ASSESSING DIFFERENCES IN PERCEPTIONS AND ACTUAL HEALTH STATUS: A NATIONAL CROSS-SECTIONAL ANALYSIS

by

KARA ROSS

B.Sc., University of Guelph, 2003
M.S., Kansas State University, 2005

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2010

Abstract

Public health policies seek to address health issues that pose significant concerns to public health policymakers. Because these initiatives have economic costs, economic agents' response to them would be driven by the outcome of their benefit-cost assessment of the policies. Therefore, the congruence between perception and reality of economic agents' health becomes important in evaluating the potential effectiveness of these initiatives.

This research sought to determine the extent of congruence between objective and subjective health status at the individual level. The results would contribute to the framing and implementation of health policies that have higher probability of adoption by economic agents.

The National Health and Nutrition Examination Survey (NHANES) 2005-2006 data were used for this research. The dependent variables defined in the study are subjective health status perception and objective metrics of individuals' health status proxied by their body mass index (BMI), waist circumference, high density lipoprotein (HDL) cholesterol level, and fasting blood glucose. The nature of these dependent variables demanded that both categorical dependent variable and ordinary least squares models be employed in the estimation of the models. Chow tests were used to determine the extent of congruence between perception and reality of respondents' health status.

The study did not find any differences between perception and reality based on waist circumference but the same could not be said about BMI. Additionally, there were differences between subjective health perceptions and objective measures of health status based on receiving information about their health status from a health care professional.

If it is assumed that the cost of responding to health policies are reduced with higher congruence between subjective and objective health status, then this study's results suggest that

policy must begin with increasing the objective information that people have about their health. While the provision of this information at the individual level could be expensive, it will improve the success rate of health promotion initiatives. The increase in these initiatives' success should contribute to a reduction in the nation's health care costs attributable to lifestyle related diseases such as obesity.

ASSESSING DIFFERENCES IN PERCEPTIONS AND ACTUAL HEALTH STATUS: A NATIONAL CROSS-SECTIONAL ANALYSIS

by

KARA ROSS

B.Sc., University of Guelph, 2003
M.S., Kansas State University, 2005

A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2010

Approved by:

Major Professor
Vincent Amanor-Boadu

Copyright

Abstract

Public health policies seek to address health issues that pose significant concerns to public health policymakers. Because these initiatives have economic costs, economic agents' response to them would be driven by the outcome of their benefit-cost assessment of the policies. Therefore, the congruence between perception and reality of economic agents' health becomes important in evaluating the potential effectiveness of these initiatives.

This research sought to determine the extent of congruence between objective and subjective health status at the individual level. The results would contribute to the framing and implementation of health policies that have higher probability of adoption by economic agents.

The National Health and Nutrition Examination Survey (NHANES) 2005-2006 data were used for this research. The dependent variables defined in the study are subjective health status perception and objective metrics of individuals' health status proxied by their body mass index (BMI), waist circumference, high density lipoprotein (HDL) cholesterol level, and fasting blood glucose. The nature of these dependent variables demanded that both categorical dependent variable and ordinary least squares models be employed in the estimation of the models. Chow tests were used to determine the extent of congruence between perception and reality of respondents' health status.

The study did not find any differences between perception and reality based on waist circumference but the same could not be said about BMI. Additionally, there were differences between subjective health perceptions and objective measures of health status based on receiving information about their health status from a health care professional.

If it is assumed that the cost of responding to health policies are reduced with higher congruence between subjective and objective health status, then this study's results suggest that

policy must begin with increasing the objective information that people have about their health. While the provision of this information at the individual level could be expensive, it will improve the success rate of health promotion initiatives. The increase in these initiatives' success should contribute to a reduction in the nation's health care costs attributable to lifestyle related diseases such as obesity.

Table of Contents

List of Figures

List of Tables

Acknowledgements

First and foremost, I would like to express my gratitude to my advisor Dr. Vincent Amanor-Boadu for his guidance, advice, patience, and support. I am extremely grateful to him for encouraging me to study at Kansas State University. He has been an excellent teacher, mentor, and friend over the years. He has introduced me to ideas and concepts that have forever changed the way I view the world and everything in it. All I can say is a simple thank you for making me a better student, researcher, and person.

I would also like to thank my committee members, Dr. Yang Ming Chang, Dr. Sean Fox, and Dr. Hikaru Peterson, and Dr. David Dzewaltowski, for their support and encouragement throughout this research process. Their perspectives and helpful suggestions have improved the quality of this research.

I would like to extend my gratitude to Dr. Carol Shanklin, Dr. Kevin Lease, Megan Miller, Courtney George, and the rest of the Graduate School team for their encouragement, support, and friendship. Working with you has been a pleasure and I am grateful for the opportunities you have given me.

Thank you to all of my K-State colleagues, Steven Bellinger, Paul Clark, Dr. Kelly Chen, Pedro Garay, Dr. Alexandra Gregory, Amélie Jouault, Dr. Daniel Kuester, Mohan Reddy, Jeri Stroade, Dr. Leah Tsoodle, Chi-Yin Wu, and Dr. Yacob Zereyesus for their unending, encouragement, support, and friendship. A special thanks to Dan, Jeri, Leah, Paul, and Steven for willing to discuss and proof-read my research. Your help is sincerely appreciated.

I would like to thank the Department of Agricultural Economics and the Graduate School at Kansas State University for funding me throughout my graduate school career.

A final thank you goes to my family. Without fail, they have always been there for me, and I am grateful for their love and support. Their belief in me makes accomplishing the impossible possible. I am incredibly fortunate to have such an amazing family.

Dedication

To my mom and sister

Chapter 1 - Introduction

Public health initiatives aim to address health issues that are posing a significant concerns for policy makers. For instance, numerous international and national health campaigns, such as "MyPyramid" and "The Global Strategy on Diet, Physical Activity and Health," have been developed to address concerns about the prevalence of lifestyle related health conditions such as obesity and Type II diabetes. These concerns are, in part, driven by the economics of health care. For example, the estimated total cost of obesity in the US in 2000 was $117 billion, of which $61 billion was related to direct medical costs such as services provided by health care professionals and $56 billion for indirect costs, such as income lost from decreased productivity and future earnings lost by premature death (Wolf and Colditz, 1998). The estimated cost of obesity was as high as $147 billion in 2008 (Finkelstein et al., 2009).   The American Heart Association (2010) estimated that the direct and indirect cost of cardiovascular diseases (CVD) and stroke in the US in 2009 was $475.3 billion The Centers for Disease Control and Prevention (CDC) project that these costs will increase to $503 billion in 2010 (CDC, 2010). For diabetes, the estimated total cost in 2007 for diagnosed diabetes in the US was $174 billion with direct costs estimated to be $116 billion and the indirect costs were estimated to be $58 billion (CDC, 2008). Medical care expenditures are estimated to be 2.3 times higher for a diabetic individual compared to that of a non-diabetic (CDC, 2008).

Gaps between perceived and real health statuses may contribute to some of the costs associated with these diseases because they can lead to the mismanagement of preventable health conditions. The costs associated with preventative measures for such chronic diseases as those initiated by obesity and Type II diabetes are less expensive than the cost associated with curing those chronic diseases. Because the prevention of these diseases generally require behavioral or lifestyle modifications, their economic costs often exceed their accounting costs, requiring that benefits are structured to be higher if those costs are going to be borne.

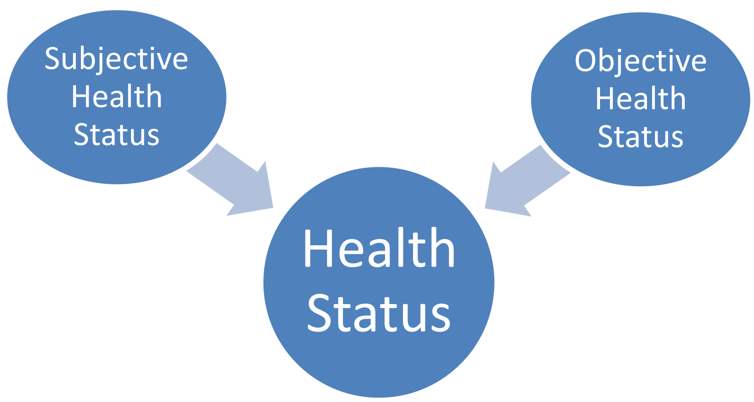
A properly designed and implemented public health campaign can produce successful results. For instance, the US Department of Health and Human Services' *Healthy People 2000* initiative was successful in obtaining its goal of reducing infant mortality, teenage pregnancy, death rates associated with coronary heart disease and stroke, and the incidence of unintentional injuries. Advancements in cancer diagnosis and treatment have been made and childhood vaccination levels are at their highest recorded rate in the US. However, some health problems, such as diabetes, obesity, and other chronic health conditions, continue to pose a large concern. Yet, perception influences the evaluative analysis conducted by individual decision-makers. In the absence of coercion, economic agents select actions that enhance their well-being based on the information they have or choose to use (Mises, 1963). Intervention policies and programs can only be effective if they are aligned with the perceptive variables determining or influencing individual action (Weick, 1995).

The extent of to which an individual's perception of self condition may deviate from their actual condition may cause tension in cognitive situation, a tension that Festinger (1957) referred to as cognitive dissonance The distress associated with cognitive dissonance has been found to cause people to sometimes act to avoid awareness of information that could lead to cognitive dissonance (Bailis, Segall, and Chipperfield, 2003). A person can avoid feedback that may not be in line with their self-view such as focusing, or active striving, on important self-relevant domains (Cantor and Kihlsotrom, 1987); selective interaction and comparisons to others (Taylor and Lobel, 1989; Tesser and Campbell, 1984); and selective attention to and biased interpretation of the feedback provided by others (Greenwald, 1980; Markus, 1977). Through the use of active striving and cognitive buffering mechanisms, people can ensure a degree of consistency between their self-perception and empirical information on the subject that is broadly adaptive for human functioning (Antonovsky, 1987; Ryff and Singer, 1998; Schulz and Heckhausen, 1996; Steele, 1988).

It is important to understand how perceptions are formed since perceptions play a large role in a person's decision-making process. Perception is the process by which humans arrange sensory stimulation into organized, meaningful experiences (Lindsay and Norman, 1977). It is a complex outcome of past experiences, culture, environment, and sensemaking (Weick, 1995). By definition, perceptions are subjective and are likely to deviate from reality more frequently than not (Fiske and Taylor, 1984; Nisbett and Ross, 1980). The gap between perception and reality could make a difference in the compliance of preventative measures and curative healthcare recommendations and ameliorating the identified health conditions.

Advancements in screening programs have been motivated by the belief that early detection could lead to prevention or at least delay the onset of long-term health effects (Engelgau, Venkat Narayan, and Herman, 2000). Although early detection programs may help with illness detection, success in disease prevention or delaying the onset of disease is completely dependent on the patient's acceptance of the information learned from screening for the illness and their ability and willingness to engage in proper self-care (Thoolen et al., 2008). These programs, along with public health policies, tend to be focused on objective health measures that provide tangible measurements such as waist circumference measurements and cholesterol levels. It is because these objective measurements provide a clear benchmark for analysis that they are used in public health initiatives and programs.

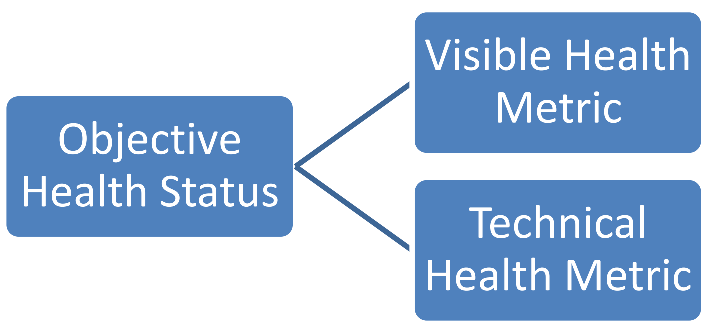
Figure 1.1: Schema of the Components of Health Status



Subjective health measures such as self-reported health status are the result of a complex aggregation process, involving information and weights known only to the individual, consciously and sub-consciously. Subjective health measures are rarely used as a determining factor in these programs and policies. For example, early detection programs for Type II diabetes are based on fasting blood glucose and not on how an individual reports their health status. However, it is expected that these two measures, objective and subjective, will reinforce each other to create a single health status perception for an individual (Figure 1.1). Unfortunately, there is evidence that this is not always the case, which leads to the gap between perception and reality. For example, Hardley and Cunningham (2005) observe that people without health insurance are as likely to perceive a need for care but only half as likely to get care.

Both subjective and objective health statuses are assumed to be functions of socio-economic and behavioral factors. Subjective health status is measured by an individual's self-reported health status. Objective health status is defined by visible and technical health metrics (Figure 1.2). Visible health metrics are health characteristics that provide sensory feedback to individuals (e.g., fever, rash, or increased waist measurement), while technical health metrics tend not to provide overt feedback (i.e., tend to be asymptomatic).

Figure 1.2: Schema of the Components of Health Status



Research Question

The concept of health is complicated (Blaxter, 1990; Brannon and Feist, 2010). It involves both subjective and objective metrics that individuals place different weights on in their assessment of their individual health status. Evaluating health status can be complicated because of the effect of asymptomatic as well as psychological challenges, e.g., hypochondriacs. The challenge is exacerbated by the incongruent health status opinions between individuals and their health care providers (Sen, 2002) and by their economic and social status (US DHHS, 2000). For example, the anxiety resulting from cognitive dissonance may contribute to people avoiding information that would cause them to alter their lifestyles. In addition, participation in early detection programs may lead to results that demand of individuals to change significant behavioral components.

The challenge of understanding the factors influencing specific subjective health perceptions health remain and understanding their influence could aid policy makers in their design and implementation efforts. Therefore, the research question for this study is this: What are the characteristics of individuals that cause their subjective health status to differ from their objective status?

Objectives

The overall objective of the study is to identify factors that may explain the differences between subjective and objective health status and to determine whether information about certain health metrics influences an individual's health status perception. The specific objectives of the study are as follows:

1. To identify the factors influencing subjective and objective health statuses and to conduct comparisons between two different groups – health risk and non-health risk groups

2. To determine if information from certain health metrics is incorporated into an individual's health evaluation.

3. To use the results to provide a framework for policy development.

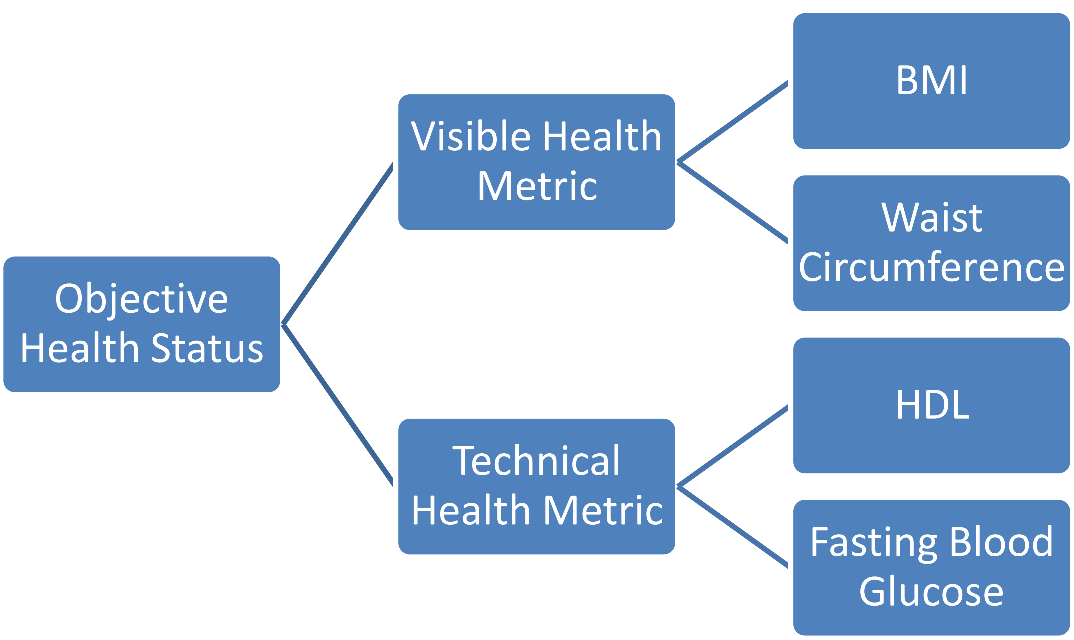
From a health promotion perspective, understanding the differences in the factors influencing subjective and objective health status can provide more effective policies. These findings can be used to better understand how to achieve a higher level of public health program adoption and effectiveness. Additionally, by determining which factors significantly influence perceptions of one's health status, policy makers could focus their efforts towards those factors that have a significant impact on health perceptions, which may lead to participation in early detection programs and healthy lifestyle behaviors. Conversely, findings from this study will provide insight into which factors do not influence health perceptions, and thus should not be employed in behavior motivating strategies or strategies to align self perceptions with reality. The development and implementation of effective and informed health promotion strategies are vital to the improvement in the overall health of a population.

Method Overview

The 2005-2006 data from the National Health and Nutrition Examination Survey (NHANES) was used to address the research objectives. Analysis of the subjective models involved estimation of categorical outcome models. The objective health metric models were estimated by linear regression models. Chow tests were used to determine if perception differences exist among the different health risk groups.

In the subjective models, the effect of socio-economic and behavioral variables on self-reported health status perception is explored. Socio-economic variables include gender, age, marital status, education, and annual household income. Behavioral variables consist of perceived diet quality, exercise, physical fitness comparisons, smoking, alcohol consumption, and frequency of health care professional visits (e.g., visiting a doctor). For the objective health metric models, the effect of the same socio-economic and behavioral variables on specific objective health metrics are investigated. Four health metrics are used separately to define objective health status. They are based on the risk factors associated with metabolic syndrome. Metabolic syndrome is a cluster of cardiovascular and Type II diabetes risk factors such as body mass index (BMI) and fasting blood glucose. These risk factors are further segmented into visible health metrics and technical health metrics (Figure 1.3). The visible health metrics are BMI and waist circumference. High density lipoprotein (HDL) and fasting blood glucose represent the technical health metrics. BMI, waist circumference, HDL, and fasting blood glucose are treated as objective health status variables because there is a strong correlation between these four health metrics and metabolic syndrome in the scientific literature (Grundy et al., 2004).

Figure 1.3: Schema of the Specific Health Metrics used to Measure Objective Health Status



In determining if information from a particular health metric is incorporated into one's subjective health assessment, a comparison of health perceptions between two different health risk groups - the health risk group and the non-health risk group – is conducted. It is assumed that people are aware of these visible health metrics and deliberately include this information in their assessment of their health status. If this assumption is correct, then it is concluded that information from the visible health metric is used in the evaluation of their health status.

In the case of technical health metrics, critical health information regarding this metric may not be known by the individual. That is, these technical health metrics tend not to give any distinct bio-feedback signals to the individual unlike visible health metric, such as body fat around the waist, would. This non-distinct feedback system may contribute to an information gap, which could lead to a low awareness of potential health risks by the individual. However, an individual may become aware of these potential health risks through information shared with them by a health care professional.

In Chapter 2, a relevant literature review is given. Following this, Chapter 3 provides a description of the conceptual model that supports the empirical approach, an explanation of the econometric method, and a discussion of the NHANES 2005-2006 data. Chapter 4 presents the results from the analyses, and Chapter 5 provides a summary of the notable findings and discusses possible implications of this study. In the final chapter, Chapter 6, conclusions from the study are presented.

Chapter 2 - Literature Review

As was noted in the previous chapter, health is a complicated concept, with physical and mental, social and economic, and technical and environmental dimensions. It was also argued that perception influences health status and how people responded to policy interventions and other solutions. Finally, it was argued that both self-reported health status and objective health status were outcomes of the socio-economic and behavioral situation of the individual. The background to these arguments is presented in this chapter.

This chapter is organized into three sections: health definition, perception and decision making, and self-reported health status. The first section addresses two questions: (1) What is health? (2) Why is it important to study health? The second section examines the concept of perceptions and their role in the decision making process. The review primarily focuses on self-perception because of the involvement of the self in assessing one’s health status. In the third and final section, the literature surrounding factors affecting self-reported health status is summarized, providing a context for understanding the complexity of developing effective policy responses to current and emerging health challenges.

What is Health?

Health Definition

Health is both a resource (Grossman, 1972) and a good (Rout and Nayak, 2007). As a resource, health allows individuals to achieve their economic and social objectives. Healthier individuals have higher labor participation and thus, tend to earn higher wages

(Zweifel and Breyer, 1997). Health is also a goal that individuals and policy makers seek to achieve. According to the World Bank's 1993 *The World Development Report*, good health is a crucial part of well-being.

As a goal, the *Healthy People 2010* initiative by the US Department of Health and Human Services (DHHS) seeks to improve the health of each individual in the US, and improve the health of each community and the Nation as a whole. The specific goals of the initiative are to increase the quality and years of healthy life in addition to eliminating health disparities across the population. According to the DHHS, health-related quality of life is a subjective measure of one's physical and mental health as well as their ability to adapt to their physical and social environments (US DHHS, 2000).

Good health goals are important because of their socio-economic implications. Thus, countries with higher health status levels tend to have higher economic well-being (US DHHS, 2000). Good health contributes to economic growth in three ways: good health increases worker productivity, increases learning, and reduces cost of medical care (Rout and Nayak, 2007).

Not only do physical, mental, and functional health factors affect productivity, but the perception of health also has a large impact on economic growth. Miilunpalo et al.(1997) discovered that poor self-rated health had a positive correlation with high absenteeism, disability, and early retirement. Therefore, the power of perception can lead to costly outcomes.

In order to accurately measure health, the concept of health must be defined. Defining health, let alone good health, is a difficult task because it is multi-faceted and multi-dimensional. Previous research has indicated that self-reported health status is dependent on morbidity associated with a disease, mental state, functional limitations, and interactions with health care professionals (Idler and Benyamini, 1997; Miilunpalo et al., 1997; Bailis, Segall, and Chipperfield, 2003; Silventoinen, Lahelma, and Kaprio, 2006). Self-reported health status is also dependent on subjective factors such as personal expectations of good health, which may stem from social and cultural factors. This variety of factors may be a driving force for the dissonance between internal and external views of one's health status (Sen, 2002).

In general, there are two distinct concepts of health: one negative and one positive. The negative concept of health relates to the absence of disease or illness and is predominately the way health is viewed within the western scientific medical model (Brannon and Feist, 2010). A positive concept of health involves defining health as a state of well-being. In its constitution, the World Health Organization (WHO) defines health as 'a state of complete physical, mental and social well-being, not merely the absence of disease and infirmity' (WHO, 1946).

The *Healthy People 2010* initiative uses the following as the leading health indicators for Americans' health: physical activity, overweight and obesity, tobacco use, substance abuse, responsible sexual behavior, mental health, injury and violence, environmental quality, immunization, and access to health care. In previous research studies, health has been measured by indicators such as mortality, morbidity, and self-perception (Miilunpalo et al., 1997; Idler and Benyamini,1997; Bailis, Segall, and Chipperfield, 2003; Silventoinen, Lahelma, and Kaprio, 2006). Under the WHO definition and the indicators of interest by DHHS, health cannot be measured by the indicators of mortality and morbidity (Epp, 1996). Additionally, using mortality as a health indicator precludes measuring quality of life and vital status (Tubeuf et al., 2008). Although there are issues of reliability and validity (Vazire and Mehl, 2008), using self-perception as a health indicator enables the researcher to adopt a broader definition of health such as the one defined by the WHO. In order to sufficiently define how health is measured using self-reported health status, a better understanding is needed of individuals' decision-making processes and how self-perceptions are formed.

Current Health Challenges

Although there have been significant improvements in the US population's health in the last ten years due in part to the US DHSS's *Healthy People 2000* initiative such as reducing infant mortality and death rates associated with coronary heart disease and stroke, there are still a significant number of serious health challenges that need to be addressed (US DHHS, 2000). The prevalence of metabolic syndrome and its related health problems, e.g., obesity, cardiovascular disease (CVD), Type II diabetes, and other chronic disease, appear to be on the rise. Metabolic syndrome consists of a cluster of closely related CVD and Type II diabetes risk factors and is important in identifying individuals who are at risk for developing CVD and Type II diabetes (Alberti et al., 2005). Metabolic syndrome risk factors include visceral obesity, dylipidemia, hyperglycemia, and hypertension. According to the American Diabetes Association and the National Cholesterol Education Program's Adult Treatment Panel III, a diagnosis of metabolic syndrome is made when three or more of these risk factors are present (Grundy et al., 2004). In a recent study, Ervin (2009) used data from NHANES 2003-2006 surveys and found that over one-third of Americans could be classified as having metabolic syndrome.

The prevalence of metabolic syndrome increased with age and more dramatically with the Body Mass Index (BMI) (Ervin, 2009).

Based on data from several NHANES surveys, the prevalence of obesity has increased in the US over the past two decades. Obesity is commonly measured by BMI, which is defined as the ratio of the individual's weight in kilograms to their height in meters squared (kg/m^2) (WHO, 2006; US DHHS, 2001; NIH, 1998). BMI greater than or equal to 25 is considered overweight and obese classification is BMI equal to or greater than 30.

From 1960 to 1994, the prevalence of obesity increased in men from 10.7 percent to 20.6 percent and from 15.7 percent to 26.0 percent in women. During the past decade, the prevalence of obesity has increased at a dramatic rate of approximately by eight percent for both men and women. In 2009, the CDC estimates show that more than 72 million American adults were obese (CDC, 2009a).

Despite being preventable, CVD and coronary heart disease are responsible for more than a third of the deaths in the US and is considered the number one cause of death in both men and women. In 2006, 631,636 Americans died from heart disease (Heron et al., 2009). Currently in 2010, more than 80 million Americans are afflicted with one or more types of heart disease. Although, heart disease is most common among people 65 years and older, the prevalence of heart disease in younger adults and adolescents is increasing (CDC, 2010).

Another serious health challenge is Type II diabetes. This disease develops due to the inadequate amount of insulin secretion by pancreatic cells. It may also be engendered by insulin insensitivity, a condition where the body is unable to respond to the same level of insulin as it once did. This disease is associated with age, obesity, family history of diabetes, history of gestational diabetes, impaired glucose metabolism, physical inactivity, and race/ethnicity. Type II diabetes is the most common form of diabetes mellitus as 90 to 95 percent of all diagnosed cases of diabetes mellitus may be classified as Type II diabetes. During 2003 to 2006, nearly 26 percent (or 57 million) of American adults were diagnosed as pre-diabetic (CDC, 2008), and they will likely develop the disease if they do not change their lifestyle and dietary habits (American Diabetes Association, 2010).

The CDC (2008) states that the complications surrounding Type II diabetes stem from the fact that many individuals are not aware that they are diabetic. More than 23 million Americans were estimated to have diabetes in 2007, but only 17.9 million people were diagnosed and aware of their health condition. Nearly six million people were diabetic but were undiagnosed. As a result, it is suspected that deaths caused by diabetes are underreported. Currently, diabetes is the seventh leading cause of death in the US; however, its ranking may potentially be higher due to the underreported diabetes caused deaths (CDC, 2008).

It is believed that achieving this study's objectives of identifying the factors that influence health status, both subjective and objective, and determining the congruency between people's perceptions of their health and their objective health status will lead to a deeper understanding of what type of public health strategies would be effective at addressing emerging health concerns.

Perception and Decision Making

Perception is the process by which humans arrange sensory stimulation into organized, meaningful experiences (Lindsay and Norman, 1977). Cognitive scientists are interested in determining how interpretations of events affect emotions and behaviors (Tavris and Wade, 1995). Dignāga, Buddhist logician, states that there are four types of perception (sensory, mental, self-cognition of all mind and mental activities, and yogic (intuition)) (Yao, 2004). Given that perception is subjective, it is likely to deviate from reality more frequently than not (Fiske and Taylor, 1984; Nisbett and Ross, 1980). This deviation frequently creates challenges for policymakers, marketers, and others who depend on individuals' feedback for developing new public health initiatives and products. For instance, the deviation between perception and reality may contribute to the potential ineffectiveness of early detection programs (Thoolen et al., 2008). Identifying these factors that contribute to this deviation may provide policymakers and others with a better appreciation of the tools that may be applied to influence behavior and achieve the desired health improvement outcomes.

