Dietary Quality, Behavioural Factors and Cardiovascular Health

An Econometric Analysis of Structural Relationships with the Data of the National Health and Nutrition Examination Survey 2005-2006, USA

Dissertation to obtain the Doctoral Degree
at the Faculty of Agricultural Sciences, Nutritional Sciences and Environmental Management,
Justus Liebig University Giessen

submitted by

Tetyana DEMYDAS

born in Kiev

First supervisor: Prof. Dr. Roland Herrmann
Second supervisor: Prof. Dr. P. Michael Schmitz

Date of disputation: October 28, 2014

Acknowledgement

This dissertation was prepared with a support and encouragement of my supervisors, colleagues, friends and family members, to whom I feel truly indebted.

My deep gratitude goes to my first supervisor, Prof. Dr. Roland Herrmann. I could not wish better guidance and support throughout the whole course of the dissertation project. A special thanks for his warm encouragement and valuable suggestions in the final phase of the thesis preparation. I also very much appreciate the involvement and input of my second supervisor, Prof. Dr. Michael Schmitz.

I extend my warm thanks to my colleagues at the institute of Agricultural Policy and Market Research for stimulating discussions and many nice memories. It was truly a pleasure to be a part of the team.

My gratitude also goes to the colleagues from the Center for International Development and Environmental Research (ZEU). It was an exciting time with interesting interdisciplinary projects and a great working atmosphere.

I thank to the University of Giessen for providing me the funding via Graduate scholarship, which allowed me to undertake this research.

Over all the years of my studies, my family and friends living in Ukraine were my "home front" that provided me with faith and motivation. To them I express my deepest gratitude.

Finally, the finalization of the thesis would not have been possible without support of my husband, John. Thank you for taking a great care of our little Philip and, thus, creating for me a space needed so much for the final preparations.

Giessen, March 2015 Tetyana Demydas

Table of contents

List of tables

List of figures

List of abbreviations

ADF	Asymptotically Distribution Free
AIC	Akaike Information Criteria s
AMDR	Acceptable Macronutrient Distribution Ranges for Adults
AMOS	Analysis of MOment Structures
BMI	Body Mass Index
CALIS	Covariance Analysis and Linear Structural Equations
CDC	Centres for Disease Control and Prevention
CFA	Confirmatory Factor Analysis
CNPP	Centre for Nutrition Policy and Promotion
CVDs	Cardiovascular Diseases
DBP	Diastolic Blood Pressure
DF	Degrees of Freedom
DGA	Dietary Guidelines for Americans
EM	Expectation Maximisation
EQS	Equations
FAO	Food and Agriculture Organisation
FGP	Food Guide Pyramide
F&V	Fruit and Vegetable
GLM	General Linear Modelling
HDI	Healthy Diet Indicator
HDL	High Density Lipoprotein
HEI	Healthy Eating Index
HHS	United States Department of Health and Human Services
Hyp	Hypothesis
INQ	Index of Nutritional Quality
LDL	Low Density Lipoprotein
LISREL	Linear Structural Relationships
MAR	Missing at Random
MCAR	Missing Completely at Random
MEC	Mobile Examination Centres
MIMIC	Multiple Causes Multiple Indicators
NHANES	National Health and Nutrition Examination Survey
NIH	National Institutes of Health
RMSEA	Root Mean Square Error of Approximation
QOL	Quality-of-Life
SBP	Systolic Blood Pressure
SE	Standard Error
SEM	Structural Equation Modelling
SPSS	Statistical Product and Service Solutions
SUR	Seemingly Unrelated Regressions
USDA	United States Department of Agriculture
WC	Waist Circumference
WHO	World Health Organisation
2SLS	Two-Stage-Least-Squares

1 Introduction

"The greatest potential for improving the health of the American people . . . is to be found in what people do and don't do to and for themselves." (FUCHS, 1967)

1.1 Problem statement and project goals

Cardiovascular diseases (CVDs) is a group of disorders of the heart and blood vessels, including coronary artery disease (e.g., heart attack), cerebrovascular disease (e.g., stroke), diseases of the aorta and arteries, hypertension, congenital heart disease and heart failure. In 2008, they were responsible for 30% of all mortalities, thus being the leading cause of death globally. Especially low- and middle-income countries are affected by CVDs (WHO, 2011). In high-income societies, a decline of the mortality rate attributable to CVDs has been observed in the last decades due to the availability of early detection services and improved medical treatment possibilities. However, the burden of the diseases remains high. In the USA, CVDs are the leading cause of mortality among men and women (ROGER *et al.*, 2012). In 2008 they were responsible for 35% of all deaths in the country. For comparison, cancers are estimated to account for 23% of deaths in the USA (WHO, 2011a).

High incidence of CVDs among the US population is connected with huge economic costs for the health care system. Currently about 17% of all health expenditures are attributable to CVDs, while a further increase in medical spending is projected due to an ageing population and an expected rise of the incidence of the diseases. By 2030, total direct medical costs of CVDs are assumed to triple, while indirect costs (i.e., productivity loss due to morbidity and premature mortality) will more than double (HEIDENREICH *et al.*, 2011).

Adverse health behaviours such as physical inactivity, smoking, harmful alcohol consumption, eating a poor diet and being overweight or obese are considered to be important risk factor of heart disorders. In the long run, these factors increase the risk of hypertension, diabetes, heart attack and stroke (ROGER *et al.*, 2012; LLOYD-JONES *et al.*, 2010). Importantly, these behaviours are modifiable and thus, in the majority of cases, CVDs can be prevented. Thereby, genetic predisposition is likely to play a role in the incidence of the diseases. Individuals with a family history of CVDs may also have an enhanced risk due to sharing common unhealthy environments and lifestyles within a family (CDC, 2013; ROGER *et al.*, 2012).

Although the share of smokers among the US population declined between 1965 and 2008 by over 50%, about 20% of all deaths in the country are attributed to tobacco usage (AMERICAN LUNG ASSOCIATION, 2011). In 2010, 21% of adult men and 18% of adult women were characterised as regular smokers (ROGER *et al.*, 2012). Furthermore, over one third of adults (33%) engage in no regular leisure-time physical activity and 20% are insufficiently active (ROGER *et al.*, 2012). American adults also fail to comply with the existing recommendations for a healthy diet (USDA and CNPP, 2013; SCHILLER *et al.*, 2012). Findings of dietary studies indicate an overconsumption of added sugars (e.g., from sugar-sweetened beverages) and saturated fats (e.g., from fast food) and under-consumption of fruits and vegetables (F&V). According to the data from NHANES 1999–2000, a diet of only 10% of Americans could be characterised as “good”, 74% of population had a diet that “needs improvement,” and 16% had “poor” diets (BASIOTIS *et al.*, 2002). No significant improvement was observed in the overall diet quality of Americans in 2007-2008 compared to 2001-2002. The overall score of the Healthy Eating Index (HEI) computed by the USDA annually was 53 and 52, respectively, out of possible 100 points indicating inadequacy of the diets (USDA and CNPP, 2013). Furthermore, of a large concern for the health care system is a dramatic raise of overweight and obesity among the population. In 2008, about 67% of US adults were characterised as overweight or obese, with 34% of them being obese. According to the estimations, about 13% of CVDs deaths were attributed to obesity in 2004. Moreover, overweight and obesity are associated with numerous other negative health conditions including asthma, cancer, and diabetes mellitus (ROGER *et al.*, 2012).

