mortality rates faced by an individual. These increased hazards are taken into account in calculating the years over which increased medical costs are incurred. However, the loss of life itself is a significant alteration in the life prospects faced by an individual. If one is interested in calculating the value of these decisions, outcomes such as length of life that are of utmost importance to an individual must be taken into account. Howard has proposed a function to model tradeoffs between annual consumption, c, and length of life as measured as the ratio of life years remaining, l, to life expectancy $\bar{l}$ [4]. Given a tradeoff parameter, η, and a risk aversion γ, the individual's utility over life prospects becomes

$$u(c,l) = -\exp\left(-\gamma c \left({}^{l}/_{\bar{l}}\right)^{\eta}\right)$$

The framework for determining the cost of lifestyle decisions can be extended using a similar approach to determine the personal value of decision making. Including the effect of decisions on length of life leads to the value of personal decisions because the individual will be facing the consequences of the decision, unlike the present calculation of expected medical costs which may or may not be borne by the individual. The risk preferences and tradeoffs acceptable to the individual will be instrumental in determining the value to the decision maker.

The role of obesity also has a significant impact on life prospects. Obesity is correlated with diabetes but also independently increases an individual's risk of numerous negative outcomes, including medical costs and mortality among others [29]. Obesity, like diabetes, is strongly influenced by personal decision making, and is also linked to sugar-sweetened beverage consumption [16]. Additional analysis on medical costs as well as the value of personal decision making due to obesity is possible. Including such considerations in the cost of the decision to consume sugar-sweetened beverages would likely increase the calculated expected costs. Future work is needed to determine the magnitude of these costs as well as their wider implications.

The results of this analysis that show significant costs associated with the decision to consume sugar-sweetened beverages should not be surprising. Significant literature and warnings exist on the consumption of excess sugar in one's diet as well as the consumption of sugar-sweetened beverages specifically. These findings are so significant that petitions have even been filed with the U.S. Food and Drug Administration requesting that warning labels be placed on beverages containing more than 1.1 gram of sugar per ounce [30]. The results of this model and analysis further indicate that significant costs are associated with sugar-sweetened beverage consumption.

REFERENCES

1. Centers for Disease Control and Prevention. 2011. National diabetes fact sheet: national estimates and general information on diabetes and prediabetes in the United States. Atlanta, GA: U.S. DHHS, CDC, 2011.
2. Hu, F.B, J.E. Manson, M.J. Stampfer, G. Colditz, S. Liu, C.G. Solomon, W.C. Willett. 2001. Diet, lifestyle, and the risk of type 2 diabetes mellitus in women. *New England Journal of Medicine*. 345(11): 790-797.
3. American Diabetes Association. 2006. Nutrition Recommendations and Interventions for diabetes-2006. *Diabetes Care*. 29(9): 2140-2157.
4. Howard, R.A. 1984. On fates comparable to death. *Management Science*. 30(4): 407-422.
5. Shepard, D.S, R.J. Zeckhauser. 1984. Survival versus consumption. *Management Science*. 30(4): 423-439.
6. Bleichrodt, H, J. Quiggin. 1999. Life-cycle preferences over consumption and health: When is cost-effectiveness analysis equivalent to cost-benefit analysis? *Journal of Health Economics*. 18(6): 681-708.
7. Smith, J.E, R.L. Keeney. 2005. Your money or your life: A prescriptive model for health, safety, and consumption decisions. *Management Science*. 51(9): 1309-1325.
8. Loomes, G, L. McKenzie. 1989. The use of QALYs in health care decision making. *Social Science in Medicine*. 28(4): 299-308.
9. Hazen, G.B. 2007. Adding extrinsic goals to the quality-adjusted life year model. *Decision Analysis*. 4(1): 3-16.
10. Keeney, R.L. 2008. Personal decisions are the leading cause of death. *Decision Analysis*. 56(6): 1335-1347.
11. Cox, D.R. 1972. Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological).* 34(2): 187-220.
12. Cox, D.R. 1984. Analysis of Survival Data. New York: Chapman and Hall.
13. Colditz, G.R, W.C. Willett, M.J. Stampfer, J.E. Manson, C.H. Hennekens, R.A. Arky, F.E. Speizer. 1990. Weight as a risk factor for clinical diabetes in women. *American Journal of Epidemiology*. 132(3): 501-513.
14. Rimm, E.B, J.E. Manson, M.J. Stampfer, G.A. Colditz, W.C. Willett, B. Rosner, C.H. Hennekens, F.E. Speizer. 1993. *American Journal of Public Health*. 83(2): 211-214.
15. Perry, I.J, S.G. Wannamethee, M.K. Walker, A.G. Thomson, P.H. Whincup, A.G. Shaper. 1995. Prospective study of risk factors for development of non-insulin dependent diabetes in middle aged British men. *British Medical Journal*. 310(4): 560-564.