Self Perception

Conventional wisdom implies that the best approach to knowing what a person is like is to ask him or her. Most people believe that they know themselves better than others know them (Pronin et al., 2001). However, recent research in personality psychology has discovered many instances where self-perceptions were inaccurate (Vazire and Mehl, 2008). Although people have access to privileged information about their mental state, such as thoughts and feelings, this information is believed to impair, instead of enhance, the accuracy of self-perception (Vazire and Mehl, 2008). Thus, the assumption that the self is the best expert is challenged by the common knowledge that self perception is biased on certain motives . The desire to view oneself in a positive manner, the desire to confirm one's existing self-view, and the desire to improve oneself are known to bias self-perception (Varize and Mehl, 2008). In regard to other biases and health, Weinstein (1980; 1984) and Kunda (1987) found that individuals tend to be over-optimistic in regards to their own health. Other misperceptions include the tendency for individuals to feel that they are less vulnerable to risks than others (Perloff and Fetzer,1986) and that they are more responsible for their successes than their failures (Miller, 1976).

Bailis, Segall, and Chipperfield (2003) argue that peoples' self-rated health may be influenced by their intentions to engage in health-related behaviors. Their research findings indicate that people are motivated by images of their future self, of what they would like to become. Others (Hooker and Kaus, 1994; Lavallee and Campbell, 1995; Markus and Nurius, 1986; Ryff, 1991) support Bailis, Segall, and Chipperfield (2003) indicating that behavior is motivated by these images, and they serve as the context for self-evaluation.

Behavioral intentions viewed in the *Theory of Reasoned Action* (Azjen and Fishbein, 1980; Fishbein and Azjen, 1975) and its successor, *Theory of Planned Behavior* (Ajzen, 1985) are thought to serve as predictors of actual behaviors. Bailis, Segall, and Chipperfield (2003) view behavioral intentions as being reflective images of self-striving or future self. This implies that future images of one's self can predict one's present behavior.

Although the accuracy of these self-reports are important to many fields of study such as health behavior and personality, studies that conduct relative predictive validity of self- and other- ratings are rare, due in part to the methodological challenges involved in defining an appropriate criterion measure. In their study, Vazire and Mehl (2008) addressed this validity issue and investigated which perception is more accurate, self or others' perception. They discovered that people believe self perceptions were more consistently accurate than others' perceptions, despite, results indicating that there are instances where self-ratings were not more accurate than others-ratings. In fact, other ratings were found to be equally accurate to self-ratings. This finding is consistent with previous research that found informant ratings, non-close observer, are at least as accurate as self-ratings (Kolar, Funder and Colvin, 1996; John and Robins, 1994; Levesque and Kenny, 1993). In another study of predictions about the longevity of dating relationships among college students, others' (or observers') predictions were more accurate than the student's who are involved in the relationship (MacDonald and Ross, 1999). MacDonald and Ross (1999) suggested that observers were not partial or discriminatory in their evaluation of the relationships and thus, were more likely to use all information, including information that may potentially threaten the stability of the relationship. In regards to evaluating the quality of the relationship, the students' involved in the relationships had higher predictive accuracy than observers, which suggests that students were exposed to additional information that contributed to their increased predictive accuracy. These results suggest that students and observers have higher predictive accuracy than each other for different aspects of the relationship. Similarly, Varize and Mehl (2008) discovered that both self- and others-perceptions had equivalent accuracy, and that perceptions from each group provided unique insight into what a person is like. That is, the self is not always the best expert on what a person is, and others can provide unique information that is not capture by self-ratings. Given this finding, it is anticipated that additional information from others will provide useful and unique insights that individuals can use in their evaluation of themselves.

Self Reported Health Status

Previous cross-sectional studies indicate that self-rated health status provides a valid summary of various measures of a person's health (Bailis, Segall, and Chipperfield, 2003; Miilunpalo et al., 1997). Subjective health status can have a higher predictive power of health indicators than objective health measures (Miilunpalo et al., 1997). It is a strong predictor of mortality, morbidity, functional disability and the use of health care services (Heistaro et al., 2001; Heidrich et al., 2002; Miilunpalo et al., 1997; Idler and Kasl, 1995; Haveman-Nies, de Groot, and Van Staveren, 2003a). Self-reported health status is a global measure that is applicable to the general population (Breslow, 1989). When measuring self-reported health status, individuals are typically asked a single question regarding their perceived health status. This question does not specify certain health-related components such as prevalence of disease or mental health, but rather it allows the individual to base their health assessment on their integrated perception of health, which may include biological, psychological, and social components as well as information that is only accessible to the individual (Miilunpalo et al., 1997). Ware, Davies-Avery, and Donald (1978) states that this type of subjective measurement allows the researcher to "tap both the objective information people have about their health status and their evaluation of that information."

Heuristics and Decision Making

Simon (1955) argued that economic models in which economic agents had unlimited knowledge and information processing capabilities were flawed and suggested that the notion of bounded rationality provided a more realistic view of human decision-making. Simon pointed out that people employed heuristics – mental short cuts or general rules of thumb – to make decisions because of bounded rationality. According to Simon (1978), if accepted that the agent has limited knowledge and mental computational capabilities, i.e., bounded rationality, then a distinction needs to be made between the real world and the agent's perception of and reasoning about it. That is, there is a need for a better understanding of the agent's decision-making process by developing a theory of the decision process that incorporates the environment, social factors, cultural factors, and other contextual factors (Simon, 1978).

Simon (1986) states that the study of rational behavior in economics is not complete without including aspects of psychological and sociological research such as the context or framing effects involved in the decision making process. In psychology, there are a variety of well-established, empirically-tested, behavioral theories that could be very beneficial to the study of economics and consumer behavior. Psychologists, Tversky and Kahneman (1974), discovered that heuristics such as availability, representativeness, anchoring, and adjustment are used by bounded rational individuals as well as simple strategies such as "elimination by aspects" to make choices. Affect heuristics are also commonly used to make judgments and decisions in relationships. Shafir, Simonson, and Tversky (1993) believed that "[p]eople's choices may occasionally stem from affective judgments that preclude a thorough evaluation of the options" (p 32), which enables the individual to make quick but maybe less informed decision. By using heuristics, decision making is quicker and possibly more efficient than other decision making suggested by classical economic assumptions. This is particularly true when the judgment or decision is complex.

It has been noted that health is a complex concept with potentially conflicting subjective and objective perspectives. This would imply that it is a good candidate for heuristic decision making when it is being evaluated by individuals. In addition to using heuristics, individuals will likely use satisficing to evaluate their current health status. Satisficing, a concept developed by Simon, implies that an individual does not choose an option that maximizes their utility, but rather one that meets the threshold of their decision criteria. In essence, the decision may not be the best option, but its characteristics are *good enough* (Schwartz et al., 2002). Given individuals' bounded rationality, many decisions are made based on satisficing instead of optimization.

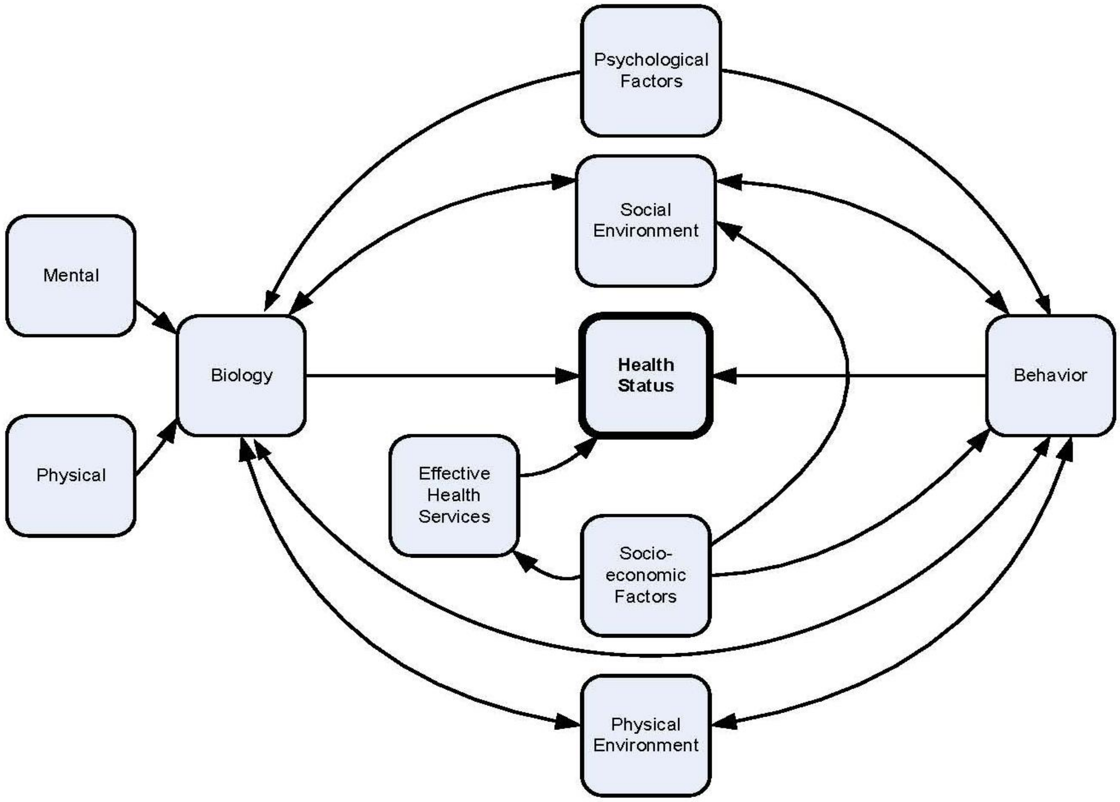
Although heuristics allow for quick decision making, they can also be misleading. Natural limitations of the experiential system and the misrepresentation of stimuli in our environment are some issues that bias, and thus, misguide our decision-making. Tversky and Kahneman (1974) observed that heuristics might lead to systematic errors.

Kahneman and Tversky's (1979) influential prospect theory captures many of the departures from rational choice as defined by economic theory. The main point of Kahneman and Tversky's (1979) prospect theory is to describe or predict behavior instead of optimize it (Thaler, 1985). Many of the key theoretical components incorporate important psychological aspects of decision making, such as the use of relative instead of absolute measures. Kahneman and Tversky (1979) state that "[o]ur perceptual apparatus is attuned to the evaluation of changes or differences rather than to the evaluation of absolute magnitudes". Prospect theory also introduces the concept of loss aversion and diminishing sensitivity in gains and losses. In order to fully understand choices, prospect theory needs to be combined with “mental accounting” or “hedonic editings” (Thaler, 1985). Using prospect theory as a guide, it is possible that when measuring one’s health status, an individual is measuring their relative health and not their absolute health status. An individual’s relative health measure may be relative to her peers, relative to last year’s perceived health status, or relative to her predisposition to certain health conditions or given her family medical history.

Factors Affecting Health Status

As indicated, health is a multi-dimension concept, and consequently, there are a variety of factors that influence health status and self reported health status (Figure 2.1). Biological factors and behavioral decisions have a direct affect on health status and on each other (US DHHS, 2000; Bailis, Segall, and Chipperfield, 2003). They also have interaction effects with social and physical environments, which affects their health status (US DHHS, 2000). Innate biological factors such as gender and genetics are key health determinants (US DHHS, 2000; Labonte, 1998; Simon-Morton, Greene, and Gottlieb, 1995) as well as self-rated physical and mental health (US DHHS, 2000; Bailis, Segall, and Chipperfield, 2003). Psychological factors such as preferences and personal values influences biological and behavioral factors (Haveman-Nies, de Groot, and Van Staveren, 2003). Lifestyle behaviors and social environments are influenced by socio-economic factors such as education, income, and social support (US DHHS, 2000; Simon-Morton, Greene, and Gottlieb, 1995). Access to health care is another key factor in determining one’s health, and it is also influenced by socio-economic factors (US DHHS, 2000; Simon-Morton, Greene, and Gottlieb, 1995).

Figure 2.1: Schematic of Factors Affecting Self Reported Health Status



Health Status and Innate Factors

Typically in self-reported health status studies, an ordinal scale is used to measure health status, which ranges from poor health status to good or excellent health status. Previous research has indicated that women report their health status more harshly than men (Goldberg et al., 2001; Tolliver, 2007; Kwaśnewska et al., 2007). In the study conducted by Tolliver (2007), these gender differences were statistically insignificant for all age groups except for the 35 - 44 year olds, in which women reported fair to poor health statuses more frequently than men. Similarly, Silvenroinen, Lahelma, and Kaprio (2006) discovered that men have a better perception of their health status than women. In contrast to these findings, Morris-Tries (2004), in her health and lifestyle survey[1], discovered that women in Fort Erie, Ontario reported higher health status than men. Similarly, McCollum et al. (2007) found diabetic women to perceive their health status as being higher than diabetic men, despite having similar or poorer health status as identified by norm-based measures.

Previous studies have consistently shown a clear negative correlation between self-rated health status and age (Morris-Tries, 2004; Havenman-Nies, de Groot, and van Staveren, 2003b; Silvenroinen and Lahelma, 2002; Miilunpalo et al., 1997). This negative relationship was found for both men and women, but women's health perception deteriorated more than men's within about a ten year period. At age sixteen, fourteen percent of women reported a less than good health status and by the age of 25, this percentage increased to eighteen percent (Silvenroinen, Lahelma, and Kaprio, 2006).

Health Status and Socio-economic Factors

According to the *Healthy People 2010: Understanding and Improving Health* report (US DHHS, 2000), high poverty rates and low education levels are associated with low health status. With higher incomes, individuals and families have access to medical care, are able to afford higher quality living conditions, such as better housing and safe neighborhoods, and have the opportunity to participate in healthy lifestyle behaviors such as joining a fitness gym (US DHHS, 2000).

---

[1] Morris -Tries' (2004) study uses primary data collected from a small community in Ontario, Canada. The study's objectives are closely related to some of the objective in this present study, and as a result, this study draws heavily on the research findings for this previous study.

Tolliver (2007) discovered that adults with less than a high school diploma report a lower health status (fair to poor health status) more frequently than adults with a high school diploma or higher level of education. In Silvenroinen, Lahelma, and Kaprio's 2006 study, education was the predominant socioeconomic factor affecting self-rated health status. There was a clear education positive gradient among both genders in which lower education was associated with lower self-rated health status. Morris-Tries (2004) found that there was a positive correlation between education and health status and income and health status. Adults within low income brackets, less than $25,000 perceived their health status as being lower more often than adults is higher income brackets (Tolliver, 2007).

Another factor, marital status, can be categorized into six categories: married, widowed, cohabiting, separated, divorced, and single. Previous research indicates a consistent relationship between marital status and health statuses (Rahman, 1993; Zick and Smith, 1991; Hu and Goldman, 1990). In comparison to married people, unmarried individuals in all unmarried categories (single, divorced, separated, and widowed) tend to view their health and well-being as lower and indicate higher levels of psychological distress, higher age-adjusted mortality rates for all causes of death, and high usage levels of health services (Barrett, 1999; Ross, 1995; Gore and Mangione, 1993; Goldman, Korenthan, and Weinstein, 1995). These results indicate that there are positive health and emotional benefits related to marriage.

Using data from the National Survey of Families and Households (1987-1988), Ren (1997) investigated the impacts of various relationship statuses on the health perception of individuals. Ren discovered that a health perception is not only dependent on marital status but also the quality of the relationship. For instance, separated individuals report a lower health status than a divorced individual. Time also played an important role in influencing health status (Ren, 1997). Ren suggests that this difference in perception is associated with the timing of events. Separated couples are usually in the midst of a drastic change in their relationship, and this emotional change can have a negative effect on health. Divorces, on the other hand, have overcome this emotional turmoil and have had time to adjust to their new status. In essence, time allows the person to become emotionally and physically healthier, thereby influencing health status.

Surprisingly, Ren found that individuals who are widowed or never married had a very small and insignificant positive relationship with health status compared to married individuals, suggesting that widowed or never married individuals reported having better health than married individuals even after adjusting for all the control variables. Cohabitation did not increase an individual's health or well-being. Similarly, Tolliver (2007) discovered that married and never-married individuals report higher health statuses more often than those who were divorced, separated, widowed, or co-habiting. In contrast to Ren's (1997) study, Kwaśniewska, Bielecki, and Drygas (2004) in their study of a Polish urban community found that widowed or divorced individuals tend to have a lower level of self-reported health status than those who are single or married.

Health Status and Lifestyle Behaviors

In the health and lifestyle behavior survey of residents in Fort Erie, Ontario, Morris-Tries (2004) found that over half of the respondents, except for those 65 years and older, reported that they did not consume the recommended five servings of fruits and vegetables a day. Forty-seven percent of those individuals who did not meet the dietary guidelines indicated their dietary habits were detrimental to their health. Of those who did not consume the recommended daily intake of fruits and vegetables, 71.5 percent of them stated that their dietary habits are fair to good. Individuals who meet their fruit and vegetable recommendations were more likely to rate their perceived dietary habits as very good or good, 41.6 percent and 30.2 percent, respectively (Morris-Tries, 2004). These findings indicate that people are consciously aware of the positive effect fruits and vegetables have on their health. Not only are they aware of the positive effect of these foods, they also take these effects into consideration when they evaluate their health status.

Individuals engaged in regular or occasional physical activity did not view their level of physical activity as being harmful to their health while inactive individuals perceived their activity level as having adverse effects on their health (Morris-Tries, 2004). Similar to diet, people are conscious of the potential effect of physical inactivity on their health. As a result, it is expected that they will incorporate this information into their health status assessment.

Results from the prospective study conducted by Miilunpalo et al. (1997) indicated a complex relationship between self-reported health status and perceived physical fitness. Of those respondents that reported their physical fitness as being good, over three-quarters stated that their health was good. However, of the respondents reporting a good or fairly good health status, slightly over a third of them also reported having good physical fitness. This implies that good physical fitness is related to good health status, but good health status does not necessarily imply good physical fitness. The inconsistency in the relationship between health status and physical fitness warrants further research.

Non-smokers and former smokers had a statistically significant and positive correlation with current and previous year's self-rated health status (Morris-Tries, 2004). That is, former smokers have appeared to, in their minds, negate any permanent health damage that their previous smoking has done. In another study, smokers reported having higher rates of health problems than non-smokers; however these results were not statistically significant (Kwaśniewska, Bielecki, and Drygas, 2004). Previous medical research conducted by the British Columbia Cancer Research Centre (BCCRC) discovered that former smokers have a significantly lower lung cancer risk than current smokers but a higher risk than non-smokers, regardless of when they ceased smoking. Approximately half of the new cases of lung cancer are found in former smokers including those who have stopped smoking for a number of years. Research from the BCCRC has indicated that tobacco smoke and other substances, like the chemicals added to the tobacco, have permanently altered cell DNA and caused DNA mutations, which potentially contributes to the former smoker's increased cancer risk (BCCRC, 2008).

In regards to alcohol and health, over 90 percent of the individuals who consume alcoholic beverages believed that alcohol was not harmful to their health; seven percent and less than one percent of the respondents stated that alcohol posed a moderate to high health risk, respectively (Morris-Tries, 2004). Poikolainen, Vartiainen, and Korhonen (1996) discovered a J-shaped relationship between alcohol intake and suboptimal health, average or poor, when controlling for several socio-economic variables. Moderate drinkers had the highest self-reported health status, followed by abstainers. The results also show that the positive effect of alcohol consumption has a limit. Heavy alcohol consumers tend to have the lowest self-perceived health status.

Previous studies have found that heavy alcohol consumption interferes with lipid oxidation, which can lead to a positive energy balance and fat accumulation (Suter, Hasler, and Vetter, 1997). However, moderate alcohol consumption has been associated with both healthy dietary habits (Tjønneland, 1999) and unhealthy dietary habits (Keese et al., 2001). High levels of alcoholic consumption are associated with increase body weight. In addition to affecting BMI and waist circumference, alcohol consumption affects HDL and fasting blood glucose levels. It increases HDL and provides cardio-protective properties, and it decreases fasting blood glucose. The exact mechanism by which this relationship occurs is not known at this time and, in fact, very little is known about the effects of alcohol consumption on glucose metabolism (Crandall et al., 2009). However, moderate alcohol consumption has been associated with greater insulin sensitivity and an inverse, U-shaped relationship between alcohol and insulin levels has been discovered (Kiechl et al., 1996).

The number of physician visits was negatively correlated with self-rated health status, where a high number of physician visits are associated with low health status (Miilunpalo et al., 1997). This result supports the expectation set by Kerkhofs and Lindeboom (1995), who used visits to a general physician as a proxy for an objective measurement of health status. They assumed that frequent visits per year to a general physician are associated with less healthy individuals compared to individuals who visit a general physician less frequently. Table 2.1 provides a summary of findings from previous literature on the various effects of explanatory variables on self-reported health status.

Table 2.1: Summary of Previous Literature Findings

Factor	Result
Gender	Males have higher PHS than females (Kwaśniewska, 2004; Silvenroinen, Lahelma and Kaprio, 2006)
	Diabetic females have higher PHS than diabetic males (McCollum et al., 2007)
	No relationship between gender and PHS (Tolliver, 2007)
	Females have higher PHS than males (Morris-Tries, 2004)
Age	Negative relationship between age and PHS (Morris-Tries, 2004, Morris-Tries, 2004; Havenman-Nies, de Groot, and van Staveren, 2003b; Silvenroinen and Lahelma, 2002; Miilunpalo et al., 1997)
Marital Status	Widowed and Divorced have lower PHS than Married or Never Married (Kwaśniewska, Bielecki, and Drygas, 2004)
	Divorced have higher PHS than Separated (Ren, 1997)
	No relationship with cohabitation and PHS (Ren, 1997)
Education	Positive relationship with education and HS and PHS (US DHHS, 2000; Morris-Tries, 2004; Silvenroinen, Lahelma and Kaprio, 2006; Tolliver, 2007)
Income	Positive relationship with income and HS and PHS (US DHHS, 2000; Morris-Tries, 2004; Tolliver, 2007)
Diet	Individuals not consuming the recommended amount of fruits and vegetable recommendation perceive their diet as being harmful to their health (Morris-Tries, 2004)
Physical Activity	Physically fit individuals report a higher PHS (Miilunpalo et al., 1997)
	Inactive individuals perceive their active level as being harmful to their health (Morris-Tries, 2004)
Smoking	Smokers have more health problems (Kwaśniewska, Bielecki, and Drygas, 2004)
	Positive relationship with non- and former smokers and PHS (Morris-Tries, 2004)
Alcohol	Individuals who consume alcohol beverages do not perceived it to be harmful to their health (Morris-Tries, 2004)
	Alcohol increases fat accumulation (Suter, Hasler, and Vetter, 1997), increases HDL cholesterol, and decreases fasting blood glucose levels (Crandall et al., 2009)
	Moderate alcohol consumption associated with healthy dietary habits (Tjønneland, 1999) and unhealthy dietary habits (Keese et al., 2001)
	J-shaped relationship between alcohol intake and suboptimal health (Poikolainen, Vartiainen, and Korhonen, 1996)
	Moderate alcohol consumption has an inverse U-shaped relationship with insulin levels (Kiechl et al., 1996)
Frequency of Health Care Professional Visits	Negative relationship with frequency of physician visits and PHS (Miilunpalo et al., 1997)

Note: PHS represents perceived health status and HS represents health status.

Chapter 3 - Methodology and Data

The models and data used in this study are discussed in this section. First, the conceptual and empirical models used are introduced with a focus on addressing some key modeling issues. Next, the data set is described and summary statistics are provided. A discussion of possible data issues is presented in the last section.

Conceptual Model

An individual's (*i*) self-reported health status (*H*) is assumed to be a function of two dimensions, socio-economic (*SE*) and behavioral (*B*). The socio-economic dimension includes demographic factors like gender (θ), and socio-economic factors like marital status and education (σ). The behavioral dimension is determined by self-reported behaviors (α) that include diet and physical activity and health maintenance behaviors (δ), such as smoking and alcohol consumption.

$$H_i = f(SE(\theta, \sigma), B(\alpha, \delta)) \qquad (3.1)$$

For simplicity and data availability, a static framework is used. In reality, a person's perception about their health status is dynamic.

Empirical Models

Categorical Dependent Variable Model

When analyzing ordinal scales, the ordered logit model is commonly used mainly because of ease of interpretation and its model parsimony (Scott, Goldberg, and Mayo, 1997). Given that the dependent variable, self-reported health status, is ordered, it is believed that the ordered logit model is the most appropriate model to use. Based on the work by McKelvey and Zavoina (1975) and Greene (2000), the ordered logit model involves an underlying variable with observed, ordered categories.

The ordered logit is similar to the ordered probit model with the difference being that the ordered logit assumes that the error term is *logistically* distributed, while the ordered probit assumes that the error term is *normally* distribution. The logistic distribution is similar to the normal except that the tails are heavier (Greene, 2000). Greene (2000) states that “it is difficult to justify the choice of one distribution over the other on theoretical grounds …. in most applications, it seems not to make much difference” (p.815).

There are three different modeling approaches associated with ordinal dependent variable analysis: cumulative, stage, and adjacent. [2] The data and the type of comparison required among the categories determine which approach is appropriate for the research. Since the self-reported health status follows an ordinal scale, which represents an underlying continuous measure, Fullerton (2009) recommends using the cumulative approach. Traditionally, the cumulative approach represents the classic ordered logit model approach.[3] In this approach, the probability of being at or below a certain category is compared to the probability of being above a certain category.

Suppose that the health status, H_i, is a linear function of K factors whose values, for individual i, are X_{ik}, $k = 1, \ldots, K$. Then the structural model is as follows:

---

[2] A review of the different approaches is beyond the scope of this research; however, Fullerton (2009) and Menard (1995) provide an excellent overview of the different approaches.

[3] McCullagh (1980) refers to this model as the proportional odds model. It derives its name from its inherent assumption, the proportional odds assumption, in which the coefficients are equal across all cut points.

$$
\begin{aligned}
H_i &= \sum_{k=1}^{K} \beta_k X_{ik} + \varepsilon_i \\
&= Z_i + \varepsilon_i
\end{aligned}
\tag{3.2}
$$

where β_k is the coefficient associated with the k^{th} variable, and ε_i is the error term. The error term, ε_i, is assumed to have a standard logistic distribution with a mean of zero and a variance of $\pi^2/3$ (Greene, 2000).

H_i is the latent variable or the unobserved dependent variable. The observed Y_i is related to the unobserved dependent variable, H_i, based on the following measurement model:

$$
\begin{aligned}
&Y_i = 1,\ if\ \ H_i \le \tau_1 \\
&Y_i = 2,\ if\ \ \tau_1 \le H_i \le \tau_2 \\
&Y_i = 3,\ if\ \ \tau_2 \le H_i \le \tau_3 \\
&Y_i = 4,\ if\ \ \tau_3 \le H_i \le \tau_4 \\
&Y_i = 5,\ if\ \ H_i \ge \tau_5
\end{aligned}
\tag{3.3}
$$

where Y_i is the category of self-reported health status, and τ is the vector of unknown threshold parameters that is estimated with the β vector. The higher the value of H, the more likely an individual is to report a higher category of self-reported health status. That is Y_i =1 if a person's perceived health status is poor, Y_i = 2 if a person's perceived health status is fair, Y_i = 3 if a person's perceived health status is good, Y_i = 4 if a person's perceived health status is very good, and Y_i = 5 if a person's perceived health status is excellent.

Probability is:

$$
\Pr\left[Y_i = j\right] = \Pr\left[H \text{ is in the } j^{th} \text{ range}\right] \tag{3.4}
$$

where j represents the different health status categories.

The probability of observing an outcome is:

$$\Pr\left[Y_i = j\right] = \Lambda\left[\tau_j - Z_i\right] - \Lambda\left[\tau_{j-1} - Z_i\right] \tag{3.5}$$

where Λ(.) =exp(.)/[1+exp(.)]. This implies:

$$\Pr\left[Y_i = j\right] = \frac{1}{1+e^{-\tau_j + Z_i}} - \frac{1}{1+e^{-\tau_{j-1} + Z_i}} \ , \tag{3.6}$$

which can be used to derive a likelihood function and, subsequently, maximum likelihood estimates of τ_j and β_k. The probabilities are calculated at their means, using the estimated coefficients at their respective means.