Various disciplines, e.g., economic, social, medical, nutritional and epidemiological, work on their contribution to the research about health determinants, which is aimed to support the nutrition and health policies with scientific knowledge and to improve the population’s health.

This dissertation project supports an idea that health-related research may benefit greatly from an interdisciplinary approach as health status is affected by numerous factors existing at every stage and in any area of human life. An individual is confronted with a number of choices, including decisions affecting his health (e.g., diet). A further complexity is due to an impact of economic constraints (e.g., income) on these choices and, furthermore, of usually unobserved personal characteristics such as genetic endowments. Application of knowledge and findings from various disciplines allows a more profound analysis of diverse health factors and their complex interrelations. Other authors (BERMAN et al., 1994; NAYGA, 2008; CHEN et al., 2002) have emphasised the benefits of such an approach.

This study employs a theoretical framework of household production that emerged out of groundwork of BECKER (1965) and its application to health and nutrition by BEHRMAN und DEOLALIKAR (1988). This framework offers a basis for investigations in the field of health and its determinants and finds numerous applications in the health-economic literature. Moreover, it is viewed as an integrating concept for interdisciplinary research dealing with human health and its determinants (NAYGA, 2008).

The main goal of the project is to contribute to the analysis of structural relations between dietary quality, lifestyles and an individual's health state related to CVDs. Among the factors of cardiovascular health, special attention is devoted to the dietary quality of American adults due to its determinative role.

Further, in this work the endogenous nature of certain health inputs is recognised and discussed. A system of structural equations is specified and followed by a simultaneous estimation of all model parameters. A special contribution of this study is the focus on the appropriate measurement of the state of health during the model specification. In contrast to the studies using a single indicator to represent human health, a latent variable approach is employed with cardiovascular health being represented by multiple indicators, which is aimed at the improvement of measurement properties of the state-of-health construct.

Empirical analysis is based on the data of the representative US National Health and Nutrition Examination Survey (NHANES) of 2005-2006. It provides information on socio-economic characteristics of the adult population in the USA, detailed data on their 2-day dietary behaviour and usual lifestyles as well as accurate medical information related to one's diet and health, obtained from blood and urine examination. This diverse information facilitates the analysis of the various factors and their interrelations affecting a person's health.

1.2 Structure of the thesis

In the second section, a review of the dietary quality assessment methods is given. Further, the section discusses existing definitions of health status and gives an overview of its measurement approaches. The third part of the dissertation work describes the theoretical background of the study. The fourth section discusses the existing estimation methods and provides the rationale for the selected methodology. The results of the empirical analysis are presented in the fifth section starting with the description of the dataset and then outlining the main characteristic of the study sample. The empirical analysis starts with the investigation of dietary quality among the U.S. adult population with a number of approaches being employed.

Further, the structural model of cardiovascular health is presented, i.e., its theoretical and empirical specification, description of the model variables and main hypotheses. The estimated model's parameters are discussed, followed by the formulation of an alternative structural model, its test and models' comparison. This section concludes with a critical consideration of the performed empirical analysis. In the final sixth section, the insights of this study are summarised and suggestions for future research are given.

2 Dietary quality and health: definition and measurement approaches

Chapter overview

Nutrition is considered to be one of the major determinants of human health. This chapter provides an overview of the approaches used to assess the quality of a person's diet. These include single indicators such as total energy intake, under- and oversupply of particular nutrients, self-evaluations as well as more complex measures based on a number of parameters and their combinations, e.g., dietary indices. Furthermore, statistical methods such as factor and cluster analysis can be used when searching for the consumption patterns in the population of interest. The application of particular methods largely depends on the research goals and data availability. In the second subsection the concept of health is discussed. Based on the conceptualisation of the health status, a number of approaches can be applied to its measurement. These include single objective measures, e.g., clinical data on cholesterol level and country mortality rates, and subjective self-reports about illness or disability. Moreover, health status measure can be based on a number of scores derived from the answers to specific health-related questions. These scores are summed which results in an overall health score (health index). Finally, the health state can be presented as a theoretical construct (latent variable) measured by a number of indicators.

2.1 Dietary quality and its assessment

2.1.1 Theoretically defined indicators

Theoretically defined indicators of dietary quality are related to the current knowledge about the effect of specific nutrients and foods on a human's health. This effect can be beneficial or harmful to health (WAIJERS and FESKENS, 2005).

Energy and nutrients supply

The rise in the obesity rate in the US and related health disorders are partially attributed to an increase in energy intake amongst the population combined with decreased energy expenditure (HUANG *et al.*, 2004). A total energy supply is considered to be important when assessing a person's diet (RÖDER, 1998). Thereby, to evaluate its adequacy, actual intake is compared to the recommended, taking into account age, gender, and physical activity of an individual (Appendix A, Table A1)[1].

Besides information on total calories consumed, the composition of diet matters, i.e. what foods these calories come from. Therefore, further investigations such as under/overconsumption of particular nutrients and/or food groups follow.

In the USA, the Food Guide Pyramid for Americans of the United States Department of Agriculture (USDA) provides research-based guidance for the promotion of better diet among Americans. A particular focus is devoted to the limitation of fat, saturated fat, cholesterol, sugar, sodium and alcohol intakes, which is due to the evidence of overconsumption of these elements by the prevailing part of the population (USDA, 2005). On the other hand, an increase in an intake of a number of minerals and vitamins is also recommended (e.g., fibre, folate, vitamins A and C).

Several eating plans have been developed to simplify the dietary recommendations by providing examples of a balanced diet, e.g., USDA Food Guide and the DASH Eating Plan (HHS and USDA, 2005) (Appendix A, Table A2). Comparison of actual intakes of particular nutrients with the guidelines' values gives an indication about their under- or over-consumption. An element is considered to be under- or overconsumed if its intake is below 67% of the recommended amount (RÖDER, 1998: 101).

Nutrient density approach

According to the Dietary Guidelines for Americans (HHS and USDA, 2005), meeting the recommendations for a number of nutrients should be done within a person's calorie needs. In reality, most Americans consume more calories than they need without meeting the recommendations.

The nutrient density approach is a method that allows for the examination of nutritional adequacy within calorie needs of a person. Empirically, densities of the selected nutrients can be presented either as a proportion of total energy or as an intake per 1000 calories (SIEGA-RIZ *et al.*, 2000; PRYER *et al.*, 2001; WILLET *et al.*, 1997). To compare the actual density of a particular nutrient in a diet to the existing recommendation, an *Index of Nutritional Quality (INQ)* is calculated. INQ is defined as ratio of nutrient density and an amount of this nutrient recommended for maintenance of good health within a given calorie need (DREWNOWSKI,

[1] A number of studies apply various cut-offs in order to select individuals with plausible energy intakes (e.g., HUANG *et al.*, 2004; BLACK, 2000; NIELSEN and ADAIR, 2007).

2005; HUANG and MISRA, 1991). The index may range from above to below unity. The INQ values above 1 are considered to be desirable for the nutrients important to the diet and health, e.g., fibre, potassium, calcium, magnesium, and vitamins C and A, while for fats, sugar, sodium, and cholesterol, it should be below 1. A reference for computation is chosen depending on the population of interest, e.g., for the American population it is the *Dietary Guidelines for Americans* (HHS and USDA, 2005).