16. Schulze, M.B, J.E. Manson, D.S. Ludwig, G.A. Colditz, M.J. Stampfer, W.C. Willett, F.B. Hu. 2004. Sugar-sweetened beverages, weight gain, and incidence of type 2 diabetes in young and middle-aged women. *Journal of the American Medical Association*. 292(8): 927-934.

17. Montonen, J, R. Jarvinen, P. Knekt, M. Heliovaara, A. Reunanen. 2007. Consumption of sweetened beverages and intakes of fructose and glucose predict type 2 diabetes occurrence. *Journal of Nutrition*. 137(6): 1447-1454.

18. Palmer, J.R, D.A. Boggs, S. Krishnan, F.B. Hu, M.S. Singer, L. Rosenberg. 2008. *Archives of Internal Medicine*. 168(14): 1487-1492.

19. American Beverage Association. 2004. No one food increases the risk for type 2 diabetes. *ABA News Releases and Statements*. Online. < http://www.ameribev.org/news--media/news-releases--statements/more/34/>. Accessed Nov 2011.

20. Hu, F.B, M.J. Stampfer, E. Rimm, A. Ascherio, B.A. Rosner, D. Spiegelman, W.C. Willett. 1999. Dietary fat and coronary heart disease: A comparison of approaches for adjusting for toal energy intake and modeling repeated dietary measurements. *American Journal of Epidemiology*. 149(6): 531-540.

21. Narayan, K.M, J.P. Boyle, T.J. Thompson, S.W. Sorensen, D.F. Williamson. 2003. Lifetime risk for diabetes mellitus in the United States. *Journal of the American Medical Association*. 290(14): 1884-1890.

22. The Emerging Risk Factors Collaboration. 2011. Diabetes mellitus, fasting glucose, and risk of cause-specific death. *The New England Journal of Medicine*. 364: 829-841.

23. Adlerberth, A.M, A. Rosengren, L. Wilhelmsen. 1998. Diabetes and long-term risk of mortality from coronary and other causes in middle-aged Swedish men. *Diabetes Care*. 21(4): 539-545.

24. Arias, E. 2010. Unites States Life Tables, 2006. *National Vital Statistics Reports.* 58(21): 1-40.

25. American Diabetes Association. 2008. Economic costs of diabetes in the U.S. in 2007. *Diabetes Care*. 31: 596-615.

26. Centers for Medicare and Medicaid Services. 2010. National Health Care Expenditures Data. Online. <https://www.cms.gov/nationalhealthexpenddata/01_overview.asp>. Accessed Nov 2011.

27. Bleich, S.N, Y.C. Wang, Y, Wang, S.L. Gortmaker. 2009. Increasing consumption of sugar-sweetened beverages among US adults: 1988-1994 to 1999-2004. *American Journal of Clinical Nutrition*. 89: 372-381.

28. Howden, L.M, J.A. Meyer. 2011. Age and sex composition: 2010. *2010 Census Briefs*. Online. <http://www.census.gov/prod/cen2010/briefs/c2010br-03.pdf>. Accessed Nov 2011.

29. Pi-Sunyer, F.X. 2002. The obesity epidemic: Pathophysiology and consequences of obesity. *Obesity Research*. 10: 97S-104S.

30. Jacobson, M.F. 2005. Jacobson, M.F. 2005. Petition to require health messages on soft drinks containing high-fructose corn syrup and other caloric sweeteners. Online. <http://www.cspinet.org/new/pdf/final_soda_petition.pdf>. Accessed Nov 2011.