An individual's health status perception is based on characteristics of other perceptions such as diet and physical activity and socio-economic factors. Since the threshold values are unknown, the latent variable and therefore, the coefficients are not measured in natural units.

The software Stata® 10.0 is used to conduct the analysis. In Stata®, the ordered regressions do not explicitly include an intercept term. That is, in Equation 3.2 the β_k (k = 1, …K) are slope coefficients. When using Stata® to estimate ordered regressions, the intercept term is absorbed in the cutoff points, τ_j. Implicit in the cumulative approach of the ordered logit model is that the parallel line assumption[4] holds. The parallel line assumption implies that the ordinal variable can be fit by one set of regression parameters. That is, the β's are equal for each equation for the ordinal categories. In addition to

---

[4] This assumption has many different names: proportional odds assumption (Wolfe and Gould, 1998), parallel regression assumption (Long and Freese, 2003), and parallel line assumption (SAS Institute, 2004; Williams, 2007). It is important that we recognize these different names and realize that they refer to the assumption that the coefficients are equal across all cut points. For the remainder of this study, we will adopt the terminology used by the SAS Institute (2004) and Williams (2006) and refer to the assumption as the "parallel line assumption".

assuming parallel lines, the ordered logit model also assumes that the errors are homoskedastic (Williams, 2008; Williams, 2009).

Marginal Effects

Marginal effects capture the effect of an unit change in an explanatory variable on the outcome probabilities of the dependent variable, while holding all other variables constant. That is, the marginal effects are computed for each J outcome or perceived health status category. The marginal effects are calculated based on the estimated coefficients and are calculated at the mean values of the explanatory variables. For the marginal effects of continuous variables, the probabilities in equation 3.6 are differentiated with respect to the k^{th} variable:

$$\begin{aligned} \frac{\partial \Pr(Y_i = 1 | \bar{\mathbf{X}}_i)}{\partial X_{ik}} &= \frac{\partial \Lambda(\tau_1 - \bar{\mathbf{X}}_i \boldsymbol{\beta})}{\partial X_{ik}} \\ &= \lambda(\tau_1 - \bar{\mathbf{X}}_i \boldsymbol{\beta})(-\beta_k) \end{aligned} \tag{3.7}$$

$$\begin{aligned} \frac{\partial \Pr(Y_i = j | \bar{\mathbf{X}}_i)}{\partial X_{ik}} &= \frac{\partial \left[\Lambda(\tau_j - \bar{\mathbf{X}}_i \boldsymbol{\beta}) - \Lambda(\tau_{j-1} - \bar{\mathbf{X}}_i \boldsymbol{\beta}) \right]}{\partial X_{ik}} \\ &= \lambda(\tau_j - \bar{\mathbf{X}}_i \boldsymbol{\beta})(-\beta_k) - \lambda(\tau_{j-1} - \bar{\mathbf{X}}_i \boldsymbol{\beta})(-\beta_k) \\ &= \left[\lambda(\tau_{j-1} - \bar{\mathbf{X}}_i \boldsymbol{\beta}) - \lambda(\tau_j - \bar{\mathbf{X}}_i \boldsymbol{\beta}) \right](\beta_k) \end{aligned} \tag{3.8}$$

$$\begin{aligned} \frac{\partial \Pr(Y_i = J | \bar{\mathbf{X}}_i)}{\partial X_{ik}} &= \frac{\partial \left[1 - \Lambda(\tau_{J-1} - \bar{\mathbf{X}}_i \boldsymbol{\beta}) \right]}{\partial X_{ik}} \\ &= \lambda(\tau_{J-1} - \bar{\mathbf{X}}_i \boldsymbol{\beta})(\beta_k) \end{aligned} \tag{3.9}$$

The standard errors are obtained using the delta method. Because the total outcome probabilities sum to one, the marginal effects of the probabilities sum to zero.

For the marginal effects for the lowest category, the effects are opposite in sign to β_k. If β_k is positive (negative), then an increase in X_k will reduce (increase) the probability of the lowest category. Conversely, marginal effects for the highest category are similar in sign to β_k. Therefore if β_k is positive, then an increase in X_k will reduce Pr(Y_i =1) but will also increase Pr(Y_i =J).

Marginal effects of the single dummy variables such as gender are computed as:

$$\Delta \Pr\left[Y_i = j \middle| \bar{\mathbf{X}}_i\right] = \Pr\left[Y_i = j \middle| \bar{\mathbf{X}}_i + \Delta\bar{\mathbf{X}}_k\right] - \Pr\left[Y_i = j \middle| \bar{\mathbf{X}}_i\right]. \qquad (3.10)$$

Since the dummy variables are binary variables, the marginal effects are determined by the differences of the estimated probabilities at its boundaries of one and zero. Equation 3.10 can be re-written as:

$$\Pr\left[Y_i = j \middle| \bar{\mathbf{X}}_i = 1\right] - \Pr\left[Y_i = j \middle| \bar{\mathbf{X}}_i = 0\right]. \qquad (3.11)$$

In the case of grouped dummy variables such as marital status, the marginal effects of each variable are computed at their respective value, while holding the remaining group variables at zero.

Violation of the Parallel Line Assumption

Prior to fitting the ordered logit model, the parallel line assumption can be tested. If the assumption is not met, then at least one of the parameters differs across the ordinal categories. Violation of the parallel line assumption can lead to results being incorrect, incomplete, or misleading (Boes and Winkelmann, 2004; Williams, 2006). Among researchers, there is a general agreement that the parallel line assumption is very restrictive and is frequently violated (Lall et al., 2002; Long and Freese, 2003). In these cases, Long and Freese (2003) and Williams (2006) recommend that another regression model that does not impose the strict constraints of parallel regression, be considered. Suggested alternative models are multinomial logit or generalized ordered logit models such as the partial constrained ordered logit (PCOL) and the stereotype models (Lall et al., 2002; Williams, 2006)[5]. Generalized ordered logit models are considered to be an extension of the ordered logit model and are primarily used in sociology, epidemiology and medical statistics literature (Long and Freese, 2003; Fullerton, 2009; Williams, 2006; Lall et al., 2002; Long, 1997). If the parallel line assumption is not violated, then the ordered logit model is estimated.

Of the two alternative options, the multinomial logit is the least preferred because it does not take into account ordering information, thereby rendering the model inefficient (Boes and Winkelmann, 2004). It also estimates more parameters than is necessary making the interpretation more difficult (Williams, 2006). However, the PCOL model, which is a special case of the generalized ordered logit model, can overcome these limitations. The generalized ordered logit models can estimate models that are less restrictive than ordered logit models and more parsimonious and interpretable than multinomial logit model. The PCOL model relaxes the constraints on the variables when the parallel line assumption is violated, and simultaneously retains the information obtained from the ordering of the data (Polsky et al., 2006). In the generalized ordered logit models, there is a possibility that negative probabilities could occur. Predicted probabilities are computed to identify if any negative probabilities exist. If a large or non-

[5] A common name for the partial constrained ordered logit model is the partial proportional odds model (Fullerton, 2009).

trivial number of cases of negative probability occur, then it is recommended that the model be modified or a different statistical technique used, such as a multinomial model.

Before estimating a less restrictive model such as the PCOL model, Fullerton (2009) suggests estimating another ordinal regression model with a different link function such as an ordered probit model. Fullerton (2009) and Winship and Mare (1984) suggest that a violation in the parallel line assumption or other key model assumptions may be influenced by the type of link used in the model e.g., logit or probit. In the case where the parallel line assumption is rejected in the ordered logit model, we estimate an ordered probit model before estimating a generalized ordered logit model.

To test the parallel line assumption, two approaches are used; (1) the Brant Test, and (2) the *autofit* option in Richard William's *gologit2* STATA command. The Brant Test (Brant, 1990) is a Wald test that examines the parallel line assumption in a global test (i.e., all coefficients simultaneously) as well as each variable individually. The *autofit* option is also a Wald test; however, it uses a backwards stepwise-like selection procedure to determine if any variables violate the parallel line assumption. The procedure starts with the least parsimonious model and gradually imposes constraints (Williams, 2006). A key feature with the *autofit* option is that the violating variables are easily identified in the Stata output summary.

Generalized Ordered Logit Model

The generalized ordered logit model may be presented as follows:

$$\Pr(Y_i > j) = g(X_i\beta_j) = \frac{\exp(\alpha_j + X_i\beta_j)}{1+\left[\exp(\alpha_j + X_i\beta_j)\right]},\ \ j=1, 2, ..., J\text{-}1 \qquad (3.12)$$

where i represents the individual, j is the different health status categories, and J is the number of health status categories. The generalized ordered logit model estimates results, coefficients and standard errors, for $J-1$ health status categories, and these results are similar to estimating a series of binary logistic regressions. In the first series of estimated coefficients, the lower health status category is compared to all other health status categories, and the second regression result compares the lower two health status categories with the other categories. This pattern continues until the last regression result compares the highest health status category to all other lower categories.

The probabilities that Y will take on each of the values 1,…., J is equal to:

$$\begin{aligned} &\Pr(Y_i = 1) = 1 - g(X_i\beta_j) \\ &\Pr(Y_i = j) = g(X_i\beta_{j-1}) - g(X_i\beta_j) \;\; j = 2,..., J-1 \\ &\Pr(Y_i = J) = 1 - g(X_i\beta_{J-1}). \end{aligned} \tag{3.13}$$

In this study, this type of the generalized ordered logit model is referred to as the unconstrained generalized ordered logit model (UGOL). The ordered logit model is a special case of the generalized ordered logit model and is written as follows:

$$\Pr(Y_i > j) = g(X_i\beta) = \frac{\exp(\alpha_j + X_i\beta)}{1+\exp(\alpha_j + X_i\beta)}, \;\; j=1,2,..., J\text{-}1 \tag{3.14}$$

Equations (3.12) and (3.14) are very similar except that the ordered logit model (3.14) does not have subscripts on the β's, which indicates that the β's are constant for each category j. The probability curve for each category is parallel to each other and thus, the parallel line assumption is not violated (Williams, 2006). As mentioned above, the β's frequently differ across the different values of j and violate the parallel line assumption (Williams, 2006)

In the PCOL model, the parallel line assumption is relaxed for only those variables that violate the assumption; this means that some of the β's can be the same for all values of j, while other β's can differ across the different health categories (j's) (Williams, 2006).

$$\Pr(Y_i > j) = g(X_i\beta) = \frac{\exp(\alpha_j + X_{1i}\beta_1 + X_{2i}\beta_{2j})}{1+\exp(\alpha_j + X_{1i}\beta_1 + X_{2i}\beta_{2j})}, \quad j=1,2,..., J\text{-}1. \tag{3.15}$$

For instance, equation (3.15) indicates that the coefficients for variable X_1 are constant for all values of j, while X_2's coefficient can vary across the different values of j (Williams, 2006). In the generalized ordered logit models, variables that meet the parallel line assumption are interpreted in the same manner as if they were estimated in an ordered logit model. For the variables that violate the assumption, an examination of the pattern of the coefficients will provide a unique perspective into the nature of the variable's effect that may have been hidden if an ordered logit model was estimated (Williams, 2006). According to Williams (2009) and Fullerton (2009), the PCOL model represents a good balance between the ordered logit model and the unconstrained generalized ordered logit model because it relaxes the assumption for the violating variables and minimizes the number of parameters estimated (Polsky et al., 2006).

Objective Health Metric Models

Recall Equation 3.1 where self-reported health status was hypothesized to be a function of two dimensions, socio-economic (*SE*) and behavioral (*B*). The goal is to determine the different effect of these socio-economic and behavioral factors on explaining the four different objective dimensions of health status: BMI, waist circumference, HDL, and fasting blood glucose. That is, Equation 3.1 was re-specified as

$$\text{Health Metric}_i = h(SE(\theta, \sigma), B(\alpha, \delta)) \tag{3.16}$$

where i represents BMI, waist circumference, HDL, and fasting blood glucose. Because these health metrics are continuous variables, Equation 3.16 may be estimated with ordinary least square (OLS) model.

It is argued that if economic agents are using all available information about their health to evaluate their health status, then the explanatory variables should have similar effects on these health metrics, if not in magnitude then definitely in the sign. Since self-reported health status is ordered from poor to excellent health status, a positive sign on the coefficient is associated with higher probable health status levels and a negative sign is related to lower probable health status levels. Close attention must be used when comparing the effects of the variables between the subjective and objective models. High BMI, waist circumference and fasting blood glucose are all associated with lower health statuses (Kwaśniewska et al., 2007) while the opposite is true for HDL (American Heart Association, 2009). Therefore, variables that exhibit positive effects on HDL imply a positive effect on health status while variables with the same positive relationship with BMI, waist circumference, and fasting blood glucose imply negative effects on health status.

Group Comparison Analysis

To determine if the information from the health metric is incorporated into individuals' assessments of their health, two comparison analyses are conducted. In the first comparison analysis, the health status perception model is estimated for two groups of individuals: those with at least one health risk determined by the cut-off point for the different health metrics and those with no health risk (Table 3.1). A Chow test is used to test if any differences in subjective perceptions of health status existed between the health risk group and the non health risk group.

Table 3.1: Metabolic Syndrome Risk Factors

Risk Factor	Criteria
Central Obesity	
BMI	> 25kg/m^2
or Waist Circumference	> 40 inches (102 cm) in males
	> 35 inches (88 cm) in females
Glucose Intolerance	
Fasting Glucose Level	> 100 mg/dL
or OGTT (2 hour)	> 140-200 mg/dL
Blood Pressure	Sytolic >130 mmHg
	Diastolic > 85 mmHg
Atherogenic Dyslipidemia	
HDL-cholesterol	< 40 mg/dL for males
	< 50 mg/dL for females
Triglyceride Levels	> 150 mg/dL

Source: American Diabetes Association (2009)

Recall that the objective health metric may be divided into two groups: visible and technical. BMI and waist circumference are visible metrics because people can infer them without any intervention from others. Consequently, individuals may incorporate information about these visible health metrics into their health status perception. HDL and fasting blood glucose, on the other hand, require tests and healthcare professional's intervention. They are not "visible" and individuals may be unable to incorporate them into their decisions if they have not been informed about whether or not these technical health metrics pose a health risk to the individuals.

Therefore, the second comparison analysis is based on health information and whether individuals incorporate it in their health status evaluation. The health status perception model is estimated for two groups of individuals: those who are informed of health risks and those who are not. Once again, a Chow test is used to test if differences exist between the health perceptions of these two groups. The following hypotheses are developed for each comparative analysis::

Hypothesis One: The health perception of individuals exhibiting at least one visible health risk factor, as determined by the metabolic syndrome criteria, will present different health perceptions from those who do not exhibit any health risk.

Hypothesis Two: The perception of individuals who are informed about their health risks will be significantly different those who have received no such information, even if they have health risks.

The Chow test determines whether there are any statistical significant differences between the health risk and non-health risk groups in the first comparison and if there are any statistical significant differences between the informed group and un-informed group in the second comparison. The null hypothesis is that the group variable and all of its interactions are equal to zero. If we fail to reject the null hypothesis, then there is no difference between the two comparison groups. The F-statistic (or Chow Statistic) is computed as follows:

$$F = \frac{[SSR_R - (SSR_1 + SSR_2)}{SSR_1 + SSR_2} \cdot \frac{[n - 2(k+1)]}{k+1} \tag{3.17}$$

where SSR_R is the restricted sum of squared residuals (SSR) from pooling the groups, SSR_1 is the SSR for the first group and SSR_2 is the SSR for the second group, n is the total number of observations, and k is the number of explanatory variables.

Data

The data used in the study are obtained from the 2005-2006 NHANES survey (CDC, 2009b, 2009c). The Centers for Disease Control and Preventive (CDC) and the National Center for Health Statistics (NCHS) developed the National Health and Nutrition

Examination Survey (NHANES), a cross-sectional nationally representative health and nutrition examination survey. NHANES has a very complex survey design, using a stratified, multistage probability sampling technique and covering the civilian non-institutionalized US population. Data collection consists of both household interviews and physical examinations performed at a mobile examination center (MEC) [6]. Data from all of the variables in the behavioral dimension and the visible health metric variable, BMI and waist circumference, are from the demographics or household interview questionnaire section. The medical dimension data were collected using the MEC. Although the data covered all age groups, the study focused on respondents 20 years and older, a group that accounted for about 47.4 percent of the sample of 10,348.

Data Measures

Description of the Dependent Variables

Two principal regression models are the categorical dependent variable model and the OLS model. The categorical dependent variable model uses the self-reported current health status variable as its dependent variable and is referred to as the subjective model. In the objective or OLS models, the four health metrics (BMI, waist circumference, HDL, and fasting blood glucose) are each used as the dependent variables. Table 2 provides a summary of these health metric variables.

The self-reported current health status variable is measured by the question "Would you say your health in general is *excellent, very good, good, fair* or *poor*?" Higher scores correspond to higher perceived health status. Due to the relatively small

---

[6] Detailed methodology of the NHANES survey has already been published in previous reports (CDC, 2006).

number of respondents indicating poor health category, the category was merged with the fair health status category to create the poor-fair health category. This decision was based on Fullerton's (2010) suggestion that categories less than five percent of the sample be combined with other categories to avoid statistical issues with the model.

The objective variables encompass BMI, waist circumference, HDL and fasting blood glucose[7]. BMI and waist circumference were used as measurements for central obesity. Although there are controversies surrounding the efficiency of BMI measurement as a health indicator (Prentice and Jebb, 2001; Cawely and Burkhauser, 2006), it is currently considered the standard in determining body composition and health risk conditions (US DHHS, 2000). Waist circumference is often used as an alternative measurement to BMI. There is some debate as to whether waist circumference is a more reliable obesity-related health risk measurement than BMI (Janssen, Katzmarzyk, and Ross, 2004; Ford, Mokdad, and Giles, 2003; Zhu et al., 2002).

An individual with a BMI greater than $25kg/m^2$ is considered to be at risk for the development of Type II diabetes, cardiovascular disease, and a variety of other illnesses (Ervin, 2009). According to the International Diabetes Federation, waist circumference measurements are gender and ethnicity specific (Alberti et al., 2005). However, the American Diabetes Association only focuses on the gender specific criteria. Following the American Diabetes Association criteria, gender specifications for waist circumference are accounted for in this study. A waist circumference of greater than 102 cm for a male

---

[7] For a description of the anthropometric and venipuncture procedures used to obtain these health metrics, please refer to the NHANES anthropometry, laboratory, and physician examination procedure manuals (CDC, 2004a; CDC, 2004b; CDC 2003).

or 88 cm for a female indicates a risk factor of metabolic syndrome (American Diabetes Association, 2009).

High density lipoprotein (HDL) is considered to be good cholesterol as it is believed to either transport cholesterol to the liver and away from the arteries or it removes excess cholesterol from the arteries to slow the formation of plaque development there. Low levels of HDL are associated with heart disease, while high levels of HDL are believed to be protective against heart disease (American Heart Association, 2009). Atherogenic dyslipidemia is a risk factor for metabolic syndrome, and it is characterized by having HDL-cholesterol less than 40mg/dL for males and less than 50mg/dL for females.

NHANES uses three independent measures for diabetes: fasting blood glucose, two-hour oral glucose tolerance test (OGTT), and serum insulin. This study uses the results of the first measurement. Based on the metabolic syndrome risk factors developed by the American Diabetes Association, an individual with a fasting blood glucose level greater than 100 mg/dL suggests she has an increased risk of developing Type II diabetes or CVD (Table 2).

Demographic and Socio-economic variables

The demographic variables included in the study are gender and age. Respondent's socio-economic status is evaluated by three variables; education, income, and marital status. Education is divided into five dummy variable categories of less than Grade 9, less than high school, high school graduate or equivalent, some college or an Associates in Arts (AA) degree, or at least a college degree. Total annual household income has values ranging from $0 to more than $75,000, with the income categories increasing in increments of approximately $10,000. The third variable is marital status, which is represented by six dummy variables; married, widowed, divorced, separated, cohabiting and single. Education and marital status were treated as categorical variables using at least college education as the reference category for education and using single as the reference category for marital status.

Health Maintenance and Lifestyle Behaviors

Health maintenance behaviors included in the study are diet quality and physical activity. Diet quality is assessed using a similar question as the self-reported health status (five dummy variables represent the poor, fair, good, very good, and excellent). Measurement of physical activity is based on self-reported data on participation in physical activity. An overall exercise variable is developed to determine an individual's average level of physical activity. According to the US DHHS's *2008 Physical Activity Guidelines for Americans*, to be considered physically active, an individual must engage in: (1) 150 minutes per week of moderate activity (metabolic equivalent, MET, value of 3 to 5.9); (2) 75 minutes per week of vigorous activity (MET value of 6 or more); or (3) some combination of moderate or vigorous activity.[8] An individual's exercise score takes into account all of the activities that the individual participates in per month. The exercise score is based on the sum of the product of all the activities' MET value, the number of times the individual has participated in each activity per month, and the duration of each activity. Scaling of the exercise variable was performed by dividing the exercise score by

[8] Metabolic equivalent, MET, is a universally accepted unit of measure for energy expenditure during physical activities relative to an individual's body weight. It is based on a ratio of the working/exercise metabolic rate, the amount oxygen used by the body during physical activity, and the resting metabolic rate. One MET is defined as the energy expenditure needed for basic functions such as breathing and sitting quietly and is the value for the resting metabolic rate (US DHHS, 1999).

the minimum US DHHS requirement score to be considered physically active. A binary variable was created to divide respondents into active and inactive groups. Additionally, how a person compares herself to her peers in terms of physical fitness was included in the study. An individual can perceive herself as being more physically fit, less physically fit, or at the same fitness level as others her own age.

Lifestyle behaviors are represented by smoking status, alcohol consumption, and frequency of health care professional visits per year. The varying degrees for smoking status and alcohol consumption are represented in Table 3.2. Six dummy variables representing no health care professional visits, one visit, two to three visits, four to nine visits, ten to twelve visits, or thirteen or more visits are included in the model. Annual visits to a health care professional are considered to be part of a good health maintenance program; however, frequent visits to a health care professional suggest poor health (Kerkhofs and Lindeboom, 1994).

Table 3.2: Categories for the Smoking and Alcohol Consumption Behaviors

Health Behavior	Criteria
Smoking Status	
Never	Individual has never smoked or has smoked less than 100 cigarettes in her lifetime
Former	Individual has smoked at least 100 cigarettes in her lifetime, but she does not currently smoke cigarettes
Current	Individual has smoked at least 100 cigarettes in her lifetime, and she currently smoke cigarettes
Alcohol Consumption[a]	
Non-Drinker/ Abstainer	Individual consumes less than twelve alcoholic beverages per year
Light Drinker	Individual consumes one or fewer alcoholic beverages per day
Moderate Drinker	Individual consumes more than one but no more than two alcoholic beverages per day
Heavy Drinker	Individual consumes more than two alcoholic beverages per day

[a] Alcohol consumption categories are based on a study conducted by Sink et al. (2009).

Summary Statistics

The summary statistics shown in Table 3.3 provide an overview of the respondents involved in this sample. The average survey respondent is female, married, approximately 47 years old, has some college education or an AA degree, and with an annual household income of $43,299. The average respondent is a non-smoker, abstains from alcohol, and visits a health care professional two to three times a year. Almost 87 percent of the respondents report their health status as being good, very good, or excellent, and over 19 percent of them believe that they have excellent health. The majority of the respondents perceive their current diet quality as being good. The average respondent is physically active, which means that they exceed the physically active standards set by the US DHHS, and is just as physically fit as her peers. This finding is consistent with the US DHHS' *Healthy People 2010*, in which the majority of adults engage in a sufficient amount of leisure time physical activity.[9] However, lack of physical activity is still an important health concern. Close to 40 percent of adults do not engage in a sufficient amount of leisure time physical (US DHSS, 2000), which is similar to the 32 percent of adults in this study.

Within the health metrics, the mean BMI measure is 28.71, ranging from 18.52 to 76.07. Thus, the average respondent has a BMI score within the health risk range. Overweight or obese individuals make up over two-thirds of the sample, with obese individuals having the highest prevalence (34.52 percent). This trend is consistent with data from the NHANES data on the *Prevalence of Overweight and Obese Adults – United*

---

[9] Södergren et al., (2008) defines leisure time physical activity as being exercise that is planned, structured, repeatedly done and its main purpose is to improve one's physical fitness.

States, 2003-2004. Based on the 2003-2004 NHANES data, 66 percent of the adults 20 years and older were considered overweight or obese, and 32 percent were considered obese (CDC, 2009a). For the whole sample, the mean waist circumference is 97.64 cm with a range of 64 cm to 175 cm. For men, the average waist circumference measurement of 100.20 cm is barely below the health risk criteria of 102 cm. Women have a mean waist circumference measurement that is considered to be in the health risk range (95.25 cm). Nearly 53 percent of the respondents in the sample have a waist circumference that is in the health risk range. This is in contrast to the 69 percent of the respondents in the BMI health risk category.

The mean HDL is 55.59 mg/dL with a range of 17 to 151 mg/dL. With respect to HDL cholesterol levels, the higher the level the more heart protective benefits are present. HDL cholesterol levels greater than 60 mg/dL provides protection against heart disease. In the average man, the acceptable HDL cholesterol level is between 40 to 50 mg/dL, and for the average woman, the acceptable range is between 50 to 60 mg/dL (American Heart Association, 2009). In this study, HDL measurement for the average man and woman is 49.47 mg/dL and 61.39 mg/dL, respectively. Approximately 23 percent of the respondents have a HDL measurement within the health risk range, and 33 percent have a beneficial HDL measurement over 60 mg/dL.