Food groups' intake

Since we obtain nutrients from foods, an attention needs to be given to what foods we consume as well as to their proportions. Dietary guidelines for Americans give recommendations on intake amounts from major food groups (Appendix A, Table A3).

An importance of variety of foods in one's diet is stressed (HHS and USDA, 2005). At the same time, while some food groups should be consumed in moderation, e.g., fats, oils, and sweets, higher intakes of others are desirable, e.g., grains and F&V. This study puts a particular focus on F&V intake among American adults. This is due to broad scientific evidence on the importance of F&V as naturally healthy, nutrient-dense[2] and low-energy foods, in a balanced diet and in prevention of many chronic diseases including cardiovascular disease, diabetes and some types of cancer (VAN DUYN and PIVONKA, 2000; STEINMETZ and POTTER, 1996).

Biological markers

In the medical and epidemiological literature, biological markers derived from blood and urine examinations (e.g., vitamins, minerals and fats in the blood) are employed for assessment of nutritional status of an individual. Biomarkers are considered to be an objective measure of dietary quality as they are believed to contain less error than self-reported dietary information (POTISCHMAN, 2003). However, the collection of these data is connected with higher costs and is done only in a limited number of population surveys. NHANES used in this study contains detailed information obtained in laboratory conditions, among which are results of blood analyses that can be used for dietary and health state assessments.

Biological markers can be used to (dis)confirm the results obtained from usual dietary assessment methods such as 24h recall or food frequency questionnaire (see e.g., NEUHOUSER *et al.*, 2003, POTISCHMAN, 2003). However, it should be kept in mind that similar to the dietary

[2] See Table A4 in Appendix A for nutrient contributions from the F&V food group.

data, biomarkers present a diet in only a snapshot of time. Additionally, alcohol, antibiotics and particular diseases might influence the concentration of these elements in blood or urine.

A number of biomarkers are employed in the literature for characterization of an individual's dietary status. They can be divided into blood plasma biomarkers (e.g., serum albumin, serum- total protein, haemoglobin, triglyceride, cholesterol, vitamins, and folate), urine markers and hair samples (HAVEMAN-NIES *et al.*, 2001; KANT and GRAUBARD, 2008; WALTER *et al.*, 2008).

Anthropometric measures

Anthropometric measures, e.g., a person's height, weight, arm circumference, birth weight, body mass index (BMI), waist circumference (WC) and waist-to-hip ratio are often used as indicators of nutritional status, especially in studies on developing countries (BEHRMAN and DEOLALIKAR, 1988; SAVY *et al.*, 2005). A person's BMI is calculated by dividing a person's weight (in kg) by a squared measure of his/her height (in m). It is a recognised marker of obesity. Moreover, BMI and WC showed to be related to the risks for hypertension, diabetes mellitus, cardiovascular disease, arthritis, various forms of cancer, and other diseases. Scientific evidence suggests that WC is a better predictor of cardiovascular disease compared to BMI or waist-to-hip ratio (DOBBELSTEYN *et al.*, 2001; BUCHHOLZ and BUGARESTI, 2005).

Indices of dietary quality

Diet indices (scores) represent an approach that allows measuring dietary quality as a whole by assessing a supply of a number of nutrients simultaneously as well as their combination in the diet. Diet scores represent current nutrition guidelines and have shown to be useful for the identification of groups with good/poor nutritional status (HAINES *et al.*, 1999). However, several drawbacks of this method can be mentioned, e.g., arbitrary choices of components, cut-offs and scoring.

Various diet indices have been developed for particular populations and its groups. They differ by the construction of scores and by components included. They can be nutrient- or foods-based as well as a combination of both.

To evaluate the dietary quality of Americans, in 1995 the USDA introduced the Healthy Eating Index (HEI), which was revised in 2006[3]. It is a tool to measure compliance of diets

[3] HEI was updated again in 2012 to reflect the 2010 Dietary Guidelines for Americans (GUENTHER *et al.*, 2013).

with the diet-related recommendations of the 2005 *Dietary Guidelines for Americans.* The HEI-2005 consists of 12 components: total fruit; whole fruit (forms other than juice); total vegetables; dark green and orange vegetables and legumes; total grains; whole grains; milk; meat and beans (all meat, fish, eggs, soybean products, nuts, and seeds); oils; saturated fat; sodium; calories from solid fats, alcoholic beverages and added sugars (SoFAAS) (GUENTNER *et al.*, 2008). Each component receives a score from zero to a maximum of 5-20 depending on the food group. All component scores are summed up, producing a total score ranging between 0 (lowest compliance with recommendations) and 100 (best score indicating a full compliance with guidelines). The HEI index is calculated by the National Centre for Health Statistics annually for various population groups.

Examples of other dietary indices are a Healthy Diet Indicator (HDI) of HUIJBREGTS *et al.* (1997) and indices developed by THIELE *et al.* (2004). The Healthy Diet Indicator (HDI) (HUIJBREGTS *et al.* 1997) is based on the WHO dietary guidelines for the prevention of chronic diseases (WHO, 1990). It consists of nine food and nutrient groups: saturated fatty acids; poly-unsaturated fatty acids; protein; complex carbohydrates; dietary fibre; fruit and vegetables; pulses/nuts/seeds; mono- and disaccharides; and cholesterol. In the case where a person's intake is within the recommended borders of the WHO guidelines, the element receives “1” and “0” if otherwise. HUIJBREGTS *et al.* (1997) applied the index to study dietary patterns among Finnish, Italian and Dutch populations and showed a negative association between HDI and mortality.

Using the data from the first German Nutrition Survey 1998, THIELE *et al.* (2004) constructed two indices of dietary quality. The deficiency index consists of 13 vitamins and 12 minerals, while an excess index is made up of fats, cholesterol, sugar, alcohol etc. Application of these indices gives an indication on whether a particular diet is a result of overconsumption or underconsumption of specific nutrients. The outcomes of the study showed a positive association between dietary quality on the one side, and higher income, education level, increasing age and healthier lifestyles on the other side.

Dietary diversity/variety approach

The Dietary Guidelines for Americans and the Food Guide Pyramid stress an importance of diversity in a diet. An application of dietary diversity/variety measures to assessment of overall dietary quality can be found in a number of studies (SAVY *et al.*, 2005, STEWART and HARRIS, 2005, DRESCHER *et al.*, 2007). However, the empirical results on associations between food diversity and health outcomes are ambiguous. While some studies show that low food diversity was connected with an increased risk of early mortality (KANT *et al.*, 1993), others demonstrated opposite results (e.g., MCCANN *et al.*, 1994). On the one hand, an increased number of different foods consumed might bring an individual a higher range of different nutrients and lead to a better diet. However, on the other hand, a higher diversity in consumption may be accompanied by a generally higher total energy intake and result in over-consumption (RÖDER, 1998).