The average fasting blood glucose is 101.14 mg/dL with a range of 60 to 364 mg/dL. Non-diabetic individuals typically have a fasting blood glucose less than 100 mg/dL (American Diabetic Association, 2009). Pre-diabetics are those individuals with a fasting blood glucose between 100 to 125 mg/dL, and therefore have an increased risk of developing diabetes. Thus, the average respondent in our sample is considered

Table 3.3: Summary Statistics

Summary Statistics	Code	Definition	Obs.	Mean (%) [a]	Std. Dev.	Min.	Max.
Dependent Variables							
Self Reported Health Condition			2,275	3.58	0.98	1	5
	HS1	1 if Poor	33	1.45			
	HS2	2 if Fair	269	11.82			
	HS3	3 if Good	768	33.76			
	HS4	4 if Very Good	759	33.36			
	HS5	5 if Excellent	446	19.60			
Body Mass Index		n/a	2,262	28.71	6.26	18.52	76.07
Waist Circumference		cm	2,256	97.64	15.46	64.00	175.00
High Density Lipoprotein (HDL)		mg/dL	2,185	55.59	16.35	17.00	151.00
Fasting Blood Glucose		mg/dL	1,091	101.14	25.42	60.00	364.00
Comparison Groups							
Health Risk Group - Waist Circumference (WC)	*MRISKWC*	1 if have at least a Health Risk associated with WC, 0 if otherwise	1,058	0.52	0.50	0	1
Health Risk Group - Overweight BMI (VBMI)	*BMIHR25*	1 if 25 ≤VBMI< 30, 0 if otherwise	2,262	0.69	0.46	0	1
Health Risk Group - Obese BMI (OBMI)	*BMIHR30*	1 if OBMI ≥ 30, 0 if otherwise	2,262	0.35	0.48	0	1
Informed Group	*INFORM1*	1 if informed of a potential Health Risk , 0 if otherwise	1,612	0.58	0.49	0	1
Socio-Economic Factors							
Gender	*gend1*	1 if Male, 0 if Female	2,275	0.48	0.50	0	1
Age	*ridageyr*	Years	2,275	44.64	17.33	20	85
Marital Status			2,275	2.44	1.87	1	6
Marital Status -Married	*MS1*	1 if Married, 0 if Single	1,296	56.97			
Marital Status - Widowed	*MS2*	1 if Widowed, 0 if Single	112	4.92			
Marital Status - Divorced	*MS3*	1 if Divorced, 0 if Single	221	9.71			
Marital Status - Separated	*MS4*	1 if Separated, 0 if Single	55	2.42			
Marital Status - Cohabitation	*MS6*	1 if Cohabitation, 0 if Single	192	8.44			
Education			2,275	3.69	1.15	1	5
Education - Less than Grade Nine	*ed1*	1 if ≤ Grade 9, 0 if College Grad	129	5.67			
Education - Less than High School (HSC)	*ed2*	1 if ≤ HSC, 0 if College Grad	235	10.33			
Education - High School Graduate or Equivalent	*ed3*	1 if HSC, 0 if College Grad	499	21.93			
Education - Some College or AA Degree	*ed4*	1 if Some College or AA Degree, 0 if College Grad	768	33.76			
Household Income	*Hhinc*	US Dollars	2,275	43,299	28,731	2,500	75,000
Behavioral Factors							
Diet Quality			2,275	3.13	1.00	1	5
Diet Quality -Poor	*DQ1*	1 if Poor, 0 if Excellent	110	4.84			
Diet Quality - Fair	*DQ2*	1 if Fair, 0 if Excellent	472	20.75			
Diet Quality - Good	*DQ3*	1 if Good, 0 if Excellent	904	39.74			
Diet Quality - Very Good	*DQ4*	1 if Very Good, 0 if Excellent	591	25.98			
Exercise			2,275	0.32	0.46	0	1
Inactive	*EX2*	1 if Inactive, 0 if Active	717	31.52			
Physical Fitness			2,275	1.99	0.91	1	3

Summary Statistics	Code	Definition	Obs.	Mean (%) [a]	Std. Dev.	Min.	Max.
Physical Fitness Comparison - Less	*fit2*	1 if Less, 0 if Same	400	17.58			
Physical Fitness Comparison - More	*fit1*	1 if More, 0 if Same	923	40.57			
Smoke			2,275	1.63	0.79	1	3
Smoke - Former	*smk2*	1 if Former Smoker, 0 if Non-Smoker	548	24.09			
Smoke - Current	*smk3*	1 if Current Smoker, 0 if Non-Smoker	437	19.21			
Alcohol Consumption			2,275	2.44	1.18	1	4
Alcohol Consumption - Light	*drink2*	1 if Light Drinker, 0 if Abstainer	486	21.36			
Alcohol Consumption - Moderate	*drink3*	1 if Moderate Drinker, 0 if Abstainer	479	21.05			
Alcohol Consumption - Heavy	*drink4*	1 if Heavy Drinker, 0 if Abstainer	614	26.99			
Doctor Visits			2,275	2.13	1.42	0	5
Doctor Visits - 1 Time/Yr	*doc2*	1 if Visit 1 Time/Year, 0 if No Visits	425	18.68			
Doctor Visits - 2-3 Times/Yr	*doc3*	1 if Visit 2 to 3 Times/Year, 0 if No Visits	622	27.34			
Doctor Visits - 4-9 Times/Yr	*doc4*	1 if Visit 4-9 Times/Year, 0 if No Visits	546	24.00			
Doctor Visits - 10-12 Times/Yr	*doc5*	1 if Visit 10-12 Times/Year, 0 if No Visits	153	6.73			
Doctor Visits - 13 or More Times/Yr	*doc6*	1 if Visit 13 Times or More/Year, 0 if No Visits	184	8.09			

[a] When reporting the individual binary variables, the percentage of the sample exhibiting the specific characteristic is reported instead of the sample mean.

pre-diabetic. According to the US DHHS, approximately one in every four American adults had pre-diabetes in 2007 (National Diabetes Information Clearinghouse, 2008).

The average individual is considered to be in the health risk group, which means that they at least exhibit one health risk in regards to their waist circumference. This makes sense given that over half of the sample has a waist circumference measurement in the health risk range. On average, individuals are informed of their health risk.

A correlation analysis was performed to address possible multicollinearity issues between the independent variables (Table 3.5). In each pairwise comparison, the correlation coefficient is less than 0.70, which implies that multicollinearity is not a large issue in this analysis. Also, the

Variance Inflation Factors are less than ten and have a tolerance level greater than 0.10 suggesting that no severe multicollinearity issues are present within the model.

Possible Data Issues

As with any data set, sampling and non-sampling errors, as well as measurement errors, may be present in the NHANES data. Data from the household interview questionnaire are based on self-reports and are subject to non-sampling errors such as recall problems, and/or misunderstanding of the questions. Data from the examination and laboratory components of the dataset are subject to measurement variation and human error. High standards in data collection and data processing are employed in the NHANES program to try to minimize the sampling and non-sampling errors (National Center for Health Statistics, 2006).

Previous studies indicated that there are some measurement biases present in self-reported measures. Measurement bias is the extent to which the mean value is over- or under-estimated. Associations among variables may or may not be affected by this measurement bias. Due to social stigma, behaviors such as smoking and alcohol consumption tend to be under- reported. On the other hand, physical activity tends to be over-reported, partly due to this behavior being socially desirable. Although measurement bias occurs, the degree of the bias is relatively low (Williams et al., 1989).

MacCallum et al. (2002) suggest that the common practice of turning continuous variables into binary variables based on standard cutpoints such as heavy drinking for those who consume three or more drinks per day may compound sampling variability of correlation estimates. This may result in some estimates that greatly overestimate population values. Although dichotomizing variables could present some estimation issues, model structural limitations required this.

Table 3.4: Correlation Matrix

	HCred	gend2	age	MS1	MS2	MS3	MS4	MS6	ed1	ed2	ed3	ed4	hhinc	DQ1	DQ2	DQ3	DQ4	fit2	fit1	EX2	smk2	smk3	drink2	drink3	drink4	doc2	doc3	doc4	doc5	doc6
HCred	1.00																													
gend2	-0.01	1.00																												
age	-0.09	0.06	1.00																											
MS1	0.09	0.03	0.16	1.00																										
MS2	-0.06	-0.10	0.34	-0.26	1.00																									
MS3	-0.08	-0.04	0.14	-0.38	-0.07	1.00																								
MS4	-0.05	0.00	-0.01	-0.18	-0.04	-0.05	1.00																							
MS6	-0.03	0.02	-0.20	-0.35	-0.07	-0.10	-0.05	1.00																						
ed1	-0.19	0.03	0.09	0.02	0.04	-0.05	0.02	0.01	1.00																					
ed2	-0.11	0.02	-0.01	-0.07	0.04	0.01	0.05	0.05	-0.08	1.00																				
ed3	-0.10	0.01	0.04	-0.01	0.02	0.02	0.00	0.04	-0.13	-0.18	1.00																			
ed4	0.02	-0.01	-0.10	-0.05	0.00	0.00	0.00	-0.02	-0.18	-0.24	-0.38	1.00																		
hhinc	0.22	0.03	-0.06	0.29	-0.17	-0.13	-0.08	-0.04	-0.18	-0.20	-0.12	0.00	1.00																	
DQ1	-0.13	0.00	-0.10	-0.09	0.01	0.04	0.03	0.04	0.04	0.02	0.01	0.03	-0.04	1.00																
DQ2	-0.23	0.00	-0.14	-0.10	-0.01	0.02	0.03	0.09	0.04	0.07	0.04	0.01	-0.07	-0.12	1.00															
DQ3	-0.02	-0.01	-0.04	0.03	-0.02	-0.02	-0.01	-0.05	0.00	-0.02	0.01	0.03	0.01	-0.18	-0.42	1.00														
DQ4	0.19	0.00	0.15	0.09	0.01	-0.03	-0.03	-0.04	-0.08	-0.05	-0.04	-0.01	0.09	-0.13	-0.30	-0.48	1.00													
fit2	-0.22	-0.12	-0.12	-0.03	-0.04	0.02	0.03	0.00	-0.04	-0.04	0.05	0.05	-0.04	0.16	0.13	-0.02	-0.12	1.00												
fit1	0.21	0.14	0.22	0.05	0.04	0.02	0.02	-0.04	0.00	-0.01	-0.03	-0.02	0.07	-0.10	-0.14	-0.08	0.16	-0.39	1.00											
EX2	-0.09	-0.10	0.06	0.04	0.04	0.03	-0.03	-0.01	0.05	0.01	0.04	0.03	-0.07	0.05	0.08	0.00	-0.05	0.21	-0.20	1.00										
smk2	0.00	0.08	0.25	0.08	0.06	0.00	0.00	-0.03	0.00	-0.06	-0.01	0.03	0.04	-0.05	-0.07	0.00	0.05	0.02	0.06	-0.01	1.00									
smk3	-0.09	0.13	-0.11	-0.15	-0.05	0.10	0.02	0.12	0.02	0.11	0.07	-0.01	-0.11	0.10	0.08	-0.02	-0.07	0.00	0.00	-0.02	-0.27	1.00								
drink2	0.07	-0.06	0.17	0.11	0.02	-0.01	-0.07	-0.04	-0.06	-0.06	-0.04	-0.03	0.11	-0.04	-0.08	-0.01	0.09	-0.02	0.04	-0.01	0.09	-0.12	1.00							
drink3	0.08	0.03	0.01	0.00	-0.01	0.03	0.02	-0.02	-0.06	-0.04	-0.04	0.02	0.06	-0.04	-0.01	-0.03	0.05	0.00	0.05	-0.04	0.05	0.00	-0.27	1.00						
drink4	-0.05	0.26	-0.26	-0.11	-0.08	-0.03	0.05	0.11	0.00	0.04	0.04	0.04	0.00	0.06	0.07	0.04	-0.10	-0.01	-0.02	-0.09	0.03	0.27	-0.32	-0.31	1.00					
doc2	0.08	0.08	-0.07	-0.01	-0.04	0.01	-0.02	0.00	-0.01	-0.03	-0.01	0.01	0.03	0.02	0.04	-0.04	0.00	-0.02	0.00	0.01	-0.03	0.00	-0.03	0.03	0.03	1.00				
doc3	0.05	-0.04	0.05	0.01	-0.02	0.00	-0.06	-0.01	-0.01	0.01	-0.02	-0.02	0.04	0.00	-0.04	0.00	0.04	-0.03	0.01	-0.03	0.00	-0.04	0.01	0.02	-0.03	-0.29	1.00			
doc4	-0.04	-0.10	0.14	0.00	0.08	0.02	0.03	-0.02	-0.01	-0.01	-0.02	0.01	0.02	-0.03	-0.01	0.00	0.01	0.03	-0.02	0.03	0.07	-0.05	0.06	0.03	-0.08	-0.27	-0.34	1.00		
doc5	-0.08	-0.07	0.02	0.06	0.00	0.02	0.00	-0.04	-0.02	-0.01	0.03	0.00	-0.01	0.01	-0.03	0.04	-0.02	0.04	-0.01	0.03	0.04	-0.02	0.02	-0.07	-0.06	-0.13	-0.16	-0.15	1.00	
doc6	-0.11	-0.11	0.00	0.00	0.01	0.02	0.03	0.01	-0.03	-0.04	0.03	0.01	0.00	-0.01	0.00	0.03	-0.03	0.07	-0.03	0.01	0.04	-0.01	0.02	0.00	-0.02	-0.14	-0.18	-0.17	-0.08	1.00

Most cross-section datasets do not sample the entire population, and thus some sampling biases may occur. In NHANES, low-income persons, adolescents (aged 15 to 19), and persons aged 60 or older are over-sampled to provide reliable estimates for these participant groups (National Center for Health Statistics, 2006). Additionally, African Americans and Mexican Americans are over-sampled to ensure accurate estimates. To correct for over-sampling, sample weights developed by NHANES are used to compensate for the unequal representation of these over-sampled populations (Kreuter and Valliant, 2007). Failure to use the correct survey design elements of stratification, clustering, and sampling weights could result in inaccurate point estimates and standard errors being underestimated, which could lead to false positives.

Chapter 4 - Results

The analysis is divided into four sections: subjective health status analysis, objective health metric analysis, summary of the explanatory factors, and comparisons among different health risk groups. The reference category for the subjective health status model and the objective health metric models is female, single, with at least a college education, a self-reported excellent diet quality, a same perceived fitness level as her peers, is physically active by US DHHS standards, is a non-smoker, abstains from alcohol, and does not visit a health care professional annually. Over 60 percent of the individuals report good or very good health status. Individuals are least likely to report a poor/fair health status (13.27 percent).

Subjective Health Status Analysis

Confirming the Parallel Line Assumption

Results from both the Brant Test and the *autofit* option indicate that the Parallel Line Assumption (PLA) was violated by five variables at the five percent significance level: four diet quality variables and light alcoholic consumption. See Table 3.3 (Summary Table) for the description of the variables. Thus, the ordered logit model is rejected, and either an ordered probit or a generalized ordered logit model is recommended. Changing the link function from logit to probit in the ordinal regression model did not result in the acceptance of the parallel line assumption. See Appendix A for results of the ordered probit model.

Since the ordered logit model is nested within the Partial Constrained Ordered Logit (PCOL) model, which is itself nested within the Unconstrained Generalized Ordered Logit (UGOL) model, comparisons between the models can be performed using likelihood ratio tests. The deviance between the ordered logit and the PCOL models, which is measured by the difference in the likelihood ratios of the two models, indicates that the PCOL model is a better fit for the data ($LR\chi^2(10)=51.45$ with p =0.0000). The UGOL model is a better fitting model than the ordered logit model ($LR\chi^2(58)=103.49$ with p =0.0002), but it does not fit the data better than the PCOL model ($LR\chi^2(48)=52.04$ with p =0.3195). Consequently, the PCOL model is the preferred model of the three. In the PCOL and UGOL models, there is a possibility that negative probabilities could occur. Predicted probabilities are computed to identify if any negative probabilities exist[10]. If a large or non-trivial number of cases of negative probability occur, then it is recommended that the model be modified or a different statistical technique used, such as a multinomial model. No negative probabilities are predicted in the PCOL model, and thus, we do not need to modify our model.

Specification tests including Pregibon's Link Test and the Ramsey's RESET Test are performed for the ordered logit and PCOL models. The ordered logit and PCOL models universally passed these specification tests, indicating that the models are not mis-specified. The goodness-of-fit of the ordered logit and the PCOL models are tested using the *Akaike Information Criterion* (AIC) and the *Bayesian Information Criterion* (BIC). Based on the AIC, the PCOL model is a better fit than the ordered logit model, but the BIC does not support this result (Table 4.1). These results are consistent with a study by Polsky et al. (2006) in which the ordered logit is compared to a generalized ordered logit model with similar results.

---

[10] Stata also displays a warning message if negative probabilities occur. No warning message was received with the UGOL or PCOL model.

Table 4.1: Measures of Goodness-of-fit of the Ordered Logit, PCOL, and UGOL Models

	Ordered Logit	PCOL	UGOL
Log likelihood (Full Model)	-2631.575	-2601.357	-2579.8279
Likelihood Ratio Chi-Squared	744.324	804.760	847.820
Degrees of Freedom	29	39	87
p-value	0.000	0.000	0.000
McFadden's Adjusted R^2	0.113	0.104	0.141
Cragg-Uhler(Nagelkerke) R^2	0.300	0.321	-
AIC*n	5327.150	5382.714	-
BIC'	-520.162	-503.300	-
AIC used by Stata	5327.150	5286.714	-

Note: Similar to Polsky et al. (2006), information for the Akaike Information Criterion and the Bayesian Information Criterion is not available for the generalized ordered logit in Stata.

Model 1: Partial Constrained Generalized Ordered Logit Model

Table 4.2 shows the estimated coefficients from the PCOL model, with excellent self-reported health status being treated as the reference health status category. See Appendix A for the results of the ordered logit and UGOL models.

The likelihood ratio chi-square test indicates that the fitted model is significantly different from the null model, meaning that we can reject the null hypothesis that all of the predictor effects are zero. Nineteen of the 29 variables are statistically significant at the ten percent level or higher. The majority of the variables in the PCOL model are similar in sign and magnitude to the ordered logit and the UGOL models. The ordered logit and the PCOL models essentially have the same significant variables with two exceptions in diet quality. Good and very good diet quality are significant in the ordered logit model but not in the PCOL model for the lowest, poor/fair, health status category. The non-parallel nature of good and very good diet quality may explain why there is a difference between the ordered logit and the PCOL models in terms of significant variables.

Table 4.2: Estimated Coefficients if the PCOL Model

Dependent Variable	Health Status = Poor/Fair	Health Status = Good	Health Status = Very Good
Independent Variables			
Gender - Male	**-0.185****		
	(0.0880)		
Age (in yrs)	**-0.0212*****		
	(0.00310)		
Marital Status -Married	0.00716		
	(0.120)		
Marital Status - Widowed	0.0141		
	(0.232)		
Marital Status - Divorced	**-0.345****		
	(0.172)		
Marital Status - Separated	-0.306		
	(0.288)		
Marital Status - Cohabitation	-0.234		
	(0.167)		
Education - Less than Grade9	**-1.977*****		
	(0.204)		
Education - Less than High School	**-1.071*****		
	(0.156)		
Education - High School Grad or Equivalent	**-0.751*****		
	(0.120)		
Education - Some College or an AA Degree	**-0.469*****		
	(0.105)		
Household Income	**0.0693*****		
	(0.0162)		
Diet Quality - Poor	**-1.085*****	**-1.858*****	**-2.502*****
	(0.336)	(0.288)	(0.456)
Diet Quality - Fair	**-1.048*****	**-1.802*****	**-2.149*****
	(0.270)	(0.206)	(0.226)
Diet Quality - Good	0.133	**-1.104*****	**-1.793*****
	(0.271)	(0.190)	(0.186)
Diet Quality - Very Good	0.274	**-0.485****	**-1.182*****
	(0.297)	(0.198)	(0.184)
Physical Fitness Comparison - Less	**-0.726*****		
	(0.118)		
Physical Fitness Comparison - More	**0.489*****		
	(0.0919)		
Exercise - Inactive	**0.172***		
	(0.0896)		
Smoke - Former	0.00519		
	(0.102)		
Smoke - Current	-0.0744		
	(0.113)		
Alcohol Consumption - Light	**0.564*****	**0.234***	-0.0418
	(0.204)	(0.132)	(0.152)
Alcohol Consumption - Moderate	**0.214***		
	(0.117)		
Alcohol Consumption - Heavy	-0.0629		
	(0.120)		
Doctor Visits - 1 Time/Yr	-0.0513		
	(0.140)		
Doctor Visits - 2-3 Times/Yr	**-0.254***		
	(0.133)		
Doctor Visits - 4-9 Times/Yr	**-0.511*****		
	(0.139)		
Doctor Visits - 10-12 Times/Yr	**-0.992*****		
	(0.193)		
Doctor Visits - 13 or More Times/Yr	**-1.263*****		
	(0.183)		
Constant - Cutpoint 1	**3.673*****		
	(0.338)		
Constant - Cutpoint 2	**2.408*****		
	(0.290)		
Constant - Cutpoint 3	**1.141*****		
	(0.280)		
Observations	2,275		
LR Chi-Square	795.77		
p	0		
Pseudo R^2	0.1325		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reference Category is female, single, with at least a college education, a self-reported excellent diet quality, a same perceived physical fitness level as her peers, is physically active by US DHHS standards, is a non-smoker, abstains from alcohol, and does not visit a doctor annually.

Marginal Effects

Within the biometric and public health literature, results from limited dependent variable models are typically interpreted in terms of odds ratios (Long, 1997; Lance, 2008); however, odds ratios are somewhat non-intuitive (Davies, Crombie, and Tavakoli, 1998) and many researchers, particularly those in economics, prefer reporting marginal effects.

When interpreting marginal effects in this model, it is essential to bear in mind two crucial points. First, an estimated marginal effect represents the impact of the corresponding explanatory variable on the dependent variables with respect to the reference category of the explanatory variable. Second, the preceding statement holds only when all other explanatory variables other than the one examined are held constant. For example, while all other variables are held constant, divorced individuals have a 0.055 (or 5.5 percent) higher probability of reporting a good health status compared to single individuals. Like the coefficients, the marginal effects across the three discrete choice models are similar in sign and magnitude. Marginal effects of the PCOL model (Table 4.3) are discussed below, and the marginal effects for the ordered logit and UGOL models are presented in Appendix A.

According to the estimated results, holding all other variables constant, the probability of males reporting a poor/fair or good health status is approximately 1.5 percent and 3.1 percent, respectively, more than females. However, males have a lower probability of reporting a very good or excellent health status than women by 2.3 percent and 2.3 percent, respectively. Although it was expected that females would report a lower health status than men, the results indicate that the converse is true; men have a lower perceived health status than women, supporting Morris-Tries’ (2004) findings.

Table 4.3: Estimated Marginal Effects of the PCOL Model

	Health Status = Poor/Fair	Health Status = Good	Health Status = Very Good	Health Status = Excellent
Gender - Male	**0.0150 ****	**0.0310 ****	**-0.0231 ****	**-0.0229 ****
Age (in yrs)	**0.0017 *****	**0.0036 *****	**-0.0027 *****	**-0.0026 *****
Marital Status -Married	-0.0006	-0.0012	0.0009	0.0009
Marital Status - Widowed	-0.0011	-0.0024	0.0018	0.0018
Marital Status - Divorced	**0.0313 ***	**0.0547 ****	**-0.0472 ***	**-0.0387 ****
Marital Status - Separated	0.0279	0.0484	-0.0421	-0.0342
Marital Status - Cohabitation	0.0205	0.0379	-0.0313	-0.0271
Education - Less than Grade 9	**0.3058 *****	**0.1021 *****	**-0.2740 *****	**-0.1340 *****
Education - Less than High School	**0.1227 *****	**0.1330 *****	**-0.1572 *****	**-0.0984 *****
Education - High School Grad or Equivalent	**0.0727 *****	**0.1125 *****	**-0.1047 *****	**-0.0805 *****
Education - Some College or an AA Degree	**0.0405 *****	**0.0761 *****	**-0.0614 *****	**-0.0552 *****
Household Income	**-0.0056 *****	**-0.0117 *****	**0.0087 *****	**0.0086 *****
Diet Quality - Poor	**0.1302 ****	**0.2597 *****	**-0.2445 *****	**-0.1454 *****
Diet Quality - Fair	**0.1099 *****	**0.2976 *****	**-0.2280 *****	**-0.1796 *****
Diet Quality - Good	-0.0106	**0.2799 *****	**-0.0667 ***	**-0.2027 *****
Diet Quality - Very Good	-0.0210	**0.1416 *****	0.0008	**-0.1214 *****
Physical Fitness Comparison - Less	**0.0715 *****	**0.1073 *****	**-0.1025 *****	**-0.0763 *****
Physical Fitness Comparison - More	**-0.0385 *****	**-0.0825 *****	**0.0584 *****	**0.0626 *****
Exercise - Inactive	**-0.0136 ****	**-0.0292 ***	**0.0209 ****	**0.0219 ***
Smoke - Former	-0.0004	-0.0009	0.0006	0.0006
Smoke - Current	0.0061	0.0124	-0.0095	-0.0091
Alcohol Consumption - Light	**-0.0402 *****	-0.0178	**0.0631 ****	-0.0051
Alcohol Consumption - Moderate	**-0.0164 ***	**-0.0366 ***	**0.0253 ***	**0.0277 ***
Alcohol Consumption - Heavy	0.0051	0.0105	-0.0080	-0.0077
Doctor Visits - 1 Time/Yr	0.0042	0.0086	-0.0065	-0.0063
Doctor Visits - 2-3 Times/Yr	**0.0215 ***	**0.0418 ***	**-0.0331 ***	**-0.0302 ****
Doctor Visits - 4-9 Times/Yr	**0.0463 *****	**0.0808 *****	**-0.0693 *****	**-0.0578 *****
Doctor Visits - 10 -12 Times/Yr	**0.1138 *****	**0.1236 *****	**-0.1468 *****	**-0.0906 *****
Doctor Visits - 13 or More Times/Yr	**0.1563 *****	**0.1375 *****	**-0.1860 *****	**-0.1078 *****

*** p<0.01, ** p<0.05, * p<0.1

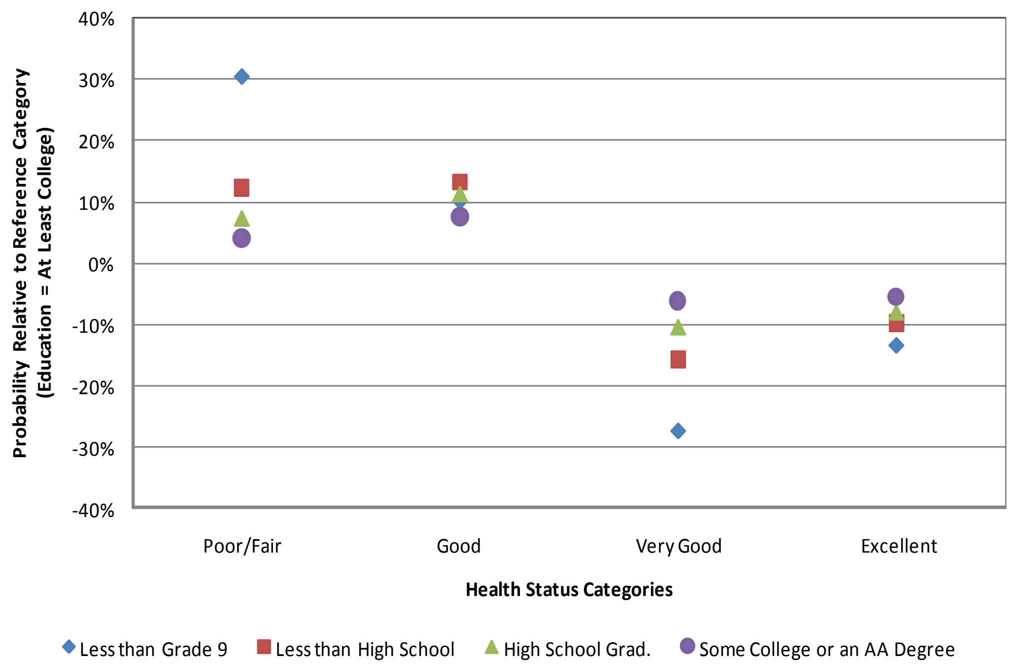
The results show that a one-unit increase in age increases the probability of reporting poor/fair or good health status by 0.17 percent and 0.36 percent, respectively, ceteris paribus. Meanwhile, the likelihood of this same individual reporting a very good or excellent health status decreases by 0.27 percent and 0.26 percent, respectively. This finding is in-line with this study's expectations.

Contrary to what Ren (1997) stated, being divorced has a negative influence on self-reported health status, while marital separation has no discernible relationship with self-reported health status. Compared to single individuals, divorced individuals have a higher probability of reporting a poor/fair or good health status by 3.1 percent and 5.4 percent, respectively. These same individuals have a lower probability of reporting a very good or excellent health status by 4.7 percent and 3.9 percent, respectively. These results support the findings of Kwaśniewska, Bielecki and Drygas' (2004). The results concerning divorced individuals having a lower health status than single individuals is consistent with this study's expectations.

Consistent with previous literature citing a positive relationship between education and health status (US DHHS, 2000; Morris-Tries, 2004; Silvenroinen, Lahelma and Kaprio, 2006; Tolliver, 2007), the results indicate that lower education leads to an increased probability of individuals perceiving their health status as being low. The reference category for education is individuals with at least a college education. Therefore, all probabilities are measured relative to this category. The results show that the probability that individuals with less than a Grade nine education will report a poor/fair and good health status is 30.5 percent and 10.2 percent higher, respectively, than individuals with at least a college education, ceteris paribus. Conversely, individuals with less than a Grade 9 education have a lower probability of reporting a very good and excellent health status by 27.4 percent and 13.4 percent, respectively, than individuals with at least a college education (Figure 4.1). Compared to individuals in the reference category, individuals with less than high school have a higher probability of reporting a poor/fair or good health status by 12.3 percent and 13.3 percent, respectively, and a lower probability of reporting a very good or excellent health status by 15.7 and 9.8 percent, respectively.

The probability that an individual with a high school diploma or equivalent will report a poor/fair health status is 7.2 percent higher than the reference group. The probability that the same individual will report a good health status is about 11.3 percent higher than the reference group. On the other hand, the probability that a high school graduate will report a very good health status is 10.5 percent lower than the reference group and an excellent health status is about 8.1 percent lower.