A number of approaches to measure dietary diversity have been developed. In some studies, the *count diet diversity measure* is applied. This index counts the total number of foods/food groups consumed daily (KANT *et al.*, 1993; RÖDER, 1998, SAVY *et al.*, 2005). For instance, the Dietary Variety Score developed by DREWNOWSKI *et al.* (1997) is based on the cumulative number of 164 different foods consumed over a 15-day period**.** In contrast to count indices, the Berry-Index (also known as the Simpson Index) allows for assessing dietary diversity not only in terms of the number of foods consumed but also in terms of food distribution (THIELE and WEISS, 2003; STEWART and HARRIS, 2005; LEE, 1987). DRESCHER *et al.* (2007) developed a healthy food diversity indicator (HFD - Index) that in addition to the number and the distribution aspects also considered a health value of consumed foods. This indicator reflected healthy food diversity in the study more appropriately than the Count-Index and the Berry-Index.

2.1.2 Empirically derived dietary patterns

The methods described above are called “a-priori” methods because they are based on the existing knowledge about a “healthy” diet (incorporate population dietary guidelines). Dietary quality can also be investigated by means of an “a posteriori” approach, which applies statistical methods such as factor and cluster analysis to find the consumption patterns (if any) in the population of interest. These methods are also subject to criticism due to the fact that they are based on available empirical data and might not represent optimal consumption patterns (RANDALL *et al.*, 1990; WAIJERS and FESKENS, 2005).

Cluster analysis is employed to group individuals with similar diets into homogeneous, mutually exclusive groups. Diverse criteria can be chosen as a basis for segmentation, e.g., the frequency of food consumed (MILLEN *et al.*, 1996), percentage of energy contributed by each food or food group (WIRFÄLT and JEFFERY, 1997) and average food intakes (g) (HAVEMAN-NIES *et al.*, 2001). In factor analysis, the dietary patterns, i.e., factors, are derived based on the correlations between variables, e.g., foods or food groups. In order to interpret the identified patterns, both these techniques are usually followed by further statistical analyses to investigate the relation between various eating patterns and the outcome of interest, e.g., cardiovascular risk factors or and biochemical indicators of health (WAIJERS and FESKENS, 2005).

2.1.3 Subjective (self-assessed) dietary quality

Dietary quality can also be assessed by respondents themselves, who are asked to judge the overall healthiness of their diet using a particular scale, ranged, for instance, from “excellent” to “poor” (NAYGA, 1994). Under focus of research is also the correspondence between perceived and actual dietary quality that is investigated by a comparison of a subjective diet assessment with objective indicators (KENNEDY *et al.*, 1995). In the study of Variyam *et al.* (2001), about 40% of the investigated population of household meal planner/preparers overestimate the quality of their diets.

2.2 Health status: definition and measurement

> *“Because the concept of health is so complex, its quantitative definition will necessarily be derived from a composite of several measures, rather than a direct observation on a single scale”* (BUSH *et al.*, 1972).

2.2.1 Concept of health

Health literature provides a number of diverse conceptual models of health. The *medical model,* which is the most basic one, defines health in physical terms, i.e., as absence of disease and disability, and is primarily used by physicians (LARSON, 1997). In the *wellness model,* the focus is given to the physical health, but the feelings of an individual about his overall health and its possible improvements are also taken into account (LARSON, 1997). Finally, the *environmental model* focuses on a complex interaction between individual and its environment (e.g., capability of growth and development in a particular environment), which is believed to affect one’s health more than single medical interventions (LARSON, 1997).

In 1946, the WHO proposed the most widely quoted definition of health. It refers to health as to "a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity" (WHO, 2006: 1). Several decades later, the WHO’s Ottawa Charter formulated a new concept of health according to which health is not just a state of well-being, but “a resource for living” (WHO, 1986). Accordingly, health can be assessed, for instance, in terms of health-related behaviours (e.g., smoking and exercising) as they may have future health consequences. Or, in case of a physical health dimension, a person's BMI or blood pressure can indicate a person's health state (BRESLOW, 2006).

A recent trend in health status measurement is connected with a concept of quality of life (QOL). WHO defines QOL as a broad multidimensional concept that addresses individuals' perceptions of positive and negative dimensions of life, e.g., aspects of physical, psychological, social and spiritual life (THE WHOQOL GROUP, 1995). A further development presents a concept of health-related quality of life (HRQOL) that focuses on those aspects of overall quality of life that may have an impact on physical/mental health (CDC, 2000).

Different measures of health status have been developed based on the outlined concepts. Some of them, such as comprehensive health surveys, aim to incorporate the aspects of several/all of the above presented concepts, while others focus on particular aspects of one/several health problems (e.g., disease-specific health status assessment such as cancer or CVDs). In the following, a more detailed overview of the existing measurement approaches is given.

2.2.2 Measurement approaches

The measurement of health status should be based on an accepted health concept. However, due to the absence of agreement on the appropriate health definition, a large number of instruments to measure health status have been developed (MCHORNEY, 1999; BEHRMAN and DEOLALIKAR 1988: 650; BEHRMAN *et al.*, 1988; BOWLING, 1991: 2-11). Generally, health indicators employed in the empirical studies can be divided into objective and subjective ones.

Objective measures include clinical and biochemical data such as blood pressure and cholesterol level (KENKEL, 1995; CHEN *et al.*, 2002; CATANZARO and SUEN, 1996), anthropometric measures such as a person's BMI (LOUREIRO and NAYGA, 2005; RASHAD, 2006; BEHRMAN *et al.*, 1988), mortality rates (death rates, life expectancy) and statistics on health-service utilisation in a country (OR, 2000).

Subjective health assessment is based on self-reports about illness or disability as well as on behavioural data, e.g., smoking status (DENTON und WALTERS, 1999; BLAYLOCK and BLISARD, 1992; CONTOYANNIS and JONES, 2004, FU *et al.*, 2004). On the one hand, self-reports are claimed to be subject to measurement error as they might be correlated with respondent's education, culture and socioeconomic status. Thus, persons with higher socio-economic status might possess better health information and awareness of own health status due to better access to medical services (STRAUSS, 1999; STRAUSS and THOMAS, 1996: 1919). On the other hand, self-reports are believed to be essential if the aim of the study is to obtain insights into a person's subjective experiences or perceptions (BOWLING, 1991: 17). There are empirical studies showing that the self-assessed health status is a more powerful predictor of mortality in comparison to objective health indicators (DOMINICK *et al.*, 2002; DESALVO *et al.*, 2006).

Further, health measurements can be in a form of a *single-item measure* (i.e., a single question or a measurement) such as blood glucose level, having teeth or eye sight problems, being actually treated for an illness, and not being able to work or to give blood. Alternatively, health status constructs can be based on the *multi-item scales*. The latter consist of a number of indicators (i.e., questions in the questionnaires related to a number of health conditions, illnesses or symptoms) receiving numerical scores depending on the given answer. These scores are summed into an overall health score called a *"health index"* (MCDOWELL and NEWELL, 1987: 12; KAZIS *et al.*, 1989; DWYER and MITCHELL, 1999). Scaling methods for item responses may reflect, for instance, the respondent's opinion presented on the nominal (agree or disagree), categorical (strongly agree, disagree, no opinion, agree or strongly disagree), or continuous scale (a rating scale from "death" at 0 to "full health" at 100) (BOWLING, 1991: 17; GERDTHAM *et al.*, 1999).

An example of the multi-item instruments is the standardised EuroQoL EQ-5D self-administered questionnaire developed in 1987 by an international research network. It has been used in a number of population surveys in the UK, Holland, Spain, Germany, and the USA (GREINER *et al.*, 2003; KÖNIG *et al.*, 2005; JOHNSON *et al.*, 1998). It measures five dimensions of health: mobility, self-care, usual activities (work, study, housework, family, or leisure), pain/discomfort, and anxiety/depression. Respondents' statements indicate whether they have no problem in the respective dimension, a moderate problem, or an extreme problem. Combination of responses provides a single index value for health status and may describe 243 different health states. Additionally, persons are asked to rate the perception of their overall health on the scale from 0 to 100 with higher scores standing for a perception of a better health (GREINER *et al.*, 2003). An example for its application to the adult American population can be found in JOHNSON *et al.* (1998).

In recent decades, a number of instruments have been developed based on the quality-of-life concept, e.g., the Quality-of-Life Instrument (WHOQOL) of the World Health Organization and the Health-Related Quality-of-Life Measure (HRQOL) of the Centre for Disease Control and Prevention (CDC). The latter is an instrument of the CDC in the USA applied to assess the health state of the American population. This tool incorporates a set of questions also called the "Healthy Days Measures", i.e., the days in the past 30 days when both physical and mental health was good (CDC, 2000). Since 2000, the Healthy Days Measures are a part of the National Health and Nutrition Examination Survey (NHANES). HAYES *et al.* (2008) showed that a lower HRQOL was associated with several negative health conditions, e.g., hypertension.

The approaches to the health status measurement (single indicators and indices) discussed above are not without shortcomings. Health status is a complex theoretical construct that is not directly observable. Consequently, a researcher must choose among available measurable variables a single one that is believed to be reliable and able to capture important features of the theoretical construct, which in practice may not be fulfilled. Moreover, both a single indicator and an index (based on several observable variables) are believed to contain at least moderate amounts of error (HUGHES *et al.*, 1986).

Another approach is to estimate theoretical constructs from the multiple indicator measures in a form of *latent variables*, which are also called unmeasured variables, factors, constructs, or true scores (BOLLEN, 2002). Latent variables are part of a number of statistical and data analyses models such as latent structure analysis, latent curve model, factor analysis and structural equation modelling. It is particularly often used in psychology and social sciences that usually have to deal with unobserved constructs, e.g., intelligence and self-esteem. This method has several strengths. First, it allows assessment of the adequacy with which theoretical constructs have been measured. Second, analysis of structural relationships among unobservable constructs can be performed. Third, this approach has a conceptual value because it provides a framework for theory conceptualization that involves thorough theoretical considerations involved in construction and statistical models testing (HUGHES *et al.*, 1986). Latent variables can be formed a posteriori (derived from the data analysis via exploratory factor analysis procedure) or a priori (hypothesised before data analysis and tested via confirmatory factor analysis) (BOLLEN, 2002). Further information related to latent variables, their construction, representation and estimation is given in section 4.3.

To summarise, the diet is an important factor that may cause chronic diseases including heart disease, stroke, certain types of cancer, and diabetes. Section 2 gave an overview of various approaches used to assess an individual's diet. While individual components of dietary quality such as intakes of particular nutrients give an indication on what nutrients are under- or over-consumed, dietary indices deliver information about a diet as a whole and on how these elements are combined in the diet. The application of statistical methods to diet assessment, e.g., cluster and factor analysis, takes into account interrelations and correlations between foods into a diet and allows the derivation of homogeneous dietary patterns from collected data on food intake. However, both approaches have their drawbacks. The same is true for self-assessment of the diet. An application of more objective indicators of nutritional quality derived, e.g., from blood analysis is usually confronted with high costs of such measurements and unavailability of these data.

The second subsection focuses on the concept of health presenting its definitions and measurement approaches. The overview shows that the researcher is faced with many alternatives in the process of health status conceptualization and measurement selection. The choice is dependent upon a particular health problem relevant to the study goals as well as methodological considerations. The section discussed a latent-variable approach, which offers a number of advantages and is an alternative to a single health indicator and derived health indices. A detailed description of this method is given in section 4.3.

3 Theoretical approach to explaining health-related behaviour and outcomes

"The only way to keep your health is to eat what you don't want, drink what you don't like, and do what you'd rather not" Mark Twain's quote in MEDICAL NEWS TODAY (2009).

Chapter overview

The chapter presents a theoretical approach to the analysis of health-related behaviour and outcomes. First, the theory of consumer demand is discussed. It is followed by the concept of household production introduced by BECKER (1965) and its extension to the field of health developed by GROSSMAN (1972). Thereby, a number of literature sources are used to provide the view of different authors with regard to the discussed theoretical approaches, i.e., their conceptualisation, main features, strengths and points for critical discussion. After the introduction of the theoretical approach, the empirical presentation of household production function follows. A number of alternatives for the empirical presentation (e.g., reduced-form or quasi-reduced health function) that are employed in the literature are presented. Further, an overview of the potential difficulties connected with an empirical estimation of a health production function is provided. Among others, the endogeneity problem and biases that may result due to its occurrence in the model are discussed. It is stressed that an empirical analysis of the health production model needs a complex modelling approach that would provide a consistent and careful estimation.

3.1 Consumer demand theory

The consumer demand theory assumes that a consumption unit (a household) chooses from the alternatives available on the market such quantities of goods and services x_i, which maximise utility U (3.1). Accordingly, consumers are believed to be rational and to make their choices taking into account the expected satisfaction from the chosen goods (YOUNG, 1996). Thereby, the choices are limited by the available resources (3.2) (BECKER, 1965):

(3.1) $U = u(x_1, x_2, \ldots, x_n)$

(3.2) $\sum p_i x_i = I = W + V,$

where p_i are prices of the purchased goods and services x_i, I is monetary income, W is salary, and V stands for other non-labour incomes.

The consumer demand theory attributes the differences in behaviour mainly to the changes in goods' prices and consumer incomes. Thus, a solution of the utility maximisation problem (3.1) presents a system of Marshallian demand functions depicting how changes in prices and income influence consumer's optimal choices (DRESCHER, 2007: 84). Unexplained variations in demand are considered to be related to the changes in consumer tastes and preferences (MICHAEL and BECKER, 1973). Although preferences play an important role in an explanation of consumer behaviour, the process of their formation and the possibility to forecast their effects are not discussed (MICHAEL and BECKER, 1973; DAVIS, 1982). Additionally, socio-demographic characteristics are not assumed to affect the demand explicitly, but rather via their impact on the preferences structure of an individual or household (DAVIS, 1982). Further critique of the traditional theory examines the limitations in respect to the non-incorporation in the analysis of non-monetary variables (e.g., attitudes, beliefs, and knowledge) that may also influence consumer choices (YOUNG, 1996; DRESCHER, 2007: 84). MORITZ (1993: 127) discusses that although the consumer demand theory provides a theoretical explanation of the demand behaviour of many goods, in some cases it may be treated as a "base model", which, if modified appropriately, can deliver the framework for the analysis of further (more) complex problems.

Another aspect important for further discussion is the assumption that goods purchased on the market deliver direct satisfaction of consumer needs. While some goods exist in the market in the "ready-to-consume" form, many of them presume a need for further transformation (MORITZ, 1993: 127). For example, meal preparation is connected with such inputs as particular foods obtained on the market (e.g., rice, vegetables), as well as time input of the household members needed for cooking and human capital (e.g., cooking knowledge and abilities).