Figure 4.1: Education and Perception of Health Status

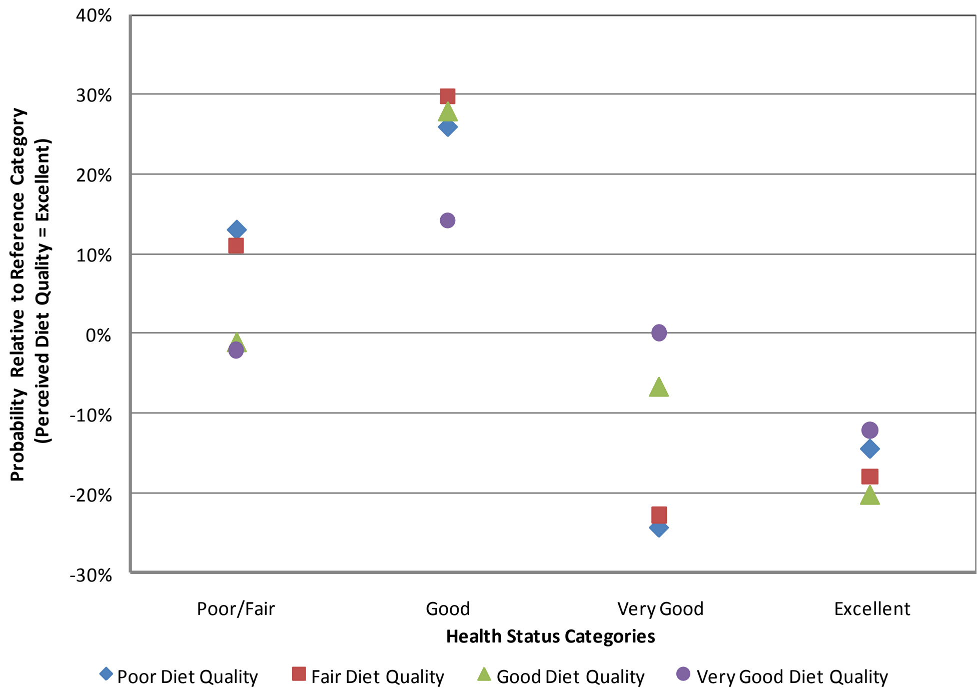


For individuals with some college education or an AA degree, they have a higher probability of reporting a poor/fair or good health status by 4.1 percent and 7.6 percent, respectively, compared to individuals in the reference category. Those same individuals have a decreased probability of reporting a very good or excellent health status by 6.1 percent and 5.5 percent, respectively, compared to individuals with at least a high school education. Compared to the reference group, the largest marginal effects are expressed in the lower education levels (Figure 4.1).

Annual household income has a negative relationship with low health status levels and a positive relationship with higher health status levels. These results support findings from previous studies (US DHHS, 2000; Morris-Tries, 2004; Tolliver, 2007). Holding all other variables constant, when an individual's annual household income increases by one income level, which is approximately $10,000, the probability of reporting a poor/fair or good health status level decreases by 0.56 percent and 1.2 percent, respectively, and the probability of reporting a very good or excellent health status increases by 0.87 percent and 0.86 percent, respectively.

The reference category for diet quality is excellent diet quality. Individuals with a self-reported poor diet quality have a higher probability of reporting a poor/fair or good health status by 13.0 percent and 26.0 percent, respectively, and a lower probability of reporting a very good or excellent health status by 24.5 percent and 14.5 percent, respectively (Figure 4.2). Likewise, individuals with a perceived fair diet quality have a higher probability of reporting a poor/fair or good health status by 11.0 percent and 29.8 percent, respectively, and a lower probability of reporting a very good or excellent health status by 22.8 percent and 18.0 percent, respectively. Individuals with a perceived good diet quality have a higher probability of reporting a good health status by 28.0 percent and a lower probability of reporting a very good or excellent health status by 6.7 percent and 20.3 percent, respectively, holding all other variables constant. Compared to individuals with a self-reported excellent health status, individuals with a very good perceived diet quality have a probability of reporting a good health status that is 14.2 percent higher and a probability of reporting an excellent health status that is 12.1 percent less, ceteris paribus.

Figure 4.2: Perceived Diet Quality and Perception of Health Status



To maintain clarity and minimize confusion when analyzing the results, individuals who view themselves as being less physically fit than their peers are referred to as having unfavorable physical fitness perceptions, and individuals who view themselves as being more physically fit than their peers are classified as having favorable physically fitness perceptions. Holding all other variables constant, individuals viewing themselves as being less physically fit than their peers have a higher probability of reporting a poor/fair and good health status by 7.2 percent and 10.7 percent, respectively, compared to individuals who perceive their physical fitness level as being the same as their peers. Also, individuals with an unfavorable physical fitness perception have a lower probability of reporting a very good or excellent health status by 10.3 percent and 7.6 percent, respectively.

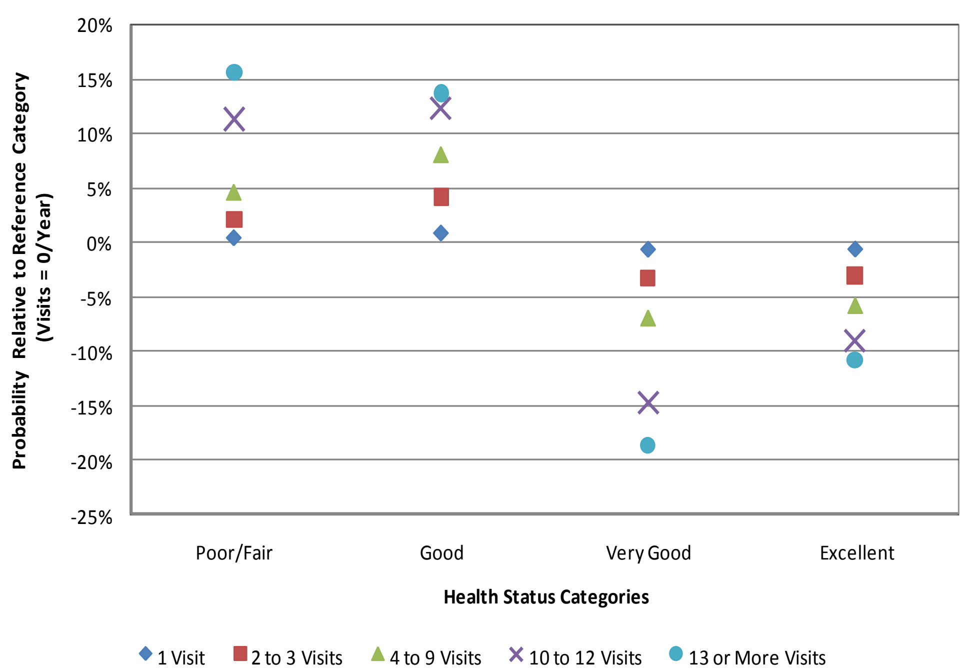
The probability of those individuals viewing themselves as being more physically fit than their peers will report a poor/fair or good health status is 3.9 percent and 8.3 percent, respectively, less than individuals in the reference category, holding all other variables the same. Additionally, individuals with a favorable physical fitness perception have a higher probability of reporting a very good or excellent health status by 5.8 percent and 6.3 percent, respectively. These results are consistent with this study's expectations on how an individual compares themselves to others and how it reflects their health status.

The US DHHS recommends that individual engage in 150 minutes per week of moderate activity, 75 minutes of vigorous activity or a combination of moderate and vigorous activity. Individuals meeting this recommendation are considered active and are the reference category. Compared to active individuals, the probability that individuals who do not meet these requirements (i.e., inactive individuals) will report a poor/fair and good health status has decreased by 1.4 percent and 2.9 percent, respectively. Conversely, inactive individuals have a higher probability of reporting a very good or excellent health status by 2.1 percent and 2.2 percent, respectively, holding everything else unchanged. This result is not as expected and nor does it support Morris-Tries' (2004) finding in which inactive individuals reported a negative relationship between their activity level and their health. It also does not support Miilunpalo et al.'s (1997) findings in which good physical activity is related to good health.

Light and moderate drinking has a negative effect on reporting a low health status, but a positive effect on reporting a high health status. Compared to individuals who abstain from alcohol, the probability of light drinkers reporting poor/fair is decreased by 4.0 percent, ceteris paribus. Light drinkers also have a higher probability of reporting a very good health status by 6.3 percent, respectively. The probability that moderate drinkers will report a poor/fair or good health status is 1.6 percent and 3.7 percent, respectively, less than non-drinkers. Also, moderate drinkers have a higher probability of reporting a very good and excellent health status by 2.5 percent and 2.8 percent, respectively. These results support the findings from Morris-Tries' (2004) study.

Visiting a health care professional more than once a year has a negative impact on reporting a higher health status and a positive impact on reporting a lower health status. The largest magnitude of the marginal effects is expressed in the higher frequency of health care professional visits (Figure 4.3). That is, individuals visiting a health care professional thirteen or more times have the highest probability of reporting a poor/fair health status and the lowest probability of reporting a excellent health status compared to the reference category. These results are consist with the findings from Miilunpalo et al. (1997) that suggest that there is a negative relationship between the frequency of visits to a health care professional and health status.

Figure 4.3: Frequency of Health Care Professional Visits and Perception of Health Status



Holding all else constant, individuals who visit a health care professional two to three times a year have a higher probability of reporting a poor/fair and good health status by 2.2 percent and 4.2 percent, respectively, compared to the reference group of individuals who do not visit a health care professional annually. Individuals who visit a health care professional two to three times per year have a lower probability of reporting very good and excellent health status by 3.3 percent and 3.0 percent, respectively. Individuals visiting a health care professional four to nine times per year have a higher probability of reporting a poor/fair and good health status by 4.6 percent and 8.1 percent, respectively, than individuals in the reference group. Compared to this same group, individuals visiting a health care professional four to nine times per year have a decreased probability of reporting a very good or excellent health status by 6.9 percent and 5.8 percent, respectively, holding everything else constant.

With respect to individuals visiting a health care professional ten to twelve times per year, the probability of reporting a poor/fair and good health status increases by 11.4 percent and 12.4 percent, respectively, compared to individuals who do not visit a health care professional annually. Conversely, the probability of those individuals reporting a very good or excellent health status decreases by 14.7 percent and 9.1 percent, respectively. The probability of individuals who visit a health care professional thirteen or more times is 15.6 percent and 13.8 percent, respectively, ceteris paribus. This same group of individuals has a lower probability of reporting a very good and excellent health status by 18.6 percent and 10.8 percent, respectively.

Objective Health Metric Models

The objective health metric segment of the study encompasses four models, each with a different health status measure, instead of self-reported health status. These four models are based on the two types of objective health metrics considered in this study: visible and technical.

The visible metrics are BMI and waist circumference and are described as such because they are visible to both the decision maker and others. The technical metrics are HDL cholesterol and fasting blood glucose and can be determined through laboratory tests. These technical metrics are therefore invisible to decision makers unless someone draws their blood, conducts the tests and provides them with the results. It was hypothesized that the visible metric will influence perceived health status and therefore exhibit similar relationships to the explanatory variables as perceived health status. On the other hand, the technical metrics are external to the individual's control and may respond differently to the explanatory variable than the perceived health status.

The four health metrics are continuous. Therefore, OLS regression models are estimated for all four of them. Pregibon's Link Test is performed on all the objective health metric models. All but one of the models, *Model: HDL Cholesterol*, passed the link test at the five percent level, indicating that three of the four models are not mis-specified. The results from the four models are presented in Table 4.4.

The reference category for the objective health metric models is the same as the subjective health status model: female, single, with at least a college education, a self-reported excellent diet quality, a same perceived fitness level as her peers, is physically active by US DHHS standards, is a non-smoker, abstains from alcohol, and does not visit a health care professional annually.

Visible Health Metric Models

Model: BMI

In the model where BMI is the dependent variable, the *F*-test is significant at the one percent level and thus, we reject the null hypothesis that all of the coefficients in the equation are

Table 4.4: Estimated Coefficients of the Objective Health Metric Models

Dependent Variable	BMI	Waist Circumference	HDL	Fasting Blood Glucose
Independent Variables				
Gender - Male	0.368	**7.068*** **	**-13.270*** **	**6.278*** **
	(0.269)	(0.674)	(0.679)	(1.669)
Age (in yrs)	**0.029*** **	**0.159*** **	0.008	**0.427*** **
	(0.010)	(0.023)	(0.025)	(0.058)
Marital Status - Married	0.030	**2.255** **	-1.463	1.599
	(0.411)	(0.967)	(0.991)	(1.815)
Marital Status - Widowed	-0.745	-0.986	0.238	6.277
	(0.726)	(1.692)	(2.059)	(5.314)
Marital Status - Divorced	0.627	**2.679***	-0.983	1.735
	(0.623)	(1.438)	(1.379)	(2.681)
Marital Status - Separated	1.173	2.291	-2.856	0.792
	(1.081)	(2.379)	(2.101)	(3.342)
Marital Status - Cohabitation	0.074	1.747	**-3.554*** **	-1.052
	(0.569)	(1.397)	(1.285)	(1.562)
Education - Less than Grade 9	-0.190	-1.370	**-3.185** **	5.011
	(0.591)	(1.414)	(1.519)	(5.221)
Education - Less than High School	**1.154** **	**2.300** **	-1.965	**6.602** **
	(0.497)	(1.172)	(1.338)	(3.203)
Education - High School Graduate or Equivalent	**1.036*** **	**2.145** **	**-3.185*** **	2.646
	(0.373)	(0.906)	(0.950)	(2.059)
Education - Some College or an AA Degree	**1.100*** **	**1.899** **	**-2.417*** **	**3.387** **
	(0.320)	(0.768)	(0.849)	(1.725)
Household Income	-0.0834	**-0.241***	0.169	0.016
	(0.0542)	(0.127)	(0.131)	(0.289)
Diet Quality - Poor	**3.758*** **	**7.062*** **	**-6.662*** **	3.087
	(0.976)	(2.131)	(1.709)	(4.364)
Diet Quality - Fair	**1.604*** **	**2.727** **	**-4.090*** **	4.570
	(0.533)	(1.276)	(1.340)	(2.980)
Diet Quality - Good	**0.834***	1.583	**-4.082*** **	1.343
	(0.470)	(1.139)	(1.220)	(2.496)
Diet Quality - Very Good	-0.239	-0.610	-1.132	0.833
	(0.463)	(1.149)	(1.237)	(2.420)
Physical Fitness Comparison - Less	**2.496*** **	**6.459*** **	**-2.650*** **	**4.582***
	(0.446)	(1.020)	(0.930)	(2.704)
Physical Fitness Comparison - More	**-1.225*** **	**-3.946*** **	**2.790*** **	**-4.266*** **
	(0.269)	(0.665)	(0.739)	(1.392)
Exercise - Inactive	-0.049	0.173	**1.401***	-2.066
	(0.293)	(0.698)	(0.749)	(1.737)
Smoke - Former	-0.149	0.819	0.465	-0.974
	(0.321)	(0.772)	(0.788)	(1.745)
Smoke - Current	**-1.291*** **	**-2.139** **	**-1.551***	-1.275
	(0.380)	(0.917)	(0.886)	(2.088)
Alcohol Consumption - Light	**-1.167*** **	**-2.273** **	**2.657*** **	-1.060
	(0.378)	(0.907)	(0.906)	(2.665)
Alcohol Consumption - Moderate	**-1.177*** **	**-2.205** **	**5.096*** **	**-3.617***
	(0.374)	(0.888)	(0.980)	(2.185)
Alcohol Consumption - Heavy	**-0.989** **	**-1.823***	**5.204*** **	-2.106
	(0.394)	(0.946)	(0.930)	(2.292)
Doctor Visits - 1 Time/Yr	0.146	0.919	-0.064	2.756
	(0.409)	(1.029)	(1.103)	(2.286)
Doctor Visits - 2-3 Times/Yr	0.332	1.513	0.663	**3.145***
	(0.401)	(0.993)	(1.039)	(1.799)
Doctor Visits - 4-9 Times/Yr	**1.421*** **	**4.805*** **	0.401	**3.761** **
	(0.441)	(1.045)	(1.084)	(1.846)
Doctor Visits - 10-12 Times/Yr	0.072	**2.532***	**3.273***	1.912
	(0.575)	(1.430)	(1.675)	(2.796)
Doctor Visits - 13 or More Times/Yr	**1.494** **	**5.732*** **	0.594	0.488
	(0.619)	(1.431)	(1.391)	(2.241)
Constant	**26.88*** **	**84.41*** **	**62.11*** **	**74.47*** **
	(0.884)	(2.114)	(2.209)	(3.919)
Observations	2,263	2,257	2,186	1,071
R^2	0.123	0.173	0.201	0.133
Adjusted R^2	0.117	0.162	0.190	0.109
F-test	9.040	16.460	19.980	7.930
p	0	0	0	0

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Reference Category is female, single, with at least a college education, a self-reported excellent diet quality, a same perceived physical fitness level as her peers, is physically active by US DHHS standards, is a non-smoker, abstains from alcohol, and does not visit a doctor annually.

simultaneously equal to zero. The R^2 is 0.123, which implies that 12.3 percent of the variability in BMI health status is explained by the independent variables. The following fifteen variables are significant at the five percent level or higher: age, all of the education variables except for less than Grade 9, poor and fair diet quality variables, favorable and unfavorable physical fitness comparison, current smoker, all of the alcohol consumption categories, four to nine health care professional visits per year, and thirteen or more health care professional visits per year. Good diet quality is significant at the ten percent level.

The results show a positive and significant relationship between age and BMI. BMI increases by 0.03 units for every year increase in age, holding all other variables constant. Individuals with less than a Grade 12 education have a 1.15 units higher BMI measurement compared to those with at least a college education. A similar result occurs for individuals with a high school diploma and for those with some college education or an AA degree. Compared to individuals with at least a college education, high school graduates and those with some college education or an AA degree have 1.04 and 1.10 units higher BMI measurement, respectively.

Individuals who perceive their diet quality as being poor, fair, or good have a higher BMI measurement than individuals who believe that they consume an excellent quality diet. Individuals with a poor, fair, or good self-reported diet quality have a BMI measurement that is 3.76, 1.60, or 0.83 units higher, respectively, than an individual with an excellent diet quality, ceteris paribus. The results also show that the BMI of individuals who believe they are less physically fit than their peers is about 2.50 units higher than those who believe they are as physically fit as their peers. Certainly, the BMI of those who believe they are more physically fit than their peers is about 1.23 units lower.

The BMI of current smokers is about 1.29 units lower than BMI of non-smokers. Albanes et al. (1987) found similar results. Indeed, the effect of smoking on weight loss has been used to justify smoking by many individuals (White, McKee, and O'Malley, 2007). The results also showed that alcohol use resulted in a statistically significant effect on BMI. For example, the BMI of light and moderate drinkers were 1.17 and 1.18 units lower than non-drinkers' BMI. On the other hand, the BMI of heavy drinkers was only 0.99 units lower suggesting that any beneficial effects for alcohol may be lost after a certain level of drinking.

Individuals who visit a health care professional four to nine times a year have a BMI measurement that is 1.42 units higher than individuals who do not visit a health care professional at all, holding all other variables constant. For individuals that visit a health care professional thirteen or more times a year, their BMI measurement is 1.49 units higher than individuals who do not visit a health care professional. Interestingly, the results indicate that visiting a health care professional ten to twelve times per year has no relationship with an individual's BMI measurement.

Model: Waist Circumference

The waist circumference model was also significant, with an F-test of 16.46 and an adjusted R^2 of 0.162. Nineteen variables were statistically significant at the ten percent level are higher. Variables that had a positive impact on waist circumference are gender, age, married and divorced marital status, all education levels except less than Grade nine, poor and fair diet quality, unfavorable physical fitness, and more than three visits per year to a health care professional. Household income, favorable physical fitness, current smoker, and all levels of alcohol consumption have a negative influence on waist circumference.

Men are expected to have 7.07 cm larger waist circumference than women, holding all other variables constant. As a person ages by one year, her waist circumference increases by 0.16 cm. Compared to single individuals, married and divorced individuals are expected to have a 2.26 cm and 2.68 cm larger waist circumference, respectively.

Ceteris paribus, individuals with more than a Grade nine education but less than a college degree experience an increase in their waist circumference measurements when compared to those who have at least a college education. Individuals with less than a high school degree, a high school degree, or some college or AA degree have an increase in the waist circumference measurement by 2.30 cm, 2.15 cm, and 1.90 cm, respectively, compared to the reference group. As household income increases by one unit, an individual's waist size decreases by 0.24 cm. Individuals with a poor, or fair self-reported diet quality have a waist circumference that is 7.06 cm and 2.73 cm larger, respectively, than an individual with an excellent diet quality, ceteris paribus.

Similar to the results in the BMI model, individuals with a unfavorable physical fitness perception of themselves experience an increase in waist circumference measurement by 6.46 cm, compared to individuals with a similar physical fitness level perception as others, holding else constant. Individuals who view their physical fitness level as being higher than their peers' have a 3.95 cm smaller waist circumference. However, current smokers and drinkers present 2.14 cm lower waist circumference measurements than non-smokers, ceteris paribus. Light, moderate, and heavy drinkers also present smaller waist circumferences of 2.27 cm, 2.21 cm, and 1.82 cm, respectively, compared to individuals who do not drink alcoholic beverages, ceteris paribus. The foregoing results should not lead to a conclusion that drinking and smoking are healthy habits. Indeed, there are numerous studies showing their adverse effects on health status

(Room, 2004; Naimi et al., 2003; Fagerström, 2002; Perreira and Sloan, 2002; Fuchs et al., 1995). What they indicate is that individuals engaging in these behaviors exhibit lower waist circumference (visible health indicator). Their technical health indicators may be a different story. This confirms the importance of supplementing visible cues with the technical metrics. Finally, holding everything else constant, an individual who visits a health care professional four to nine times, ten to twelve times, and thirteen or more times per year has a waist circumference that is 4.81 cm, 2.53 cm, and 5.73 cm larger than an individual who does not visit a health care professional each year.

Technical Health Metric Models

Model: HDL cholesterol

The HDL cholesterol model has an *F*-test of 19.98, which is significant at the one percent level, and an adjusted R^2 of 0.190. Recall that the relationship between HDL cholesterol and health is different from the other three health metrics. HDL cholesterol has a positive effect on health. Therefore, higher HDL implies better health (American Heart Association, 2009). BMI, waist circumference, and fasting blood glucose have the opposite effect on one's health, i.e., a higher level of any of these health metrics results in an adverse effect on health status.

In the HDL model, gender, cohabitation marital status, less than Grade 9 education, high school graduate, some college or AA degree, diet qualities (poor, fair, and good), unfavorable fitness comparison, and current smoking have a significant negative effect on HDL levels. A positive relationship is found between HDL and the following variables: favorable physical fitness comparison, inactive exercise level, alcohol consumption, and ten to twelve health care professional visits per year.

Men tend to have lower HDL level than women do by about 13.27 mg/dL, holding all other variables constant. Similarly, cohabitating individuals tend to have lower HDL levels than single individuals by about 3.55 mg/dL. Compared to individuals with at least a college education, individuals with less than a Grade 9 education have a lower HDL level of 3.19 mg/dL, holding all other variables the same. High school graduates and individuals with some college or AA degree have lower HDL level by 3.19 mg/dL and 2.42 mg/dL, respectively, compared to the reference group. For individuals who perceive their diet quality as being poor, fair, or good, as opposed to excellent, their HDL levels are expected to decrease by 6.66 mg/dL, 4.09 mg/dL, and 4.08 mg/dL, respectively.

Individuals who view themselves to be more physically fit than their peers have higher HDL levels by 2.79 mg/dL compared to individuals who view their physical fitness level as the same as their peers'. Conversely, individuals who view their physical fitness levels as lower than their peers' have lower HDL levels of 2.65 mg/dL, which is almost an equal but opposite effect on HDL as the favorable physical fitness perception. A physically inactive individual has a HDL level that is 1.40 mg/dL higher than an active individual, holding everything else kept constant. Current smokers have a HDL level that is 1.55 mg/dL lower than a non-smoker, ceteris paribus. Compared to non-drinkers, light, moderate, and heavy alcohol drinkers have an expected increase change in their HDL levels of 2.66 mg/dL, 5.10 mg/dL, and 5.20 mg/dL, respectively. Individuals who visit a health care professional ten to twelve times per year were found to have a 3.27 mg/dL higher HDL than individuals who do not visit a health care professional at least once a year.

Model: Fasting Blood Glucose

The fasting blood glucose model was significant at the one percent level (*F*- value = 7.93; adjusted R^2 = 10.9 percent). Of the 29 variables included in the model, only nine were significant at the ten percent level or lower. They were gender, age, less than high school education, some college education or an AA degree, physical fitness comparisons, moderate alcohol consumption, and two to three and four to nine health care professional visits per year. This implies that for 20 variables, the null hypothesis that β=0 could not be rejected at a traditional level of statistical significance.

Men's fasting blood glucose level is 6.28 mg/dL higher than women's, holding all other variables constant. Fasting blood glucose levels increases by 0.43 mg/dL per annum, all other variables unchanged. Compared to individuals with at least a college education, individuals with less than a high school degree and individuals with some college education or AA degree have a increase in their fasting blood glucose levels by 6.60 mg/dL and 3.39 mg/dL, respectively. Individuals who have a favorable view of their physical fitness level over their peers have a lower fasting blood glucose level by 4.27 mg/dL than individuals who view their physical fitness level the same as their peers. Meanwhile, individuals who have an unfavorable view of their physical fitness level have a fasting blood glucose level that is 4.58 mg/dL higher than that of individuals in the reference group.

Moderate drinkers have a 3.62 mg/dL lower fasting blood glucose level than individuals who abstain from alcohol, ceteris paribus. Thus, as noted earlier, the physical variables may not tell a complete story about the health status of an individual. The results also showed that individuals who visit a health care professional two to three times per year or four to nine times per year have a higher fasting blood glucose level than individuals who do not visit a health care professional annually by 3.15 mg/dL and 3.76 mg/dL, respectively.

Summary of Results

In the five models, only four variables have a consistently significant influence on self-reported health status and all four objective health models: (1) some college or an AA degree; (2) favorable physical fitness; (3) unfavorable physical fitness comparison; and (4) moderate alcohol consumption. Gender, age, less than high school education, high school graduate or equivalent, poor and fair diet qualities, light alcohol consumption, and visiting a health care professional four to nine times per year are significant in four of the five models. Good diet quality, current smoking, heavy alcohol consumption, and more than ten visits to a health care professional per year are significant in three of the model. Divorced marital status is significant in the self-reported health status model and the waist circumference model. Married and divorced are significant in the waist circumference model, and cohabitation is significant in the HDL cholesterol model. As expected, the visible health metrics exhibited similar relationships with the explanatory variables as in the perceived health status model (Table 4.5). The waist circumference model had a larger number of similar relationships with the subjective health status model than the BMI model.

In both the BMI and waist circumference models, the effects of the significant variables on health status are the same as their counterparts in the perceived health status model. Comparing the two visible health metric models, there are differences in the significance levels of some of the variables. In the waist circumference model, gender, married marital status, and visiting a health care professional ten to twelve times per year are significant at the one percent level, five percent level, and ten percent level, respectively. Divorced marital status and household income are now significant at the ten percent level. Fair diet quality, current smoker, and alcohol consumption (light and moderate) are significant at the five percent level compared to the one percent level in the BMI model. Good diet quality is not significant and heavy alcohol consumption is significant only at the ten percent level. Lastly, thirteen or more visits to a health care professional is significant at the one percent level.