Therefore, the conventional consumer theory cannot provide an explanation to the demand for goods that do not exist in a final form on the market. The production-related activities performed within households are usually neglected. Health of an individual can also be considered to be produced inside a household, and along with other goods being a source of satisfaction.

The next section presents a development of the demand theory proposed by BECKER (1965). This theory is an important contribution that proposes a conceptual framework for taking into account the production process that takes place within a household. It presumes that market goods are transformed into final "commodities", which are the sources of actual utility in a household. It allows an explicit integration of non-market variables (e.g., household socio-demographic factors, attitudes, knowledge) into the traditional demand theory and thus proposes a framework for its application to diverse fields and problems including those from non-economic area such as marriage, good health or prestige (MICHAEL and BECKER, 1973).

3.2 Household production theory

BECKER (1965) proposed a new formulation of consumer demand theory that was the first one to give attention to the problem of non-market (or home) goods[4] and household production processes including time allocation within a household.

According to BECKER, the utility U is obtained not from the goods available in a marketplace, but from the more basic goods produced in a household. These basic goods are called "commodities" and denoted by Z_i. They are also known in economic literature as "Z-goods". BECKER (1965) provides examples of basic goods such as "seeing a play", "leisure", "reading a book", "sleeping", "transportation" and "business lunch". In later household production literature, Z-goods are considered to be even more fundamental including such items as, e.g., "prestige", "good health", "happiness", "pleasure", "social recognition" and "respect" (STAUDIGEL, 2012)[5]. Thus, the household's utility function can be written as:

(3.3) $U = U(Z_1, Z_2, \ldots Z_n)$

A household is seen as a production unit and as a utility-maximiser. In order to produce commodities Z_i it combines market goods y_i with further inputs such as time t_i and human capital HC_i[6] within a household production function (MICHAEL and BECKER, 1973):

(3.4) $Z_i = Z_i(y_i, t_i, HC_i)$

Since available resources (income) and time of household members are limited, together with production function they present constraints to the utility maximization. Thus, the resources constraint is:

(3.5) $$\sum_{1}^{m} p_i y_i = I = V + T_w \overline{w} ,$$

[4] EVENSON (1981: 181) defines home goods as "goods which are not traded and do not have market prices".
[5] For a detailed discussion of the nature of "Z-goods" see STAUDIGEL (2012).
[6] BECKER (1993: 149) discusses that human capital (e.g., in form of abilities and knowledge of the household members) belongs to the environmental variables that are related to the art of production and the technology level of the production process.

where p_i is a vector of prices for a unit of y_i, I is a household income, T_w is a vector of working hours, $\overline{w}$ shows the earnings for a unit of T_w, and V is a non-labour income.

According to BECKER, a household allocates the total available time T either on work activities T_w or on consumption T_c (or leisure)[7]. Therefore, the time restriction can be written as:

$$(3.6)\quad \sum_{1}^{m} T_i = T_c = T - T_w \,,$$

Further, BECKER (1976: 92) discusses that the budget constraint depends on time constraint as "[…] time may be converted into goods by using less time at consumption and more at work". Therefore, he combines these two constraints into a single resource constraint S called "full income" restriction. It presents an income that households could earn if they used their available time only for working activities[8]:

$$(3.7)\quad S = \sum p_i y_i + \sum T_i \overline{w} = V + T\overline{w}$$

Thus, a household maximises utility subject to its full income constraint and to a production technology. It aspires to utility maximisation by choosing an optimal combination of commodities. In addition, it chooses the less expensive way of their production. Households allocate time between labour, home production and leisure in such a way that the cost of each commodity is minimised (EVENSON, 1981). Marginal cost of producing an additional commodity unit presents its "shadow price". It is defined as "[…] weighted average of the value of home production time and the prices of the market goods used in the production of the home good" (EVENSON, 1981: 182). The value of home production time can be evaluated in terms of money income (or wage), which could be obtained in case of alternative labour activity on the market. Besides, human capital of households and their production abilities play an important role in utility maximization (MICHAEL and BECKER, 1973; EVENSON, 1981).

At this point, it can be mentioned that due to the tendency in the last decades to rising incomes in many countries, the opportunity cost of time has increased. This affects the allocation of time in a household. For example, a household with higher opportunity costs of time may shift from time-intensive production technology such as cooking a dinner to a less-time consuming production technology aimed at satisfaction of their nutritional needs, e.g., home delivery of ready-to-eat meals or convenience products or even hiring someone to

[7] In the model of BECKER (1976) leisure is a part of home production activities. The discussion about the need of separation of leisure time, working and home production activities is available in GRONAU (1977).
[8] For a detailed derivation of the full-income constraint see BECKER (1976: 92).

perform this task for them. Although the aspect of time is critical in the model of BECKER (1965), it is usually very difficult to account for it empirically due to the unavailability of data on time allocation in households.

Importantly, traditional consumer demand theory attributes differences in behaviour not only to income and prices, but also to the differences in *consumer preferences*. However, the formation of preferences is not explained. Therefore, the changes in preferences cannot be predicted, which limits the possibilities for further research (STIGLER and BECKER, 1977). Taking the concept of household production as a base, STIGLER and BECKER (1977: 76) argue that tastes can be seen as "stable over time and similar among people". They discuss that changes in behaviour of individuals over time, i.e., changing tastes, are due to changes in the constraints, which are used to produce utility from commodities. These constraints are prices and available incomes. The authors explain their view about stable preferences on a number of examples such as consumption of addictive goods, listening to classical music or advertising. Thus, according to traditional consumer demand theory, advertising has an influence on consumers' preferences. When following the assumption of STIGLER and BECKER (1977), a consumer obtains utility not only from a good itself, but also from the information he possesses about this good, irrespective of whether the information is true or false. The notion on a yoghurt's label *"Calcium helps to maintain strong bones and teeth"* is an example of such information. Based on the household production theory, households combine market goods with time, knowledge and other inputs to maximise their utility. In this case, the knowledge is influenced by advertising. The authors (STIGLER and BECKER, 1977: 84) discuss that a Z-good that is produced by a household can be written as:

(3.8) $Z = f(x, A, E, y),$

where x is the output of the firm, A is advertising of the firm about its good, E is the human capital of consumers and y refers to other variables such as advertising of other firms. In case of no changes in advertising, human capital and other variables, the amount of the Z-good is proportional to the amount of the firm's output (x) used by the household to produce this commodity. The authors discuss that an increase in the advertising of the firm's product lowers the price of the commodity produced and consumed by the household. The rationale behind it is that the demand for the commodity rises, which in its turn changes the demand for the firm's output. According to STIGLER and BECKER (1977: 84) this is "[…] because the household is made to believe - correctly or incorrectly - that it gets a greater output of the commodity from a given input of the advertised product". The authors conclude that advertising affects consumption due to its influence on the price of the commodity, not due to the changes in consumers' taste.

The assumption of constant preferences and the Z-theory overall have been a subject of the criticism (see, e.g., COWEN, 1989). COWEN (1989: 129) argues that although the assertion about changing preferences is arbitrary to a certain degree, this is also true with regard to the changes postulated by the household production theory. Thus, the assumption that listening to classical music changes the ability of an individual to produce relaxation (Z-good) could be as arbitrary as the assumption that listening to the music changes the person's taste for music. Also, STIGLER and BECKER (1977: 84) stress with regard to their theory that "[…] it is a thesis that does not permit of direct proof because it is an assertion about the world, not a proposition in logic." Further, the abstract character of Z-goods is discussed in literature, which is related to the ambiguity of their definition and quantification (see, e.g., STAUDIGEL, 2012). In addition, several other critical points of the household production theory can be mentioned. Thus, HEIMAN *et al.* (2001) and BROWNING *et al.* (1994) emphasise the aspect of joint decisions made in households. They argue that empirical studies usually treat a household as a single decision maker ignoring the potential heterogeneity (e.g., religious and cultural factors, division of tasks) within it that may affect the behavioural outcomes. GRONAU (1977) stresses the inability of the household production model to separate leisure and home production time in the total time of home production activities and shows that work at home and leisure are affected by their determinants (e.g., socioeconomics) in a different way.

LANCASTER (1966) introduces another alternative approach to the theory of consumer behaviour. He argues that the objects of utility are not the goods, but rather the characteristics that these goods possess. Thus, consumers seek to obtain not the good itself (e.g., a meal), but the characteristics that this good contains (e.g., nutritional and aesthetic properties). Thereby, it is assumed that the characteristics of one or more goods are objective and perceived by all consumers as the same. Utility derived from these characteristics is subjective and depends on the preference structure of the individual. Thus the demand for any good is due to the demand for the characteristics of this good (DRESCHER, 2007: 108). While the overall marginal utility of a good may be positive, some of the specific characteristics of this good can be perceived by a consumer as negative. HENDLER (1975) gives an example of eating a sandwich and discusses that while a consumer enjoys this food due to its flavour, he may also experience disutility because of its high caloric value.

The contribution of Lancaster found its application especially in the studies of hedonic price analysis, in which the price of a particular good is determined by a number of objective (measurable) characteristics presented as independent variables in the equation. Applications of the hedonic model to agricultural products and foods aim to reveal how product characteristics affect the product price (TEUBER, 2010). This can be of interest for the food industry that may add certain characteristics to a particular product and, thus, gain from consumers' higher willingness to pay.

For example, MELTON *et al.* (1996) conducted an experimental auction, where consumers were asked to evaluate and bid on several samples of fresh pork chops that varied in a number of attributes (e.g., size, colour). This was followed by an estimation of hedonic price equations, where the effect on pork price was derived from a change in the level of a number of analysed attributes and consumers' socio-demographic characteristics. Further examples in the field of food and agricultural products can be found in STEINER (2004), HUANG and LIN (2007) or WARD *et al.* (2008).

3.3 Household production of health

3.3.1 Theoretical presentation

The household production approach has been applied to a variety of empirical problems in the fields of nutrition, fertility outcomes, child mortality, and labour supply (MICHAEL and BECKER, 1973; STRAUSS and THOMAS, 1995) and is particularly applicable to health-related research (ROSENZWEIG and SCHULTZ, 1983).

Based on the theory of household production, GROSSMAN (1972) introduced the first formal economic model of health demand. In this framework, health is treated as a capital stock, which, however, is different from the other dimensions of human capital such as, for example, educational attainment[9]. He discusses that "[…] a person's stock of knowledge affects his market and nonmarket productivity; while his stock of health determines the total amount of time he can spend producing money earnings and commodities". On the one hand, the stock of health is seen as a consumption commodity that directly enters the utility function because there is a direct satisfaction from being healthy. On the other hand, it is an investment commodity because the health of an individual affects the time devoted to (non)market activities (DAVANZO and GERTLER, 1990).

[9] For further discussion on the types of human capital see, e.g., SCHULTZ (1997).

BERMAN *et al.* (1994, p.206) define the household production of health as "[…] a dynamic behavioural process through which households combine their (internal) knowledge, resources, and behavioural norms and patterns with available (external) technologies, services, information, and skills to restore, maintain and promote the health of their members". Or to put it differently: the health state of an individual (of each household member) is determined by his unique production function, which is formed by a number of health inputs, socio-demographic characteristics, own time, genetic endowment and characteristics of the environment. An overview of the variables in the health-production model is given in Table 1.

Table 1 Classification of variables in a health-production model

Exogenous variables	**Endogenous variables**
a. *Personal characteristics:*	***c.*** *Demanded inputs or proximate health factors*:
- unobserved individual endowments: e.g., genetic make-up, **μ**	e.g., diet, utilisation of and expenditures for medical care, time allocation, breastfeeding, smoking, exercising, alcohol and drugs intake, anthropometric measures, **y**
- observed individual endowments: e.g., age, gender, race, education, initial health, **x**	***d.*** *Health outcome,* **H**
b. *Observed environmental and community characteristics:*	e.g., mortality and morbidity rates, disease-specific outcomes etc.
e.g., availability of goods and services, their prices (**p**), wage rates, type and quality of health services, climate, infrastructure, availability of information on health messages and its usage, **e**	

Source: Modified from SCHULTZ (1984) and DAVANZO and GERTLER (1990).

GROSSMAN (1972) stresses the importance of individual and household characteristics for the efficiency of *health production*. Thus, education is assumed to be very important in the process of health production. Better-educated persons may be more knowledgeable about the effects of a particular behaviour on their health, may make better nutritional choices based on the information available in press or can better understand and follow the treatment prescribed by a doctor. The role of environment, e.g., availability of clean water, quality of public health services, is also recognised.

According to GROSSMAN'S health model, a consumer demands the health-related inputs and behaviours not because he values these goods, but due to the expected health impact of these inputs. For example, a regular cholesterol check does not bring a direct utility, but is valued by individuals because it may produce additional health. Therefore, demand for health inputs can be seen as "derived" from the demand for health (GROSSMAN, 1972). Decisions regarding the selection of inputs are influenced not only by the household's monetary and time constraints but also by the importance of this source of satisfaction (BERMAN *et al.*, 1994). Clearly, an individual, besides good health, may also have other goals and sources of utility.

The relative value of health in comparison to other objectives may be important for the person's decisions about health-related inputs (DAVANZO and GERTLER, 1990). Thus, WAGSTAFF (1986: 2) argues that "[…] if people valued their health above all else, they would not over-eat, smoke or drive too fast. That people do engage in such activities […] makes it clear that although people do value their health, they do not place an over-riding value on it". These different forms of values and preferences are represented in economic analysis by the utility function. Thus, a person is faced with a number of trade-offs among desires for tasteful food, good health and other goods as well as resources constraints (VARIYAM, 2003). Thereby, they might, for instance, prefer enjoyment from eating fast food today rather than pursuing a healthier diet that could positively affect their health in the long run.

An important feature of health production function is the *diminishing marginal returns of the inputs* to health status. Thus, an additional use of a health input (food, medicines etc.) in a developed country with a relatively high initial level of usage of this input will have a lower effect compared to its effect in the developing country with an initially low usage rate of this input. This may have implications for the success of health policy interventions in different settings (countries, regions etc.) (DAVANZO and GERTLER, 1990).

3.3.2 Empirical presentation

Empirically, health-production models may deliver information about the parameters of a) the health production function, i.e., the technical relationship between health inputs and health outcomes, b) the relationship between changes in the determinants of health input choices (e.g., prices, socio-demographic variables, and time) and the mix of these inputs employed by an individual, and finally c) the effect of changes in the determinants of input choices on the final health outcome (BERMAN *et al.,* 1994).