Table 4.5: Comparison of Significant Relationships in the Perceived Health Status Model and the Visible Health Metric Models

Dependent Variable	Self-Reported Health Status	BMI	Waist Circumference
Independent Variables			
Gender - Male	-**		+***
Age (in yrs)	-***	+***	+***
Marital Status - Married			+**
Marital Status - Widowed			
Marital Status - Divorced	-**		+*
Marital Status - Separated			
Marital Status - Cohabitation			
Education - Less than Grade 9	-***		
Education - Less than High School	-***	+**	+**
Education - High School Graduate or Equivalent	-***	+***	+**
Education - Some College or an AA Degree	-***	+***	+**
Household Income	+***		-*
Diet Quality - Poor	-***	+***	+***
Diet Quality - Fair	-***	+***	+**
Diet Quality - Good	-***	+*	
Diet Quality - Very Good	-***		
Physical Fitness Comparison - Less	-***	+***	+***
Physical Fitness Comparison - More	+***	-***	-***
Exercise - Inactive	+*		
Smoke - Former			
Smoke - Current		-***	-**
Alcohol Consumption - Light	+***	-***	-**
Alcohol Consumption - Moderate	+*	-***	-**
Alcohol Consumption - Heavy		-**	-*
Doctor Visits - 1 Time/Yr			
Doctor Visits - 2-3 Times/Yr	-*		
Doctor Visits - 4-9 Times/Yr	-***	+***	+***
Doctor Visits - 10-12 Times/Yr	-***		+*
Doctor Visits - 13 or More Times/Yr	-***	+**	+***

*** p<0.01, ** p<0.05, * p<0.1

In regards to the perceived health status model and the technical health status models, there were more similarities in the explanatory variables between the perceived health status model and the HDL model than the perceived health status model and the fasting blood glucose model (Table 4.6). Thirteen similarities with the explanatory variables exist between the perceived health status model and the HDL model, with all but one variable, ten to twelve visits

Table 4.6: Comparison of Significant Relationships in the Perceived Health Status Model and the Technical Health Metric Models

Dependent Variable	Self-Reported Health Status	HDL	Fasting Blood Glucose
Independent Variables			
Gender - Male	-**	-***	+***
Age (in yrs)	-***		+***
Marital Status - Married			
Marital Status - Widowed			
Marital Status - Divorced	-**		
Marital Status - Separated			
Marital Status - Cohabitation		-***	
Education - Less than Grade 9	-***	-**	
Education - Less than High School	-***		+**
Education - High School Graduate or Equivalent	-***	-***	
Education - Some College or an AA Degree	-***	-***	+**
Household Income	+***		
Diet Quality - Poor	-***	-***	
Diet Quality - Fair	-***	-***	
Diet Quality - Good	-***	-***	
Diet Quality - Very Good	-***		
Physical Fitness Comparison - Less	-***	-***	+*
Physical Fitness Comparison - More	+***	+***	-***
Exercise - Inactive	+*	+*	
Smoke - Former			
Smoke - Current		-*	
Alcohol Consumption - Light	+***	+***	
Alcohol Consumption - Moderate	+*	+***	-*
Alcohol Consumption - Heavy		+***	
Doctor Visits - 1 Time/Yr			
Doctor Visits - 2-3 Times/Yr	-*		+*
Doctor Visits - 4-9 Times/Yr	-***		+**
Doctor Visits - 10-12 Times/Yr	-***	+*	
Doctor Visits - 13 or More Times/Yr	-***		

*** p<0.01, ** p<0.05, * p<0.1

to a health care professional per year, expressing the same relationship on perceived health status and HDL. There were only nine statistically significant variables in the fasting blood glucose model, but all nine of these variables are also significant in the perceived health status model. In both the fasting blood glucose model and the perceived health status model, these common variables express the same effect on health status.

Only five variables that are statistically significant across the two technical models. Gender and favorable physical fitness comparison are significant at the one percent level in both of the models. Unfavorable physical fitness comparison and moderate alcohol consumption is significant at the one percent level in the HDL model, but they are significant at the ten percent level in the fasting blood glucose model. Having some college education or AA degree is significant at the one percent level in the HDL model as opposed to being significant at the five percent level like it is in the fasting blood glucose model.

In the HDL model, cohabitation marital status, diet quality (poor, fair, and good), and alcohol consumption (light and heavy) are statistically significant variables at the one percent level. Having less than a Grade 9 education is significant at the five percent level, while inactive, current smoker are significant at the ten percent level in the HDL model. Visiting a health care professional ten to twelve times per year are significant at the ten percent level in the HDL model and in the fasting blood glucose model, visiting a health care professional four to nine time per year and two to three times per year are significant at the five and ten percent level, respectively. Also in the fasting blood glucose model, age is significant at the one percent level and having less than a high school degree is significant at the five percent level.

Comparison of Health Risk and Informed Groups

The foregoing results show that the independent variables exhibit significant similarities between the perceived health status and the visible health metrics and differences between the perceived health status and the technical health metrics. The question that emerges is this: how consistent do the perceptions of those with indicators of health situations match their health metrics? In other words, are people's perceptions congruent with their reality?

To address this question, two groups are created: (1) a group exhibiting waist circumference related health risk, and (2) those without this risk.[11] A t-test, conducted to test the statistical significance of the difference between the two groups, indicated that they were different. This is the case for all the comparison groups. A Chow test is used to test the differences between the determinants of health status perceptions for the two groups. Recall that our hypothesis is that people who exhibit at least one visible health risk factor, as determined by metabolic syndrome criteria, will present different health perceptions.

From the analysis of the visible health risk groups and the non-health risk group, the χ^2 statistic of 27.91 with 30 degrees of freedom is statistically insignificant (p=0.58). Thus, we fail to reject the null hypothesis that the independent variables' effects on the health status perception across the two health risk groups are equal. This result does not support the hypothesis that there is a difference in health status perceptions between these two groups.

Since a significant amount of emphasis is placed on BMI in public health campaigns, we were curious if being in a certain BMI risk category influenced an individual's health status or not. A supplementary analysis using the ordered logit model[12] was conducted to examine if

---

11 That is, the health risk group consists of individuals who have a waist circumference measurement that is in the health risk range, and they may also exhibit health risk concerns in their HDL and fasting blood glucose measurements.

12 Performing the group comparisons requires the development of interaction terms and a new analysis of non-parallel variables. Increasing the number of variables in the model can lead to complications and non-convergence in the PCOL model. In the case of the supplementary group comparison, a complete investigation of the parallel line assumption was not obtained due to the cumbersome nature of the large model. Since the ordered logit model is an acceptable substitute, it was chosen to perform the supplementary group comparison analysis under the ordered logit model instead of the PCOL model.

individuals' health status perceptions are influenced by the BMI risk category in which they are classified. The comparisons include the following BMI categories: overweight versus normal BMI category and obese versus normal BMI category. The comparison revealed that individuals in the normal BMI category and individuals in the overweight BMI category did not have any differences in their health status perceptions ($\chi^2 = 34.05$ with 30 degrees of freedom and $p=0.28$). On the other hand, the comparison between the obese and normal BMI categories was statistically significant ($\chi^2 (30) = 45.3$; $p=0.04$), which implies that these two groups have differences in their health status perceptions.

The difference between the health status perceptions of informed individuals and those of uninformed individuals is also investigated. Comparison groups are individuals who have received health risk information from a health care professional indicating that they are overweight, diabetic, pre-diabetic, have high cholesterol, or some of any combination of these health risks. As previously stated, the hypothesis is that people who are informed of their health risk will present different health perceptions from those who do not exhibit any health risk. The result indicates that the difference between those who receive information about their health status and those who do not is statistically significant ($\chi^2(30) = 87.94$; $p = 0.00$). This result is consistent with the hypothesis.

Chapter 5 - Discussion

Given the complex and multidimensional nature of health, it is difficult to quantify "good" health. The purpose of this study was to shed light on the socio-economic and behavioral factors that influence both subjective and objective health status and to determine if health status perceptions are congruent with objective health indicators. By understanding the differences in the factors influencing subjective and objective health status and determining the consistency between health status perceptions and objective health measures, effective policies aimed at maintaining or improving health can be developed and implemented.

This chapter is organized into three sections: notable findings, implications, and future research. In the first section, the notable findings from the subjective and objective health status models and the group comparisons are examined. Once the key findings are identified, possible policy implications are developed in the second section. In the final section, suggestions for future research in this area are discussed.

Notable Findings

Although the result associated with gender is not consistent with the expectations, it does support findings of previous research (Morris-Tries, 2004). It was hypothesized that women are more critical of their health, particularly the visible health metrics (BMI and waist circumference) than men are (Gregory, 2008), so we expected women to have a lower subjective health status. Furthermore, if women are more conscious of their visible health indicators, then it is expected that they will be more likely to use that information in defining their health status. Therefore, a more consistent effect was expected between the health metric models and the perceived health status model for gender, and the results confirmed this. It is possible that women, being more critical of their health status, led them to have a higher level of awareness of their health than men. They may be, therefore, more likely to engage in healthier lifestyle behaviors to maintain or improve their health status. Morris-Tries (2004) discovered that more women (53.4 percent) than men (38.1 percent) consumed the recommended daily servings of fruits and vegetables, an observation that supports women's pursuit of healthier lifestyles. Also, there is a negative correlation between men and more than one visit to a health care professional per year. Given that women have a higher health status than men, the frequency of visits to a health care professional may not be indicative of a poor health status but rather of their participation in preventative health care measures. This result is further supported by the fact that women, on average, have a longer life expectancy than men. In 2006, the life expectancy at birth for a male and female living in the US was 75.1 years and 80.2 years, respectively (CDC, 2009d).

Previous studies indicated that there was a significant relationship between marital status and health status; however, this study did not find a strong relationship between all of the marital status variables and health status. Married, divorced, and cohabitation marital status were the only marital status variables that had a statistically significant effect on health status. In the subjective health status model, the divorced marital status variable had a negative influence on self-reported health status. This relationship is also expressed in the waist circumference model. In addition, the married marital status variable had a positive effect on waist circumference, and the cohabitation variable had a negative effect on HDL levels. The and Gordon-Larson (2009) discovered that extra body weight comes with marriage and a relationship commitment. According to their University of North Carolina study, married couples are twice as likely to be obese than those who are dating. Cohabiting couples are less likely than married but more likely than dating couples to be obese. Rationale for this weight gain may be attributed to the fact that these individuals are no longer in the dating pool. Gordon-Larson states that "physical attributes –especially for women – play a role in marriage markets, so you might exert more effort to have a healthy body weight if you're in the dating pool" (Ellin, 2010).

All levels of education are significant in the subjective health status model, and indicate a positive correlation between education and self-reported health status. The lower the level of education attain, the more likely the individual is to report a lower health status. This finding suggests that education is an important factor affecting self-reported health status. However, Furnée et al. (2008) report that the level of education, itself, can act as a biasing factor since it can influence an individual's ability to evaluate their own health status. It may be that highly educated individuals are more informed about the multi-dimensional nature of health and have a better understanding of how various factors interact to affect their health status.

This positive correlation between education and health status is also found in the objective health metric models. Compared to individuals with at least a college education, individuals with less education tend to have higher BMI scores, larger waist circumference measurements, lower HDL levels, and higher fasting blood glucose levels. All of these relationships suggest that lower education levels have a negative effect on health status when measured by these objective health metrics. In the waist circumference model, the positive effect on waist circumference appears to decrease as education levels increase. Similar trends are discovered in the HDL model and in the fasting blood glucose model. These findings support previous research that have found a negative relationship between education and BMI and body size (Paeratakul et al., 2002; Flegal et al., 2002; Cutler and Lleras-Muney, 2006; Webbink, Martin, and Visscher, 2010) .

Low education levels intuitively translate into low earning potential. Individuals with low income levels tend to consume less nutritious diets (Golan, et al., 2008), and this relationship is supported by the negative effect of household income on waist circumference in this study. An increase in household income tends to result in a decrease in waist circumference measurement. Also, household income has a small positive effect on self-reported health status. Drewnowski and Darmon (2005) discovered that poor food choices are strongly correlated with low incomes, resulting in people consuming high caloric and energy dense foods. In addition, healthier foods tend to be more expensive (Drewnowski and Darmon, 2005) and thus, are unlikely food options for people on a limited food budget. These poor food choices can increase an individual's BMI and waist circumference measurements since they contribute to energy surplus outcomes, i.e., higher energy/calories intake than output. Additionally, the results are supported in the objective models where low diet quality has a positive effect on BMI and waist circumference measurements. Additionally, low diet quality has a negative effect on HDL levels, implying a poor health status.

In the subjective health status model, diet quality violated the parallel line assumption and thus, unique information about diet quality's effect on self-reported health status can be gained from the interpretation of its results. Individuals with poor or fair diet quality are less likely to report a high health status, but they are especially unlikely to report a very good or excellent health status. This suggests that individuals are cognizant of the effect of diet quality on their health. Compared to those with a high self-perceived diet quality, individuals with good or very good perceived diet qualities are less likely to report a higher level of health, but they also are less likely to report a low level of health. That is, individuals will have a high probability of reporting their health status in the middle categories, good and very good health status. This pattern suggests that they have a fairly balanced view of the relationship between diet and health status. They do not tend to downplay or inflate the effect of diet quality on their health status.

In spite of having a realistic view of the influence of diet quality on health status, compliance with dietary recommendations is still low. Healthy eating has been the focus of numerous public health campaigns such as US DHHS's *Healthy People 2010*, "5-A-Day" and "MyPyramid". However, approximately only a third of the US adult population in 2005 consumed at least the recommended amount of fruit per day and only 27 percent consumed at least the recommended amount of vegetables per day (CDC, 2007a). These statistics indicate that there is room for improvement regarding these public health initiatives.

Regarding the physical fitness comparison to others, it appears that individuals have a good understanding of its effect on health status. In the subjective health status model, the mode response to how people rated their physical fitness to others was that they were the same. Individuals with higher fitness compared to their peers are more likely to report a higher health status than individuals with a perceived fitness level similar to their peers. Also, individuals with a lower fitness comparison are less likely to report a higher health status than individuals with the same fitness perception as their peers. The foregoing suggests that individuals use the assessment of their fitness level comparisons in their evaluation of health status. Results from the technical metrics also confirm these findings. Individuals with unfavorable physical fitness comparisons tend to have higher BMI, waist circumference, and fasting blood glucose measurements as well as lower HDL level. The opposite relationship was found with individuals who viewed their physical fitness level as being higher than that of their peers. The results show that there is high consistency between perception and reality in regards to physical fitness comparison.

Active individuals may be physically active because they believe that they are unhealthy. This may explain why inactive people ended up more likely to report a higher health status than active people. Also, inactive individuals tend to have a higher HDL level than those that are active, further supporting the finding that inactive individuals have a higher health status than active individuals.

Physical activity in this study was defined to encompass specific leisure time activities geared towards exercise and improving one's physical fitness e.g., running, biking, swimming, and tennis. Therefore, people whose job involves significant physical activity such as construction workers may indicate low participation in leisure time physical activity, but they may indicate a high health status because they have taken into account the positive effect of their work-related physical activity on their health status. Södergren et al., (2008) discovered that both leisure time physical activity and total physical activity, which consists of physical activity from all domains including exercise, physical activity at work, physical activity from transportation, and daily activities, were associated with high self-reported health status. Those researchers recommend that both measures of physical activity, leisure time and total, be used to evaluate the relationship between physical activity and health status.

From another perspective, an inactive individual's decision not to engage in physical activity may be based on a simple cost-benefit analysis. They have evaluated the benefits of physical activity against the costs involved such as time and energy, and they have determined that the costs outweigh the benefits. In addition to this cost-benefit analysis, inactive individuals may have convinced themselves that no amount of physical activity will improve their health status and, given their current health situation, they perceive themselves as being healthy. In a 2007 report from the CDC, fewer than half of US adults took part in enough physical activity to gain any significant health benefits (CDC, 2009b).

The results from the objective health status models indicate that lifestyle behaviors like smoking and alcohol consumption exhibit positive relationships with health status. Current smokers have lower BMI and waist circumference measurements. Although, smoking has a negative impact on an individual's health (US DHHS, 2000), these behaviors have been proven to decrease BMI and waist circumference because of their appetite suppression and metabolic rate enhancement effects (Klesges, Klesges, and Meyers, 1991; Wellman et al., 2005). But, smoking also has a negative effect on HDL levels.

Regarding the effects of alcohol consumption on self-reported health status, not only do our results support Morris-Tries' (2004) findings, but they go one step further. The study's results suggest that an individual's light or moderate alcohol consumption has a positive effect on reporting a high health status. In the subjective health status model, the light alcohol consumption variable violated the parallel line assumption. Thus, interpretation of this violating variable provides unique insight into the relationship between the independent variable and itself that would have been hidden in the ordered logit model. Light alcoholic drinkers are likely to report a higher health status than those who abstain from alcohol. However, the PCOL model reveals that there is a strong force pushing a light drinker's perception of their health status away from the lower end of the health status spectrum. Thus, consuming one or fewer alcoholic drinks per day has a strong positive effect on health status.

A study by Theobald, Johansson, and Engfeldt (2003) suggests that the positive effect between health status and alcohol consumption may be due in part to a reduced risk of fatal, coronary heart disease, which can be attributed to functional food components such as resveratrol and other antioxidants found in some alcoholic beverages, particularly red wine. Results from the subjective and technical health status metrics confirm Poikolainen, Vartiainen, and Korhonen (1996) findings of a J-shaped relationship between alcohol intake and sub-optimal health. Alcohol consumption has a negative influence on BMI, waist circumference, and fasting blood glucose, and a positive effect on HDL levels. These beneficial health effects were not limited to just the light and moderate alcoholic consumers: the heavy drinkers also experienced these beneficial health effects, albeit the effects are smaller in the BMI and waist circumference model than those for light and moderate drinkers.

Even though, smoking and alcohol consumption affect BMI and waist circumference in a manner that counters the factors associated with metabolic syndrome, e.g., weight gain and obesity trends, these lifestyle behaviors have other serious health consequences associated with them that may be more harmful than an increase in body weight, such as lung cancer and liver cirrhosis. It is these other health conditions that individuals may be taking into consideration when evaluating their health status, and the realization that heavy drinking does have some negative health consequences.

Individuals who visit a health care professional more than once a year have a higher probability of reporting a lower health status level. This finding is consistent with previous research (Miilunpalo et al., 1997). It is evident that individuals have a negative perceptions of the frequency of visits to a health care professional per year. Interestingly, a single visit to a health care professional once a year did not affect health status perception, but visiting a health care professional more than once a year does have an adverse effect on their self-perceived health status. This is confirmed by the objective health metrics showing similar effects.

Increased visits to a health care professional were associated with higher BMI, waist circumference, and fasting blood glucose measurements. Contradicting this relationship is the relationship between health care professional visits and HDL levels. Individuals who visited a health care professional ten to twelve times per year were likely to have a higher HDL level than someone who does not visit a health care professional on a yearly basis.

Group Comparisons

Comparisons of health perceptions between groups were conducted to determine if information about the objective health metric is incorporated into one's health status evaluation. In the first group comparison, it is assumed that people are aware of their waist circumference measurement and deliberately include this information in their health status evaluation. Results from the Chow test were insignificant, indicating that individuals do not incorporate the visible health information into the evaluation of their health status. Despite receiving some sensory feedback information about their health, an individual has discounted this information or treated it as being negligible. It is possible that the individual is aware of this visible feedback information but is using other information to negate its effect.

Based on the results from the BMI category comparisons, individuals who are considered to be obese are aware of their BMI health risk and consequently, view themselves differently from non-obese individuals. Conversely, overweight individuals did not have any discernable differences in their perceptions compared to individuals within the normal BMI category. From a policy perspective, this result indicates that designing policies that focus on changing the behavior of overweight individuals may not garner the response that policy makers intend since overweight individuals do not perceive their health status as being different from individuals with a normal BMI. However, it could also be the case that individuals with a normal BMI may view themselves too harshly and perceive themselves as being unhealthy and overweight instead of being in the healthy (normal) BMI range. Furthermore, policies aimed at promoting weight loss for individuals in the overweight BMI category may have negative impacts on individuals with normal BMIs. By encouraging weight loss in this overweight category without a distinction between overweight and normal BMI individuals' perceptions, individuals with a normal BMI measurement may engage in weight loss activities that are not necessary or advised.

In the second group comparison, the value of external information is examined. It is assumed that an individual may become aware of potential health risks associated with technical metrics through information shared with them by a health care professional. The Chow test results imply that informed and uninformed groups exhibit a difference in their perceptions. This difference indicates that informed individuals do take into account the information they receive from external sources when making decisions about their health status. This finding is significant because it reinforces the belief that individuals do value health information from external sources. Previous studies indicated that individuals value health information received from health care professionals (US DHHS, 2000; Duhl and Hancock, 1988) and equally value information about preventative health care and wellness strategies and information that addresses their medical concerns (US DHHS, 2000).

Policy Implications

The question that concerned this study was whether people's perception about their health was consistent with the objective indicators of their health status. The results showed that individuals do not incorporate all visible health information into the evaluation of their health status, but they do value health information from external sources.

Increasing the amount of health information delivered to individuals is key to changing people's health perceptions. By informing the individual of certain health risks, they may take an active role in maintaining or improving their health status. However, for information to be ultimately successful, it not only needs to be delivered, but it must also be presented in a form that the receiver can understand. One way to ensure that the information is accurately understood is to increase individuals' health literacy.

Health literacy is defined as " the degree to which individual's ability to obtain, process, and understand basic health information and services needed to make appropriate health decisions" (Ratzan and Parker, 2000). Based on their 2004 report, the Institute of Medicine states that over 89 million adults in the United States from all races, incomes, and education levels are estimated to have limited health literacy skills. Previous research has found that low literacy rates are associated with poor self-reported health status (Weiss et al., 1992; Barker et al., 1997), incomplete comprehension of medical conditions and health information (Barker et al., 1997; Williams et al., 1998a; Williams et al., 1998b), higher hospitalization rates (Barker et al., 1997), more frequent visits to the emergency room (Barker et al., 1997; Schillinger et al., 2002; Barker et al., 2002), and underutilization of preventative health services (Rimer, Trock, and Engstrom, 1991). Limited literacy skills are also associated with higher health care costs. On average, the annual health care costs for individuals with a low health literacy rate is four times higher than for the general population (Weiss et al., 1994).

Although numerous policies and programs can be developed to increase health literacy and promote strategies to maintain or improve health, adoption of these policies and programs is dependent on the individual and her self-interests. Based on the concept of consumer sovereignty, individuals know what is best for them and that their choices are made to satisfy their self-interests (Redmond, 2000). Individuals acting in their own interest without any coercion are always rational (Sen, 1982; Mises, 1963), and these rational economic choices reflect the consumer's true interests and preferences (Sen, 1982). Therefore, rational individuals will only adopt these policies and programs if they feel that it is in their self-interest to do so.

Another fundamental concept of consumer sovereignty is the tolerance of individual behavior. An individual should have the freedom and ability to make whatever decisions she chooses without interference from others. This tolerance is imperative given the belief that individuals are the best judge of their own welfare (Persky, 1993). Even though there is literature that states that others (e.g., observers) may have unique knowledge as to what is best for the individual, according to the consumer sovereignty notion, it is the individual and her perceptions that are the most important factor in her decision making process. Therefore based on the concept of consumer sovereignty, policies and programs that want to influence how an individual perceives her health (particularly in accordance with objective health status) need to appeal to the individual and how she perceive herself. Instead of designing policy targeted at society as a whole, it is recommended that policy be aimed at influencing lifestyle choices and behaviors at the individual level. This recommendation falls in line with the methodological individualist approach in which individuals are the irreducible unit of social and economic order and understanding how they make decisions is necessary to any relevant social or economic question (Ahdieh, 2009).

It is only through targeting an individual and determining what their motivating factors are that an individual will act. For instance, an inactive individual has determined that the costs associated with being physically active do not outweigh the benefits. If policy can be designed in such a way so that the cost-benefit ratio is improved (i.e., costs are lowered and/or the benefits are increased), then the individual will be motivated to become physically active, which would lead to possible health benefits and lower health care costs.

Across all of the models, education has a significant effect on health status, particularly self-reported health status. Based on the results in the subjective health status model, the less education you have, the less healthy you perceive yourself to be. As mentioned before, there may be an education bias that could affect an individual’s self-perceived health status differently than her objective health status. Although there may be differences in how education affects the different health statuses, this factor is important because it plays an integral part in creating successful programs and policies aimed at increasing health awareness and health literacy. The significant effect that formal education has on self-perceived health status and the objective health measures suggests that increasing health literacy and health awareness through initiatives within the formal education system would have a strong positive impact on self-reported and objective health statuses. In fact, improving health education and literacy is one of the initiatives in the US DHHS’s *Healthy People 2010* program.

A prior study found that education along with taxation, and restrictive legislation had a positive impact on shaping individuals’ choices for healthier behavior, which in turn affected their health (Jochelson, 2005). Although the positive relationship between health and education presents tremendous individual and public health opportunities, developing successful public policy initiatives involving education and health can be a challenge. These two domains, health and education, tend to be governed by separate agencies that are highly compartmentalized and engage in little to no inter-agency policy development, despite there being a large spill-over effect among the policy initiatives.

Though education and health policies may be somewhat successful in their respective domains, these policies are generally not all encompassing, and thus, they fall short of their full potential. Given the strong relationship between health and education, it is recommended that policies aimed at improving health through education be developed not in isolation of one another, but in a comprehensive or integrated approach to education and health (Furnée et al., 2008).

Future Research

For future research, it is suggested that the proper survey design elements be incorporated into the model and possibly estimate a model that addresses heteroskedasticty. Although it is possible to receive fairly accurate results when not incorporating the survey design elements such as stratification and sampling weights, it is impossible to predict how accurate those results estimated from a non-survey approach will be. Consequently, it is important to be aware of these potential pitfalls when analyzing the results. In addition to assuming parallel lines, the ordered logit model also assumes that the errors are homoskedastic. Following these two assumptions may lead to results that are incorrect and unbiased.

Allison (1999) argues that the error variances often differ across groups. Compared to OLS regressions, the presence of heteroskedasticty in ordinal regressions can lead to more severe consequences. When a binary or ordinal regression model incorrectly assumes that error variances are the same for all cases, the standard errors are wrong, and, unlike in an OLS regression, the parameter estimates are biased and inconsistent (Keele and Park, 2004; Yatchew and Griliches, 1985). To correct for heteroskedasticty, the heterogeneous choice model (Alvarez and Brehm, 1995; Keele and Park, 2004; Williams, 2009), which is also known as location-scale models (McCullagh and Nelder, 1989), is recommended. Similar to the generalized ordered logit model, the heterogeneous choice model can generate estimates that are more parsimonious and easy to interpret than alternative models, such as the multinomial logit model. Future research could involve the estimation of the heterogeneous choice model for this study.

This study used secondary data collected from the CDC. The use of secondary data always constrains the researcher in what they can accomplish outside of the original purpose of the data collection. For example, the researcher is limited by how the data were collected and presented in the data set. A case in point is the exercise variable used in this model. Based on how the data was collected, a significant amount of troubleshooting was needed when developing the exercise variable before it was compatible with the models. One of the issues with the exercise data was that the data were sparse and there appeared to be a lot of outliers within the data. Originally, the exercise variable was designed to look at the effects of the different physical activity levels, but categorizing the data in that fashion left too few observations in the categories. A possible suggestion for addressing this issue would be to use another variable from the NHANES data set as a proxy for physical activity. Ideally, this variable would measure the intensity of total physical activity that would include all domains of physical activity as recommended by Södergren et al. (2008).

Based on previous literature, income was expected to have a significant impact. The results supported this, but we found that the economic impact was small. Given that education and income are intuitively correlation (although the correlation analysis does not indicate this), these two variables may be having an effect on each other's impact on the dependent variable. By running the model without education, it can be determined if income truly does have an impact on the dependent variable as expected and if it was being overshadowed by the education dummy variables in the current model.

If the data were available, it is recommended that the waist to hip ratio be used as one of the objective health metrics instead of BMI and waist circumference. The waist to hip ratio has been determined to be a more accurate health metric than BMI or waist circumference because this ratio is a better predictor of obesity-related health risks (Srikanthan, Seeman, and Karlamangla, 2009). Unfortunately, in the 2005-2006 NHANES survey, hip measurements were not included.

A topic that warrants further research is the effect of health literacy. A 2009 study by the American Medical Association stated that poor health literacy is a better predictor of an individual's health status than age, income, employment, education, and race. Incorporating health literacy into the model and determining its impact on health status would be beneficial to investigate. Information from this variable would provide feedback in terms of whether or not recommendations for increasing health literacy in individuals would provide the expected results in health behaviors. A proxy variable would need to be developed.

Chapter 6 - Conclusions

Health is a complex concept with many dimensions and facets, which makes its accurate definition difficult. In general, health consists of two perspectives: subjective and objective health status. Although it is expected that these two measures will be in-line with each other, this is frequently not the case. This gap in perception and reality can lead to the mis-management of lifestyle-related health conditions, contributing to increased health care costs. Having an accurate view of health status is important in maintaining or improving one's health status or reducing the risks of future negative health conditions. Thus, the primary goals of this research were to provide insight into the factors influencing subjective and objective health statuses and to determine how consistently do people's perceptions of their health status match their objective health status. The first objective of the study was to assess the extent to which socio-economic and behavioral factors influence subjective and objective health status measures. Second, the extent to which different health risk groups' health perceptions are congruent with each other was examined. The final objective was to provide recommendations for public health policies to improve people's health status.

Data from the 2005-2006 NHANES was used to collect information on individuals' socio-economic and behavioral characteristics. An ordered categorical model and ordinary least squares models were used to analyze individuals' subjective and objective health status measures, respectively. Objective health status measures were represented by two types of measures: visible and technical. BMI and waist circumference are defined as visible health metrics, and HDL and fasting blood glucose are technical health metrics. A Chow test was used to determine if differences in health status perception exist among different health risk groups.

A partial constrained generalized ordered logit model fit the subjective health status data better than either the ordered logit or the unconstrained generalized ordered logit model and was used to estimate the subjective health status model. Results from the subjective health status model indicated that age, gender, divorced marital status, education, diet quality, physical fitness comparison to others, exercise, light and moderate drinking, and two or more health care professional visits per year have a statistically significant impact on an individual's self-reported health status.

All four of the diet quality variables and the light alcohol consumption variable violated the parallel line assumption. The results from the diet quality variables indicated that individuals have an accurate understanding of the relationship between diet quality and health status. Information from the alcohol variable suggests that light alcohol consumption has a significant effect of moving an individual's health perception away from the lower health status categories.

The visible objective health metric models and the perceived health status model had similar relationships between their explanatory variables and the dependent variable. Of the two visible health metric models, the waist circumference model shared a larger number of common significant explanatory variables with the perceived health status model than the BMI model. All of the significant variables in the visible health metric models indicated the same effect on health status as their significant counterparts in the perceived health status model.

In the technical models, the HDL model had more similar significant explanatory variables in common with the perceived health status model than the fasting blood glucose model, but the number of similarities were less than in the visible models. The variables in both the technical models and the perceived health status model had similar effects on health status except for the frequency of health care professional visits in the HDL model. Only four of the 29 variables were statistically significant across the five models: some college education or an AA degree, favorable and unfavorable fitness comparison and moderate alcohol consumption.

No difference in health status perception was detected in the comparison of health risk groups based on the waist circumference health metrics, but a difference was found in the health perceptions of individuals who received information from external sources and those who were uninformed. These results suggest that individuals place value on health information received from an external source. Additional comparisons between visible health risk groups indicated that obese individuals perceive themselves differently from individuals with normal BMI measurements, but there is no difference in health status perceptions between the normal and overweight BMI groups. The fact that no difference in health perceptions was detected between the health risk groups based on the visible waist circumference health metric nor between the overweight and normal BMI groups suggested that policies focused solely on visible health metrics to change individuals' health behavior might not be effective. One of Mises' (1963) *Human Action* conditions states that an individual will not act unless they are in a state of distress or discomfort. Therefore, if the health risk group does not perceive their health status differently than the non-health risk group, which may lead to a state of discomfort, then they are unlikely to be motivated to change their behaviors.

In order to motivate individuals to adjust their perceptions to be more in-line with their objective health status and encourage them to engage in public health programs, such as early detection programs, initiatives must be developed that appeal to the individual. It is only by appealing to the individual that she will be motivated to change her behavior and perceptions. Health awareness and health information are the keys to changing individual behavior. Initiatives that are focused on incorporating valid health education into the formal education system are recommended. Also, it is suggested that health and education agencies combine efforts to form a united policy approach. Another recommendation would be to develop public initiatives aimed at increasing the health literacy rate. Suggestions for future research include using the heterogeneous choice model, using a more accurate predictor of objective health status such as the waist to hip ratio, examining the effect of total physical activity on health status, and incorporating health literacy in the model.

References

Ahdieh, R. B. "Beyond Individualism in Law and Economics." Working Paper, Center on Federalism and Intersystemic Governance, Emory University School of Law, 2009.

Ajzen, I. and M. Fishbein. *Understanding attitudes and predicting social behavior*. Englewood Cliffs, NJ: Prentice-Hall, 1980.

Albanes, D., Y. Jones, M. S. Micozzi, and M. E. Mattson. "Associations between Smoking and Body Weight in the US Population: Analysis of NHANES II." *American Journal of Public Health.* 77(1987):439-444.

Alberti K.G., P. Zimmet, J. Shaw and IDF Epidemiology Task Force Consensus Group. *"The metabolic syndrome – a new worldwide definition"* Lancet 366(2005):1059-1062.

Allison, P. "Comparing Logit and Probit Coefficients Across Groups." *Sociological Methods and Research.* 28(1999):186-208.

Alvarez, R.M. and J. Brehm. "American ambivalence towards abortion policy: Developments of a heteroskedastic probit model of competing values." *American Journal of Political Science*. 39(1995):1055-1082.

American Diabetic Association. Diabetes Statistics. Internet Site: http://www.diabetes.org/diabetes-basics/diabetes-statistics/. (Revised 2010).

American Diabetic Association. Diabetes Basics. Internet Site: http://www.diabetes.org/diabetes-basics/?utm_source=WWW&utm_medium=GlobalNavDB&utm_campaign=CON (Revised 2009).

American Heart Association. Good vs. Bad Cholesterol. Internet Site: http://www.heart.org/HEARTORG/Conditions/Cholesterol/AboutCholesterol/Good-vs-Bad-Cholesterol_UCM_305561_Article.jsp (Revised 2009).

American Heart Association. Cardiovascular Disease Cost. Internet site: http://www.americanheart.org/presenter.jhtml?identifier=4475 (Revised 2010).

American Medical Association. Health Literacy. Internet site: http://www.ama-assn.org/ama/pub/about-ama/our-people/member-groups-sections/medical-student-section/community-service/health-literacy.shtml (Revised 2009).

Antonovsky, A. *Unraveling the mystery of health: How people manage stress and stay well*. San Francisco: Jossey-Bass, 1987.

Bailis, D.S., A. Segall and J. G. Chipperfield. "Two views of self-rated general health status" *Social Science and Medicine.* 56(2003):203-217.

Baker, D.W., R.M. Parker, M.V. Williams, W.S. Clark WS, and J. Nurss. "The relationship of patient reading ability to self-reported health and use of health services." *American Journal of Public Health.* 87(1997):1027–30.

Baker D.W., J.A. Gazmararian, M.V. Williams, T. Scott, R. M. Parker, D. Green, J. Ren, and J. Peel. "Functional health literacy and the risk of hospital admission among Medicare managed care enrollees." *American Journal of Public Health*. 92(2002):1278–83.

Barrett, A.E. "Social Support and Life Satisfaction among the Never Married: Examining the Effects of Age." *Research on Aging*. 21(1999):46-72.

Bergner, M. "Measurement of Health Status." *Medical Care*. 23(1985): 696-704.

Blaxter, M. *Health and Lifestyles*. New York, NY: Routledge, 1990.

(BCCRC) British Columbia Cancer Research Centre. "Lung Health Study." British Columbia Agency. Revised August 12, 2008. http://www.bccrc.ca/ci/lc02_title.html.

Boes, S. and R. Winkelmann. "Income and Happiness: New Results from Generalized Threshold and Sequential Models." IZA Discussion Papers 1175, Germany: Institute for the Study of Labor, 2004.

Brannon, L. and J. Feist. Health Psychology: An Introduction to Behavior and Health. Belmont, CA: Wadsworth, 2010.

Brant, R. " Assessing proportionality in the proportional odds model for ordinal logistic regression." *Biometrics.* 46(1990):1171-1178.

Breslow, L. "Health Status Measurement in the Evaluation of Health Promotion." *Medical Care*. 27(1989):S205-S216.

Cantor, N. and J. Kihlstrom. Personality and social intelligence. Englewood Cliffs, NJ: Prentice-Hall, 1987.

Cawley, J. and R.V. Burkhauser. "Beyond BMI: The Value of More Accurate Measures of Fatness and Obesity in Social Science Research." NBER Working Paper 12291. June 2006.

(CDC) Centers for Disease Control and Prevention - National Center for Health Statistics. National Health and Nutrition Examination Survey: Physician examination procedures manual. Internet Site: http://www.cdc.gov/nchs/data/nhanes/nhanes_03_04/PE.pdf. (Revised 2003).

_____. National Health and Nutrition Examination Survey: Anthropometry procedures manual. . Interest Site: http://www.cdc.gov/nchs/data/nhanes/nhanes_03_04/BM.pdf. (Revised 2004a).

_____. National Health and Nutrition Examination Survey. Laboratory procedures manual. Internet Site: http://www.cdc.gov/nchs/data/nhanes/nhanes_03_04/lab_pm.pdf. (Revised 2004b).

_____. Analytic and Reporting Guidelines: The National Health and Nutrition Examination Survey (NHANES). Internet Site: http://www.cdc.gov/nchs/data/nhanes/nhanes_03_04/nhanes_analytic_guidelines_dec_2005.pdf (Revised 2006).

_____."Fruit and Vegetable Consumption Among Adults - United States, 2005." *Morbidity and Mortality Weekly Report*. 56(2007a):213-217.

_____. "Physical Activity Among Adults With a Disability - United States, 2005." *Morbidity and Mortality Weekly Report*. 56(2007b):1021-1024.

_____.National diabetes fact sheet: general information and national estimates on diabetes in the United States, 2007. Atlanta, GA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, 2008.

_____.Overweight Prevalence. Internet Site: http://www.cdc.gov/nchs/fastats/overwt.htm. (Revised 2009a).

_____. National Health and Nutrition Examination Survey 2005-2006. http://www.cdc.gov/nchs/nhanes/nhanes2005-2006/nhanes05_06.htm (Revised 2009b).

_____. National Health and Nutrition Examination Survey. 2005 – 2006 Data Documentation, Codebook, and Frequencies: Demographic Variables and Sample Weights. Internet Site: http://www.cdc.gov/nchs/nhanes/nhanes2005-2006/DEMO_D.htm. (Revised 2009c).

_____. Health, United States, 2009. Internet Site: http://www.cdc.gov/nchs/data/hus/hus09.pdf. (Revised 2009d).

_____. Heart Disease and Stroke Prevention: Addressing the Nation's Leading Killers: At A Glance 2010. Internet Site: http://www.cdc.gov/chronicdisease/resources/publications/aag/pdf/2010/dhdsp.pdf (Revised 2010).

Chipperfield, J.G. "Incongruence between health perceptions and health problems: Implications for survival among seniors" *Journal of Aging and Health.* 5(1993):475-496.

Crandall, J. P., S. Polsky, A. A. Howard, L. Perreault, G. A. Bray, E. Barrett-Connor, J. Brown-Friday, T. Whittington, S. Foo, Y. Ma, and S. L. Edelstein for the Diabetes Prevention

Program Research Group. “Alcohol consumption and diabetes risk in the Diabetes Prevention Program.” *American Journal of Clinical Nutrition*. 90(2009):595-601.

Cutler, D.M. and A. Lleras-Muney. “Education and health: evaluating theories and evidence.” NBER Working Paper 12352, 2006.

Davies, H. T. O., I. K. Crombie, and M. Tavakoli. “When can odds ratios mislead?” *British Medical Journal.* 316(1998):989–991.

Drewnowski, A. and N. Darmon. “Food Choices and Diet Costs: an Economic Analysis.” *The Journal of Nutrition.* 135(2005):900-904.

Duhl, L. and T. Hancock. “Assessing Healthy Cities.” *World Health Organization Healthy Cities Papers*. Copenhagen, Denmark: World Health Organization,1988.

Dunning, D., C. Heath, and J.M. Suls. “Flawed Self-Assessment: Implications for Health Education, and the Workplace.” *Psychological Science in the Public Interest.* 5(2004); 69-106.

Ellin, A. “For Better, for Worse, for B.M.I.” *The New York Times*, June 11, 2010, accessed July 1, 2010, http://www.nytimes.com/2010/06/13/fashion/weddings/13FIELD.html.

Engelgau, M.M., K.M. Venkat Narayan, and W.H. Herman. “Screening for type 2 diabetes” *Diabetes Care*. 23(2000):1563-1580.

Epp, J. “Achieving health for all: A framework for health promotion.” *Health Promotion International.* 1(1986):419-428.

Ervin, R.B. “Prevalence of Metabolic Syndrome Among Adults 20 Years of Age and Over, by Sex, Age, race and Ethnicity, and Body Mass Index: United States, 2003-2006” Hyattsville, MD: U.S. Department of Health and Human Service, National Health Statistics Reports No. 13, 2009.

Fagerström, K. “The Epidemiology of Smoking: Health Consequences and Benefits of Cessation.” *Drugs*. 62(2002):1-9.

Festinger, L. *A theory of cognitive dissonance*. Stanford, CA: Stanford University Press, 1957.

Finkelstein, E.A., J. G. Trogdon, J.W. Cohen, and W. Dietz. “Annual Medical Spending Attributable To Obesity: Payer- And Service-Specific Estimates.” *Health Affairs*. 28(2009): w822-w831.

Fishbein, M. and I. Ajzen. *Belief, attitude, intention, and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley, 1975.

Fiske, S. T. and S. E. Taylor. *Social cognition*. Reading, MA: Addison-Wesley, 1984.

Flegal, K. M., M. D. Carroll, C. L. Ogden, and C. L. Johnson. "Prevalence and trends in obesity among US adults , 1999-2000." *Journal of the American Medical Association*. 288(2002):1723-1727.

Ford, E. S., A. H. Mokdad, and W. H. Giles. "Trends in Waist Circumference among U.S. Adults." *Obesity Research*. 11(2003):1223- 1231.

Fuchs, C. S., M. J. Stampfer, G. A. Colditz, E. L. Giovannucci, J. E. Manson, I. Kawachi, D. J. Hunter, S. E. Hankinson, C. H. Hennekens, and B. Rosner. "Alcohol consumption and mortality among women." *The New England Journal of Medicine*. 332(1995):1245-50.

Fullerton, A. "A Conceptual Framework for Ordered Logistic Regression Models." *Sociological Methods and Research.* 32(2009):306-347.

Fullerton, A. Personal Communication. Oklahoma State University, March 2010.

Furnée, C., W.Groot, H. Maassen van den Brink. "The health effects of education: a meta-analysis." *European Journal of Public Health.* 18(2008):417-421.

Golan, E., H. Stewart, F. Kuchler, and D. Dong. "Can Low-income Americans Afford a Healthy Diet?" *Amber Waves*. November 2008 (2008):26-63.

Goldberg, P. A. Guéguen, A. Schmaus, J-P. Nakache and M. Goldberg. "Longitudinal study of associations between perceived health status and self reported diseases in the French Gazel cohort." *Journal of Epidemiology and Community Health.* 55(2001):233-238.

Goldman, N., S. Korenamn, and R. Weinstein. "Marital Status and Health among the Elderly." *Social Science and Medicine.* 40(1995):1717-1730.

Gore, S. and T. W. Mangione. "Social Roles, Sex Roles and Psychological Distress: Additive and Interactive Models of Sex Differences." *Journal Health and Social Behavior*. 24(1993): 300-312.

Greene, W.H. *Econometric Analysis.* NJ: Prentice Hall, Englewood Cliffs, 2000.

Greenwald, A.G. "The totalitarian ego: Fabrication and revision of personal history" *American Psychologist.* 35(1980):603-618.

Gregory, C. O., H. M. Blanck, C. Gillespie, L.M. Maynard, and M. K. Serdule. "Health Perceptions and Demographic Characteristics Associated With Underassessment of Body Weight." *Obesity*. 16(2008):979-986.

Grossman, M. "On the Concept of Health Capital and the Demand for Health" *Journal of Political Economy.* 30(1972):223-255.

Grundy, S.M., H.B. Jr. Brewer, J.I. Cleeman, S.C. Jr. Smith, and C. Lenfant. "Definition of metabolic syndrome: Report of the National Heart, Lung, and Blood Institute/American Heart Association conference on scientific issues related to definition." *Circulation.* 109(2004):433-438.

Hadley, J. and P. J. Cunningham. *Perception, Reality and Health Insurance: Uninsured As Likely As Insured To Perceive Need For Care But Half As Likely to Get Care*. Washington, DC: Center for Studying Health System Change. Issue Brief No.100, 2005.

Haveman-Niles, A., L. C. P. G. M. de Groot and W. A. van Staveren. "Relation to dietary quality, physical activity, and smoking habits to 10 year changes in health status in older Europeans in the SENECA study." *American Journal of Public Health* 93(2003a):318-323.

Haveman-Niles, A., L. C. P. G. M. de Groot and W. A. van Staveren. "Dietary quality, lifestyle factors and healthy ageing in Europe: the SENECA study." *Age and Ageing.* 32(2003b):427–434.

Heidrich, J., A. D. Liese, H. Lowel, and U. Keil. "Self-rated health and its relation to all-cause and cardiovascular mortality in southern Germany. Results from the MONICA Augsburg Cohort Study 1984–1995." *Annals of Epidemiology*. 12(2002):338-345.

Heistaro, S., P. Jousilahti, E. Lahelma, E. Vartiainen, and P. Puska. "Self rated health and mortality: a long term prospective study in eastern Finland." *Journal of Epidemiology and Community Health.* 55(2001):227-232.

Heron , M.P., D.L. Hoyert, S.L. Murphy, J.Q. Xu, K.D. Kochanek, and B. Tejada-Vera. *Deaths: Final data for 2006.* Hyattsville, MD: National Center for Health Statistics, National Vital Statistics Reports 57, 2009.

Hooker, K. and C. R. Kaus. "Health-related possible selves in young and middle adulthood." *Psychology and Aging*. 9(1994):126-133.

Hu, Y.R. and N. Goldman. "Mortality Differentials by Marital Status: An International Comparison." *Demography.* 27(1990):223-250.

Idler, E. L. and S.V. Kasl. "Self-Rating of Health: Do They Also Predict Change in Functional Ability?" *Journal of Gerontology.* 50(1995):S344-53.

Idler, E.L. and Y. Benyamini, "Self-Rated Health and Mortality: A Review of Twenty-Seven Community Studies," *Journal of Health and Social Behavior*. 38(1997): 21–37.

Institute of Medicine. *Health Literacy: A Prescription to End Confusion*. Washington DC: National Academy of Sciences, Report Brief, October 2004.

Janssen, I., P. T. Katzmarzyk, and R. Ross. “Waist circumference and not body mass index explains obesity related health risk.” *American Journal of Clinical Nutrition*. 79(2004):379-84.

Jochelson, K. “Nanny or Steward? The role of government in public health.” Working Paper, King’s Fund, London, UK, October 2005.

John, O. P. and R.W. Robins. “Accuracy and bias in self-perception: Individual differences in self-enhancement and the role of narcissism.” *Journal of Personality and Social Psychology* 66(1994):206-219.

Kahneman, D. and A. Tversky. “Prospect Theory: An analysis of decision under risk.” *Econometrica*. 47(1979):263-291.

Keele, L. and D. K. Park. “Difficult Choice: An Evaluation of Heterogeneous Choice Models.” Paper presented at the conference of Midwest Political Science Association, Chicago, IL, 2004.

Kerkhofs, M. and M. Lindeboom. “Subjective Health Measures and State Dependent Reporting Errors” *Health Economics*. 4(1995) 221-235.

Kesse, E. F. Clavel-Chapelon, N. Slimani, M. Liere, and the E3N Group. “Do eating habits differ according to alcohol consumption? Results of a study of the French cohort of the European Prospective Investigation into Cancer and Nutrition (E3N-EPIC).” *American Journal of Clinical Nutrition.* 74(2001):322-7.

Kiechl, S., J. Willeit, W. Poewe, G. Egger, F. Oberhollenzer, M. Muggeo, and E. Bonora. “Insulin sensitivity and regular alcohol consumption: large, prospective, cross sectional population study (Bruneck study).” *British Medical Journal*. 313(1996):1040-1044.

Klesges, R.C., L.M. Klesges, and A.W. Meyers. “Relationship of smoking status, energy balance, and body weight: an analysis of the Second National Health and Nutrition Examination Survey.” *Journal of Consulting and Clinical Psychology.* 59(1991):899-905.

Kolar, D. W., D.C. Funder and C.R. Colvin. “Comparing the accuracy of personality judgments by the self and knowledgeable others” *Journal of Personality* 64(1996):311-337.

Kreuter, F. and R. Valliant. “A survey on survey statistics: What is done and can be done in Stata.” *The Stata Journal.* 7(2007):1-21.

Kunda, Z. “Motivated inference: self-serving generation and evaluation of causal theories.” *Journal of Personality and Social Psychology*. 53(1987):636-647.

Kwaśniewska, M., D. Kaleta, E. Dziankowska-Zaborszczyk, W. Drygas, and T. Makoweiec-Dabrowska. “Lifestyle Index and Self-rated Health Status” *International Journal of Occupational Medicine and Environmental Health.* 20(2007):349-356.

Kwaśniewska, M., W. Bielecki, and W. Drygas. "Sociodemographic and clinical determinants of quality of life in urban population of Poland." *Central European Journal of Public Health.* 12(2004):63-68.

Labonte, R. *A community development approach to health promotion: a background paper on practice, tensions, strategic models and accountability requirements for health authority work on the broad determinants of health.* Edinburgh: Health Education Board of Scotland, 1998.

Lall, R. M. J. Campbell, S. J. Walters, K. Morgan, and MRC CFAS Co-operative. "A review of ordinal regression models applied on health-related quality of life assessments" *Statistical Methods in Medical Research*. 11(2002): 49-67.

Lance, P.M. "Odds ratios: A brief helicopter tour of odds ratios, risk ratios and marginal effects." Working Paper, Carolina Population Center, University of North Carolina at Chapel Hill, 2008.

Lavallee, L. F. and J.D. Campbell. "Impact of personal goals on self-regulation processes elicited by daily negative events." *Journal of Personality and Social Psychology*. 69(1995):341-352.

Leigh, B.C. "Peril, chance, adventure: concepts of risk, alcohol use and risky behavior in young adults." *Addiction.* 94(1999):371-83.

Levesque, M. J. and D.A. Kenny. "Accuracy of behavioral predictions at zero-acquaintance: A social relations analysis." *Journal of Personality and Social Psychology*. 65(1993):1178-1187.

Lindsay, P. and D. A. Norman. *Human Information Processing: An Introduction to Psychology*. New York: Academic Press, 1977.

Long, J.S. *Regression Models for Categorical and Limited Dependent Variables*. California: Sage Publications, 1997.

Long, J.S. and J. Freese. *Regression Models for Categorical Dependent Variables Using Stata*. Texas, Stata Press, 2003.

MacCallum, R.X., S. Zhang, K. J. Preacher, and D.D. Rucker. "On the practice of dichotomization of quantitative variables." *Psychological Methods*. 7(2002):19-40.

MacDonald, T. K. and M. Ross. "Assessing the Accuracy of Predictions about Dating Relationships: How and Why Do Lovers' Predictions Differ from those Made by Observers?" *Personality and Social Psychology Bulletin.* 25(1999):1417-29.

Markus, H. “Self-schemata and processing information about the self” *Journal of Personality and Social Psychology*. 35(1977):63-78.

Markus, H. R. and P. Nurius. “Possible selves.” *American Psychologist*. 41(1986):954-969.

McCollum, M., L.B. Hansen, V. Ghushchyan and P.W. Sullivan. “Inconsistent Health Perceptions for US Women and Men with Diabetes” *Journal of Women’s Health* 16(2007):1421-1428.

McCullagh, P. “Regression models for ordinal data (with discussion).” *Journal of the Royal Statistical Society*. 42(1980):109-142.

McCullagh, P. and J. Nelder. *Generalized Linear Models.* New York: Chapman and Hall, 1989.

McKelvey, R.D. and W. Zavoina. “ A statistical model for the analysis of ordinal level dependent variables.” *Journal of Mathematical Sociology*. 4(1975):103-120.

Menard, S. *Applied logistic regression analysis*. California: Sage Publications, 1995.

Miilunpalo, S., I. Vuori, P. Oja, M. Pasanen, and H. Urponen. “Self-Rated Health Status as a Health Measure: The Predictive Value of Self-Reported Health Status on the Use of Physician Services and on Mortality in the Working-Age Population.” *Journal of Clinical Epidemiology*. 50(1997):517-528.

Miller, D. T. “Ego involvement and attributions for success and failure.” *Journal of Personality and Social Psychology*. 34(1976):901-906.

Mises, L. von. *Human Action: A treatise on economics*. New Haven, CT: Yale University Press, 1963.

Morris-Tries, D.E. “Self-reported health status and lifestyle behaviour of the residents of the town of Fort Erie, Ontario, as related to the Canadian Community Health Survey” Masters Thesis, Brock University, 2004.

Naimi, T. S., R. D. Brewer, A. Mokdad, C. Denny, M. K. Serdula, J. S. Marks. “Binge Drinking Among US Adults.” *The Journal of American Medical Association*. 289(2003):70-75.

National Center for Health Statistic. *The National Health and Nutrition Examination Survey (NHANES) Analytic and Reporting Guidelines.* Hyattsville, MD: Centers for Disease Control and Prevention, 2006.

National Diabetes Information Clearinghouse. Insulin Resistance and Pre-diabetes. NIH Publication No. 09–4893. Bethesda, MD. October 2008.

(NIH) National Institutes of Health. *Clinical Guidelines on the Identification, Evaluation, and Treatment of Overweight and Obesity in Adults.* NIH Publication 98-4038. Washington, DC, 1998.

Nisbett, R. E. and L. Ross. *Human inference: Strategies and shortcomings of social judgment*. Englewood Cliffs, NJ: Prentice-Hall, 1980.

Paeratakul, S., J.C. Lovejoy, D.H. Ryan, and G.A. Bray. "The relation of gender, race and socioeconomic status to obesity and obesity comorbidities in a sample of US adults." *International Journal of Obesity.* 26(2002):1205-1210.

Perloff, L.S. and B. K. Fetzer. "Self-Other Judgments and Perceived Vulnerability to Victimization." *Journal of Personality and Social Psychology*. 50(1986):502-510.

Perreira, K. M. and F. A. Sloan "Excess alcohol consumption and health outcomes: a 6-year follow-up of men over age 50 from the health and retirement study." *Addiction*. 97(2002):301-310.

Persky, J., "Retrospectives: Consumer Sovereignty," *Journal of Economic Perspectives*. 7(1993):183-191.

Poikolainen, K., E. Vartiainen, and H.J. Korhonen. "Alcohol Intake and Subjective Health." *American Journal of Epidemiology*. 144(1996): 346-350.

Polsky, D., J.A. Doshi, J. Escarce, W. Manning, S. M. Paddock, L. Cen, and J. Rogowski. "The Health Effects of Medicare for the Near-elderly Uninsured." National Bureau of Economic Research NBER Working Paper No. 12511, Cambridge, MA. 2006.

Prentice, A.M. and S. A. Jebb. "Beyond body mass index." *Obesity Reviews*. 2(2001): 141-147.

Pronin, E., J. Kruger, K. Savitsky and L. Ross. "You don't know me, but I know you: The illusion of asymmetric insight." *Journal of Personality and Social Psychology.* 43(2001):565-578.

Ratzan S.C. and R. M. Parker. "Introduction." *National Library of Medicine Current Bibliographies in Medicine: Health Literacy.* C. R. Selden, M. Zorn, S. C. Ratzan, and R. M. Parker, eds. Bethesda, MD: National Institutes of Health, U.S. Department of Health and Human Services, 2000.

Rahman, O. "Excess Mortality for the Non-Married in Rural Bangladesh." *International Journal of Epidemiology.* 22(1993):445-56.

Redmond, W. H. "Consumer Rationality and Consumer Sovereignty". *Review of Social Economy*. 58(2000):177-196.

Ren, X. S. “Marital Status and quality of relationships: The impact on health perception.” *Social Science and Medicine*. 44(1997):241-249.

Rimer, B., B. Trock, and P. Engstrom. “Why do some women get regular mammograms?” *American Journal of Preventive Medicine*. 7(1991):69 –73.

Room, R. “Smoking and drinking as complementary behaviours.” *Biomedecine and Pharmacotherapy*. 58(2004):111-115.

Ross, C. E. “ Reconceptualizing Marital Status as a Continuum of Social Attachment.” *Journal of Marriage and Family*. 52(1995):129-140.

Ross, C. E., J. Mirowsky, and K. Goldsteen. “The Impact of the Family on Health: A Decade in Review.” *Journal of Marriage and Family*. 52(1990):341-360.

Rout, H.S. and N.C. Nayak. “Health and Health Economics: A Conceptual Framework.” *Health Economics in India*. H.S. Rout and P.K. Panda, eds., New Delhi, India: New Century Publications, 2007.

Ryff, C. D. and B. Singer. “The contours of positive human health” *Psychological Inquiry*. 9(1998):1-28.

Ryff, C.D. “Possible selves in adulthood and old age: A tale of shifting horizons.” *Psychology and Aging*. 6(1991): 286-295.

SAS Institute. SAS/STAT 9.1 User’s Guide. Cary, NC: SAS Institute Inc.; 2004.

Schillinger, D., K. Grumbach, J. Piette, F. Wang, D. Osmond, C. Daher, J. Palacios, G. Diaz Sullivan, and A. B. Bindman. “Association of health literacy with diabetes outcomes.” *Journal of the American Medical Association.* 288(2002):475– 82.

Scott, S., M. Goldberg and N. Mayo. “Statistical assessment of ordinal outcomes in comparative studies.” *Journal of Clinical Epidemiology*. 50(1997):45-55.

Schulz, R. and J. Heckhausen. “A life span model of successful aging” *American Psychologist.* 51(1996): 702-714.

Schwartz, B., A. Ward, J. Monterosso, S. Lyubomirsky, K. White, and D.R. Lehman. “Maximizing versus satisficing: Happiness is a matter of choice.” *Journal of Personality and Social Psychology***.** 83(2002): 1178-1197.

Sen, A.K. *Choice, Welfare and Measurement*. Oxford: Blackwell, 1982.

Sen, A. “Health: perception versus observation”. *British Medical Journal* 2002(324): 860-1.

Shafir, E., I. Simonson and A. Tversky. “Reason-based choice” *Cognition*. 49(1993):11-36.

Silventoinen, K. and E. Lahelma. “Health Inequalities by Education and Age in Four Nordic Countries, 1986 and 1994.” *Journal of Epidemiology and Community Health.* 56(2002):253-258.

Silventoinen, K., E. Lahelma, and J. Kaprio. “Self-Rated Health: Precursors and Implications” *Socioemotional Development and Health from Adolescence to Adulthood.* L. Pulkkinen, J. Kaprio, and R. J. Rose, eds. Cambridge, U.K.: Cambridge University Press, 2006.

Simon, H. A. “Rationality in Psychology and Economics.” *Journal of Business.* 59(1986):S209-S224.

Simon, H.A. “A Behavioral Model of Rational Choice.” *Quarterly Journal of Economics* 69(1955):99-118.

Simon, H. A. “Rationality as process and product of thought”. *American Economic Review.* 68(1978): 1-16.

Simon-Morton, B.G., W.H. Greene, and N.H. Gottlieb. *Introduction to health education and health promotion*. Prospective Heights, Illinois: Waveland Press Inc., 1995.

Sink, K. M., D. A. Mangieri, J. Lovato, A. Fitzpatrick, H. Atkinson, J. Saxton, S. Rapp, M. Carlson, S. DeKosky, R. Nahin, and J. Williamson. “Moderate Alcohol Intake is Associated with Lower Dementia Incidence: Results from the Ginkgo Evaluation of Memory Study (GEMS).” Paper presented at the Alzheimer's Association 2009 International Conference on Alzheimer's Disease, Messe Wien Exhibition and Congress Center, Vienna, Austria, July 11-16, 2009.

Södergren, M. J. Sundquist, S.E. Johansson, and K. Sundquist. “Physical activity, exercise and self-rated health: a population-based study from Sweden.” *BMC Public Health*. 8(2008): 352.

Srikanthan P., T.E. Seeman, A.S. Karlamangla.“Waist-hip-ratio as a predictor of all-cause mortality in high-functioning older adults.” Annals of Epidemiology. 19(2009):724-31.

Steele, C.M. “The psychology of self-affirmation: Sustaining the integrity of the self.” *Advances in experimental social psychology: Vol.21.* L. Berkowitz, ed. New York: Academic Press, 1988.

Suter, P. D. , E. Hasler, and W. Vetter. “Effects of Alcohol on Energy Metabolism and Body Weight Regulation: Is Alcohol a Risk Factor for Obesity?” *Nutrition Reviews*. 55(1997):157-171.

Tavris, C. and C. Wade. *Psychology in Perspective*. New York: Harper Collins College Publishers, 1995.

Taylor, S.E. and M. Lobel. "Social comparison activity under threat: Downward evaluation and upward contracts." Psychological Review. 96(1989):569-575.

Tesser, A. and J. Campbell. "Self-definition and self-evaluation maintenance." *Psychological perspectives on the self: Vol. 2*. J. Suls and A. Greenwald, eds. Hillsdale, NJ: Erlbaum, 1984.

Thaler, R.H. Mental accounting and consumer choice. *Marketing Science,* 4(1985): 199-214.

The, N. S. and P. Gordon-Larson. "Entry Into Romantic Partnership Is Associated With Obesity" *Obesity*. 17(2009):1441-1447.

Theobald, H., S. Johansson, and P. Engfeldt. "Influence of Different Types of Alcoholic Beverages on Self-Reported Health Status." *Alcohol and Alcoholism*. 38(2003):583-588.

Thoolen, B., D. De Ridder, J. Bensing, K. Gorter, G. Rutten. "No worries, no impact? A systematic review of emotional, cognitive, and behavioural response to the diagnosis of type 2 diabetes" *Health Psychology Review*. 2(2008):65-93.

Tjønneland, A. M. Grønbeck, C. Stripp, and K. Overvad. "Wine intake and diet in a random sample of 48,763 Danish men and women." *American Journal of Clinical Nutrition*. 69(1999): 49-54.

Tolliver, R. *Factors Associated with Self-Reported Health Status Among Colorado Adults, 2005*. Denver, CO: Colorado Department of Public Health and Environment, Health Watch No.62, 2007.

Tubeuf, S., F. Jusot, M. Devaux, and C. Sermet. "Social Heterogeneity in Self-Reported Health Status and Measurement of Inequalities in Health." Working paper, Institut de recherche et documentation en économie de la santé, Paris, France, 2008.

(US DHHS) United States Department of Agriculture and United States Department of Health and Human Services. *Promoting physical activity: a guide for community action*. Champaign, IL: Human Kinetics, 1999.

_____.*Healthy People 2010: Understanding and Improving Health*. 2nd ed. Washington, DC: Government Printing Office, November 2000.

_____.*The Surgeon General's Call to Action to Prevent and Decrease Overweight and Obesity.* Washington DC, 2001.

_____."Alcoholic Beverages." *Dietary Guidelines for Americans*. Washington, DC: US Government Printing Office, 2005, p. 43–46.

_____. *2008 Physical Activity Guidelines for Americans*. Washington, D.C.: United States Government Printing Office, 2008.

Vazire, S. and M. Mehl. "Knowing Me, Knowing You: The Accuracy and Unique Predictive Validity of Self-Ratings and Other-Ratings of Daily Behavior." Journal of Personality and Social Psychology. 95(2008):1202-1216.

Ware J.E. Jr., A. Davies-Avery, and C.A. Donald. *Conceptualization and measurement of health for adults in the health insurance study, Vol V: general health perceptions. R-1987/HEW.* Santa Monica, CA: The Rand Corporation, 1978.

Webbink, D., N.G. Martin, P. M. Visscher. "Does education reduce the probability of being overweight?" *Journal of Health Economics*. 29(2010): 29-38.

Weick, K. E. *Sensemaking in Organizations*. Thousand Oaks, CA: Sage, 1995.

Weinstein, N. D. "Unrealistic Optimism About Future Life Events" *Journal of Personality and Social Psychology.* 39(1980):806-820.

_____. " Why it won't happen to me: Perceptions of risk factors and susceptibility." *Health Psychology.* 3(1984): 431-457.

_____. "Unrealistic optimism about susceptibility to health problems: Conclusions from a community-wide sample." *Journal of Behavioral Medicine*. 10(1987):481-500.

Weiss, B.D., G. Hart, D.L. McGee, and S. D'Estelle. "Health status of illiterate adults: relation between literacy and health status among persons with low literacy skills." Journal of the *American Board* of *Family* Medicine. 5(1992):257– 64.

Weiss, B.D., J.S. Blanchard, D. L. McGee, G. Hart, B. Warren, M. Burgoon, and K. J. Smith. "Illiteracy among Medicaid recipients and its relationship to health care costs." *Journal* of *Health Care* for the *Poor* and *Underserved.* 5(1994):99 –111.

Wellman P.J., L.L. Bellinger, A. Cepeda-Benito, A. Susabda, D.H. Ho, K.W. Davis. "Meal patterns and body weight after nicotine in male rats as a function of chow or high-fat diet." *Pharmacology, Biochemistry, and Behavior*. 82(2005):627-634.

White, M. A., S.A. McKee, and S. S. O'Malley. "Smoke and Mirrors: Magnified beliefs that cigarette smoking suppresses weight." Addictive *Behaviors*. 32(2007):2200-2210.

Williams, E., R. C. Klesges, C.L. Hanson and L. H. Eck. "A prospective study of the reliability and convergent validity of three physical activity measures in a field research trial." *Journal of Clinical Epidemiology*. 42(1989); 1161-1170.

Williams, M.V., D. W. Baker, R.M. Parker, and J.R. Nurss. "Relationship of functional health literacy to patients' knowledge of their chronic disease: a study of patients with hypertension or diabetes." *Archives of Internal Medicine*. 158(1998a):166–72.

Williams, M.V.,D.W. Baker, E.G. Honig, T.M. Lee, and A. Nowlan. "Inadequate literacy is a barrier to asthma knowledge and self-care. *Chest.* 114*(*1998b):1008-15.

Williams, R. "Generalized Ordered Logit/Partial Proportional Odds Models for Ordinal Dependent Variables." *The Stata Journal* 6(2006):58-62.

Williams, R. "Ordinal regression models: Problems, solutions, and problems with the solutions." Paper presented at German Stata User Group Meetings, Wissenschaftszentrum Berlin für Sozialforschung, Berlin, June 27, 2008.

Williams, R. "Using Heterogeneous Choice Models to Compare Logit and Probit Coefficients across Groups." *Sociological Methods and Research*. 37(2009): 531-559.

Winship, C. and R. D. Mare. "Regression Models With Ordinal Variables." *American Sociological Review.* 49 (1984):512-525.

Wolf, A. M. and G.A. Colditz. "Current estimates of the economic cost of obesity in the United States." *Obesity Research*. 6(1998):97-106.

Wolfe, R. and W. Gould. "Continuation-ratio models for ordinal response data." *Stata Technical Bulletin,* 44(1998):18-21.

World Bank. *World Development Report: Investing in Health*. New York: Oxford University Press. 1993.

(WHO) World Health Organization. *Constitution of the World Health Organization*. Geneva, Switzerland: WHO, 1946.

_____. *Obesity and overweight: What are Overweight and Obesity?* Fact Sheet N°311. Geneva, Switzerland, 2006.

Yatchew, A. and Z. Griliches. "Specification Error in Probit Models." *The Review of Economics and Statistics*. 67(1985):134-139.

Yao, Z. "Dignāga and Four Types of Perception." *Journal of Indian Philosophy*. 32(2004):57-79.

Zick, C.D. and K. R. Smith. "Marital Transitions, Poverty, and Gender Differences in Mortality." *Journal of Marriage and the Family.* 53(1991):327-36.

Zhu S. , Z. Wang, S. Heshka, M. Heo, M. S. Faith, and S. B. Heymsfield. "Waist circumference and obesity-associated risk factors among whites in the third National Health and

Nutrition Examination Survey: clinical action thresholds." *American Journal of Clinical Nutrition*. 76(2002):743-9.

Zweifel, P. and F. Breyer. *Health Economics*. New York: Oxford University Press, 1997.

Appendix A - Technical Results

Table A.1: Estimated Coefficients for the Ordered Probit Model

	Coefficient (Standard Errors)
Independent Variables	
Gender - Male	-0.122**
	(0.0513)
Age (in yrs)	-0.0121***
	(0.00179)
Marital Status -Married	0.0162
	(0.0695)
Marital Status - Widowed	0.0494
	(0.134)
Marital Status - Divorced	-0.188*
	(0.0988)
Marital Status - Separated	-0.139
	(0.161)
Marital Status - Cohabitation	-0.112
	(0.0970)
Education - Less than Grade 9	-1.159***
	(0.118)
Education - Less than High School	-0.628***
	(0.0906)
Education - High School Grad or Equivalent	-0.437***
	(0.0697)
Education - Some College or an AA Degree	-0.270***
	(0.0613)
Household Income	0.0382***
	(0.00927)
Diet Quality - Poor	-1.174***
	(0.138)
Diet Quality - Fair	-1.122***
	(0.1000)
Diet Quality - Good	-0.685***
	(0.0909)
Diet Quality - Very Good	-0.399***
	(0.0934)
Physical Fitness Comparison - Less	-0.427***
	(0.0682)
Physical Fitness Comparison - More	0.299***
	(0.0533)
Exercise - Inactive	0.0856*
	(0.0520)
Smoke - Former	0.0148
	(0.0596)
Smoke - Current	-0.0505
	(0.0657)
Alcohol Consumption - Light	0.123*
	(0.0673)
Alcohol Consumption - Moderate	0.140**
	(0.0684)
Alcohol Consumption - Heavy	-0.0281
	(0.0695)
Doctor Visits - 1 Time/Yr	-0.0187
	(0.0809)
Doctor Visits - 2-3 Times/Yr	-0.150*
	(0.0768)
Doctor Visits - 4-9 Times/Yr	-0.306***
	(0.0801)
Doctor Visits - 10-12 Times/Yr	-0.572***
	(0.111)
Doctor Visits - 13 or More Times/Yr	-0.719***
	(0.105)
Constant - Cutpoint 1	-2.749***
	(0.163)
Constant - Cutpoint 2	-1.472***
	(0.159)
Constant - Cutpoint 3	-0.361**
	(0.156)
Observations	2,275
LR Chi-Square (29)	739.13
p	0
Pseudo R^2	0.123

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reference Category is female, single, with at least a college education, a self-reported excellent diet quality, a same perceived physical fitness level as her peers, is physically active by US DHHS standards, is a non-smoker, abstains from alcohol, and does not visit a doctor annually.

Since the PCOL was the preferred model, only its results were presented in the main part of the study. Results from the ordered logit and the UGOL models are presented in Appendix A.

Table A.2: Estimated Coefficients for the Ordered Logit Model

	Coefficient (Standard Error)
Independent Variables	
Gender - Male	**-0.187****
	(0.0861)
Age (in yrs)	**-0.0204*****
	(0.00306)
Marital Status -Married	0.00116
	(0.122)
Marital Status - Widowed	0.00886
	(0.233)
Marital Status - Divorced	**-0.351****
	(0.178)
Marital Status - Separated	-0.333
	(0.337)
Marital Status - Cohabitation	-0.248
	(0.170)
Education - Less than Grade 9	**-1.981*****
	(0.207)
Education - Less than High School	**-1.055*****
	(0.156)
Education - High School Graduate or Equivalent	**-0.728*****
	(0.119)
Education - Some College or an AA Degree	**-0.447*****
	(0.102)
Household Income	**0.0683*****
	(0.0168)
Diet Quality - Poor	**-2.173*****
	(0.276)
Diet Quality - Fair	**-2.081*****
	(0.210)
Diet Quality - Good	**-1.318*****
	(0.190)
Diet Quality - Very Good	**-0.810*****
	(0.192)
Physical Fitness Comparison - Less	**-0.710*****
	(0.118)
Physical Fitness Comparison - More	**0.499*****
	(0.0915)
Exercise - Inactive	**0.155***
	(0.0889)
Smoke - Former	0.00941
	(0.101)
Smoke - Current	-0.0694
	(0.114)
Alcohol Consumption - Light	**0.200***
	(0.113)
Alcohol Consumption - Moderate	**0.232****
	(0.118)
Alcohol Consumption - Heavy	-0.0627
	(0.121)
Doctor Visits - 1 Time/Yr	-0.0563
	(0.145)
Doctor Visits - 2-3 Times/Yr	**-0.272****
	(0.138)
Doctor Visits - 4-9 Times/Yr	**-0.520*****
	(0.145)
Doctor Visits - 10-12 Times/Yr	**-0.977*****
	(0.194)
Doctor Visits - 13 or More Times/Yr	**-1.246*****
	(0.186)
Constant - Cutpoint 1	**-4.830*****
	(0.313)
Constant - Cutpoint 2	**-2.626*****
	(0.299)
Constant - Cutpoint 3	**-0.732****
	(0.292)
Observations	2,275
LR Chi-Square (29)	746.61
p	0
Pseudo R^2	0.124

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reference Category is female, single, with at least a college education, a self-reported excellent diet quality, a same perceived physical fitness level as her peers, is physically active by US DHHS standards, is a non-smoker, abstains from alcohol, and does not visit a doctor annually.

Table A.3: Estimated Marginal Effects for the Ordered Logit Model

	Health Status = Poor/Fair		Health Status = Good		Health Status = Very Good		Health Status = Excellent	
Gender - Male	**0.0153**	**	**0.0313**	**	**-0.0235**	**	**-0.0231**	**
Age (in yrs)	**0.0017**	***	**0.0034**	***	**-0.0026**	***	**-0.0025**	***
Marital Status -Married	-0.0001		-0.0002		0.0001		0.0001	
Marital Status - Widowed	-0.0007		-0.0015		0.0011		0.0011	
Marital Status - Divorced	**0.0321**	*	**0.0553**	**	**-0.0483**	*	**-0.0392**	***
Marital Status - Separated	0.0310		0.0522		-0.0464		-0.0368	
Marital Status - Cohabitation	0.0220		0.0399		-0.0334		-0.0285	
Education - Less than Grade 9	**0.3084**	***	**0.1006**	***	**-0.2755**	***	**-0.1335**	***
Education - Less than High School	**0.1210**	***	**0.1313**	***	**-0.1554**	***	**-0.0969**	***
Education - High School Grad or Equivalent	**0.0706**	***	**0.1091**	***	**-0.1016**	***	**-0.0780**	***
Education - Some College or an AA Degree	**0.0389**	***	**0.0725**	***	**-0.0587**	***	**-0.0526**	***
Household Income	**-0.0056**	***	**-0.0115**	***	**0.0086**	***	**0.0084**	***
Diet Quality - Poor	**0.3562**	***	**0.0744**	**	**-0.2936**	***	**-0.1370**	***
Diet Quality - Fair	**0.2784**	***	**0.1776**	***	**-0.2810**	***	**-0.1749**	***
Diet Quality - Good	**0.1237**	***	**0.1944**	***	**-0.1671**	***	**-0.1510**	***
Diet Quality - Very Good	**0.0781**	***	**0.1214**	***	**-0.1118**	***	**-0.0876**	***
Physical Fitness Comparison - Less	**0.0702**	***	**0.1050**	***	**-0.1005**	***	**-0.0747**	***
Physical Fitness Comparison - More	**-0.0395**	***	**-0.0838**	***	**0.0597**	***	**0.0636**	***
Exercise - Inactive	**-0.0123**	*	**-0.0261**	*	**0.0189**	*	**0.0195**	*
Smoke - Former	-0.0008		-0.0016		0.0012		0.0012	
Smoke - Current	0.0058		0.0115		-0.0089		-0.0084	
Alcohol Consumption - Light	**-0.0155**	*	**-0.0340**	*	**0.0238**	*	**0.0257**	*
Alcohol Consumption - Moderate	**-0.0179**	**	**-0.0396**	*	**0.0274**	**	**0.0301**	*
Alcohol Consumption - Heavy	0.0052		0.0105		-0.0080		-0.0077	
Doctor Visits - 1 Time/Yr	0.0047		0.0094		-0.0072		-0.0069	
Doctor Visits - 2-3 Times/Yr	**0.0234**	*	**0.0445**	**	**-0.0357**	*	**-0.0322**	**
Doctor Visits - 4-9 Times/Yr	**0.0476**	***	**0.0817**	***	**-0.0708**	***	**-0.0585**	***
Doctor Visits - 10 -12 Times/Yr	**0.1123**	***	**0.1220**	***	**-0.1451**	***	**-0.0892**	***
Doctor Visits - 13 or More Times/Yr	**0.1544**	***	**0.1362**	***	**-0.1843**	***	**-0.1064**	***

*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Estimated Coefficients for the UGOL Model

Dependent Variable	Health Status = Poor/Fair	Health Status = Good	Health Status = Very Good
Independent Variables			
Gender - Male	**-0.257***	**-0.263****	-0.0530
	(0.154)	(0.105)	(0.127)
Age (in yrs)	**-0.0224*****	**-0.0196*****	**-0.0220*****
	(0.00530)	(0.00364)	(0.00451)
Marital Status -Married	0.148	-0.0812	0.0869
	(0.211)	(0.142)	(0.171)
Marital Status - Widowed	0.275	-0.215	0.192
	(0.365)	(0.274)	(0.368)
Marital Status - Divorced	-0.406	**-0.410****	-0.0713
	(0.270)	(0.201)	(0.259)
Marital Status - Separated	-0.569	-0.335	0.275
	(0.391)	(0.335)	(0.416)
Marital Status - Cohabitation	-0.192	-0.311	-0.0840
	(0.279)	(0.196)	(0.244)
Education - Less than Grade 9	**-2.524*****	**-2.095*****	**-1.644*****
	(0.307)	(0.267)	(0.427)
Education - Less than High School	**-1.598*****	**-1.215*****	**-0.685*****
	(0.283)	(0.184)	(0.240)
Education - High School Grad or Equivalent	**-1.298*****	**-0.803*****	**-0.623*****
	(0.250)	(0.142)	(0.177)
Education - Some College or an AA Degree	**-0.952*****	**-0.624*****	-0.206
	(0.243)	(0.127)	(0.140)
Household Income	**0.0693*****	**0.0733*****	**0.0627****
	(0.0261)	(0.0190)	(0.0245)
Diet Quality - Poor	**-1.089*****	**-1.864*****	**-2.487*****
	(0.351)	(0.292)	(0.459)
Diet Quality - Fair	**-1.046*****	**-1.821*****	**-2.122*****
	(0.280)	(0.210)	(0.232)
Diet Quality - Good	0.133	**-1.112*****	**-1.754*****
	(0.280)	(0.192)	(0.190)
Diet Quality - Very Good	0.225	**-0.481****	**-1.102*****
	(0.308)	(0.200)	(0.186)
Physical Fitness Comparison - Less	**-0.832*****	**-0.705*****	**-0.698*****
	(0.169)	(0.138)	(0.218)
Physical Fitness Comparison - More	**0.676*****	**0.414*****	0.512***
	(0.175)	(0.109)	(0.128)
Exercise - Inactive	0.103	**0.256****	0.0718
	(0.146)	(0.106)	(0.137)
Smoke - Former	0.0829	0.0278	-0.0557
	(0.178)	(0.121)	(0.147)
Smoke - Current	-0.0210	-0.0409	-0.192
	(0.183)	(0.133)	(0.176)
Alcohol Consumption - Light	**0.538****	0.190	-0.00600
	(0.219)	(0.138)	(0.169)
Alcohol Consumption - Moderate	**0.374***	0.225	0.127
	(0.209)	(0.139)	(0.167)
Alcohol Consumption - Heavy	-0.00184	-0.0927	-0.0469
	(0.195)	(0.141)	(0.176)
Doctor Visits - 1 Time/Yr	0.118	0.0545	-0.225
	(0.272)	(0.166)	(0.189)
Doctor Visits - 2-3 Times/Yr	-0.204	-0.106	**-0.447****
	(0.247)	(0.156)	(0.185)
Doctor Visits - 4-9 Times/Yr	**-0.687*****	**-0.404****	**-0.515*****
	(0.246)	(0.162)	(0.195)
Doctor Visits - 10-12 Times/Yr	**-0.986*****	**-1.032*****	**-0.846*****
	(0.308)	(0.230)	(0.303)
Doctor Visits - 13 or More Times/Yr	**-1.500*****	**-1.155*****	**-0.998*****
	(0.283)	(0.218)	(0.285)
Constant - Cutpoint 1	**4.136*****		
	(0.490)		
Constant - Cutpoint 2	**2.447*****		
	(0.325)		
Constant - Cutpoint 3	**1.012*****		
	(0.368)		
Observations	2,275		
LR Chi-Square	847.82		
p	0		
Pseudo R^2	0.141		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reference Category is female, single, with at least a college education, a self-reported excellent diet quality, a same perceived physical fitness level as her peers, is physically active by US DHHS standards, is a non-smoker, abstains from alcohol, and does not visit a doctor annually.

Table A.5: Estimated Marginal Effects for the UGOL Model

	Health Status = Poor/Fair	Health Status = Good	Health Status = Very Good	Health Status = Excellent
Gender - Male	**0.0181** *	**0.0474** *	**-0.0586** **	-0.0068
Age (in yrs)	**0.0016** ***	**0.0033** ***	**-0.0020** **	**-0.0028** ***
Marital Status -Married	-0.0105	0.0307	-0.0314	0.0112
Marital Status - Widowed	-0.0173	0.0711	-0.0801	0.0263
Marital Status - Divorced	0.0327	0.0696	-0.0932	-0.0090
Marital Status - Separated	0.0501	0.0335	-0.1224	0.0388
Marital Status - Cohabitation	0.0144	0.0633	-0.0671	-0.0106
Education - Less than Grade 9	**0.4033** ***	**0.0232**	**-0.2985** ***	**-0.1279** ***
Education - Less than High School	**0.1906** ***	**0.0962** *	**-0.2138** ***	**-0.0730** ***
Education - High School Grad or Equivalent	**0.1259** ***	**0.0717** *	**-0.1264** ***	**-0.0713** ***
Education - Some College or an AA Degree	**0.0773** ***	**0.0774** **	**-0.1288** ***	-0.0259
Household Income	**-0.0048** ***	**-0.0134** ***	**0.0101** **	**0.0081** **
Diet Quality - Poor	**0.1154** **	**0.2782** ***	**-0.2418** ***	**-0.1518** ***
Diet Quality - Fair	**0.0961** ***	**0.3167** ***	**-0.2271** ***	**-0.1857** ***
Diet Quality - Good	-0.0092	**0.2803** ***	-0.0650	**-0.2061** ***
Diet Quality - Very Good	-0.0150	**0.1347** ***	-0.0003	**-0.1194** ***
Physical Fitness Comparison - Less	**0.0737** ***	**0.1004** ***	**-0.0971** ***	**-0.0770** ***
Physical Fitness Comparison - More	**-0.0456** ***	**-0.0567** **	0.0342	**0.0682** ***
Exercise - Inactive	-0.0071	**-0.0564** **	**0.0541** **	0.0093
Smoke - Former	-0.0057	-0.0012	0.0140	-0.0071
Smoke - Current	0.0015	0.0087	0.0135	-0.0237
Alcohol Consumption - Light	**-0.0332** ***	-0.0139	0.0479	-0.0008
Alcohol Consumption - Moderate	**-0.0239** **	-0.0318	0.0390	0.0168
Alcohol Consumption - Heavy	0.0001	0.0230	-0.0171	-0.0060
Doctor Visits - 1 Time/Yr	-0.0080	-0.0056	0.0412	-0.0277
Doctor Visits - 2-3 Times/Yr	0.0148	0.0117	0.0273	**-0.0538** ***
Doctor Visits - 4-9 Times/Yr	**0.0563** **	0.0443	-0.0401	**-0.0606** ***
Doctor Visits - 10 -12 Times/Yr	**0.0991** **	**0.1476** ***	**-0.1625** ***	**-0.0843** ***
Doctor Visits - 13 or More Times/Yr	**0.1777** ***	**0.0956** *	**-0.1774** ***	**-0.0960** ***

*** p<0.01, ** p<0.05, * p<0.1