As discussed, a household aims to maximise utility by consuming a range of commodities, one of which is health. Following CHEN *et al.* (2002) and the notations used in Table 1, the *production function of* health may be presented in a general form as:

(3.9) $H = H(y, x, \boldsymbol{\mu})$

This equation is primarily concerned with the relationship between inputs (y) and output (H), whereas observed (x) and unobserved ($\boldsymbol{\mu}$) individual's characteristics may affect the efficiency of health production with given inputs.

Further, the demand functions for inputs (y) can be derived from utility maximisation, which is subject to technology, time, and income constraints. The "full-income budget constraint" separates non-labour income (V) from market wage (w) and takes into account the total time that is available to a household for health-related activities (T) (BECKER, 1965). Following the empirical application of CHEN *et al.* (2002), the general form of a *demand function for health inputs* can be written as:

(3.10) $y^* = y^* (p, V, w, T, x, \mu),$

where $y^*=\{y^*_1, y^*_2, \ldots, y^*_n\}$ is a set of utility-maximising demand functions for inputs (e.g., nutrients, medicines, exercises) and p is a vector of input prices.

Equation (3.10) is a reduced-form demand function for inputs that shows how the changes in prices, income, socio-demographic characteristics of the household's members, as well as their endowments and community characteristics affect choices of health inputs. Similarly, a *reduced-form health function* (H) can be derived:

(3.11) $H = H (p, V, w, T, x, \mu).$

This function relates input prices, personal socio-demographic and economic factors directly to health itself, and therefore describes the total effect of exogenous variables on health outcome. Thus, reduced-form equations may deliver important insights for policy makers, as they show a direct effect of key socio-demographic and economic variables on health outputs (3.11) or health-input choices (3.12).

While showing the impact of exogenous variables on health outcomes, reduced-form equations do not show the links through which prices and other exogenous variables influence health i.e., how they impact health-input choices (CONTOYANNIS and JONES, 2004; DAVANZO and GERTLER, 1990). These linkages may be of interest for researchers as "[…] household characteristics generally do not affect health directly, but indirectly through the behaviours they affect" (DAVANZO and GERTLER, 1990: 19). Moreover, a reduced health equation does not provide information on how lifestyles affect health. Further, BERMAN *et al.* (1994: 209) point out that "[…] since households are assumed to make their decisions on inputs in part with reference to their expectations about the health production function, these two dimensions of choice occur simultaneously or are interdependent". Therefore, the *two-stage model* incorporating simultaneously the production technology (3.9) and input choices (3.10) is believed to be more appropriate than single-equation models (either a reduced demand equation (3.10) or a single production function (3.9)) (SCHULTZ, 1984; BERMAN *et al.*, 1994; DAVANZO and GERTLER, 1990).

Another alternative is the estimation of a quasi-reduced form of health equations (see, e.g., EDWARDS and GROSSMAN, 1979). Here, a distinction between the production and input demand stage is not made, but rather a "*hybrid" health equation,* that is a mixture of production and demand parameters, is estimated. BEHRMAN and DEOLALIKAR (1988: 648) point out that "[…] such quasi-reduced forms would seem to be of limited interest because they generally neither reveal all of the structural parameters nor the total impact of exogenous changes". A hybrid health equation usually includes one or several health inputs, household income and individual characteristics as right-hand variables (ROSENZWEIG and SCHULZ, 1983):

(3.12) $H = H(y, V, w, T, x, \mu)$

While the empirical estimation of reduced-form equations is straightforward, it is not the case with health production functions and hybrid health equations. The aspects to be considered in the empirical analysis of these equations are discussed in the following section.

3.3.3 Challenges for empirical estimation

Parameters of reduced-form equations (3.10 and 3.11) can be estimated by means of a standard ordinary-least-squares method, as all the right-hand variables in these equations are exogenous and uncorrelated. In contrast, a consistent estimation of the health production function (3.9) and the hybrid health equation (3.12) is confronted with certain difficulties. An important problem discussed in the economic literature is the *endogeneity* of health input variables and its consequences (ROSENZWEIG and SCHULTZ, 1983; BEHRMAN and DEOLALIKAR, 1988; SCHULZ, 1984). In general, if an independent variable is not exogenous, it will correlate with the residual in the outcome variable. Because of this correlation, some effects of the error term may be wrongly attributed to the explanatory variable, therefore making the estimates inconsistent. An explanatory variable may correlate with an error term due to simultaneous causation of predictor and outcome or omitted confounder variables, or because of errors in regression covariates (FOSTER and MCLANAHAN, 1996).

First, many *health endowments* (genetic or environmental) are *unobservable* to a researcher but may be known to an individual[10]. As health inputs may be affected by the same unobservable factors that affect a final health outcome, not accounting for this can lead to

[10] Exogenous health factors, which are partially known to individuals but unobserved by the researcher, are referred to as *health heterogeneity*. A correlation between these factors and health inputs may pose a problem of simultaneous-equation bias (SCHULTZ, 1984: 217-218).

simultaneity bias. For instance, if an individual has a predisposition to high blood pressure that is unobserved by the researcher, he will have a comparably poorer health status (e.g. higher risk of cardiovascular diseases) than other persons, in spite of using larger amounts of relevant health inputs, e.g., medicines. Thus, the demand for medication may be related to his propensity to a higher blood pressure (unobserved endowment). Not accounting for this endowment may result in a downward bias of the impact of medicine usage on the final health outcome.

In relation to the simultaneity problem, it is important to bear in mind that many health inputs are endogenous because they are subject to individual choice. ROSENZWEIG and SCHULZ address this aspect in their seminal paper in the health production literature (1983, p. 723) as follows: „[…] Estimates of health technology must be obtained from a behavioural model in which health inputs are themselves choices".

Usage of longitudinal data that contains repeated measurements of each individual allows the control for unobservable health heterogeneity. Empirically it is performed by the application of *fixed and random effects* methods (JONES, 2000: 269-270) as the individual effects are the same in every period of time, whereas health inputs and outcomes may vary. However, due to endogeneity of many health inputs, as discussed above, the utilisation of simultaneous equation techniques are still needed to avoid the simultaneous equation bias (MWABU, 2007)[11]. One of these methods, which is widely employed, is the *instrumental variables (IV)* approach. It presumes that a number of truly exogenous variables such as market prices and community characteristics, which are believed to affect the demand for health inputs, but do not enter directly the health production function, are employed as instruments (BEHRMAN and DEOLALIKAR, 1988: 658; SCHULTZ, 1984). Such reduced-form equations incorporating all relevant exogenous variables are estimated for all the potentially endogenous health inputs in the model. Further related methodological approaches are discussed in the following chapter.

Second, a common problem of the estimations of a health production model is connected with the *omission of relevant determinants* that correlate with those included in the model. Thus, such information as time use or some individual characteristics (e.g., occupation) if excluded from the model, may be correlated with some included variables, which may result in the *omitted-variable bias* (BEHRMAN and DEOLALIKAR, 1988: 643). For instance, the decisions on using health inputs may depend on the wage rate of individuals and input prices.

[11] For an example of the fixed effects method see BISHAI (1996), who estimates a production function of child's health using a 2SLS fixed effects model with several lagged variables, e.g., childcare time.

However, usually a researcher is confronted with lacking data. MAZZOCCHI and TRAILL (2008) discuss that socio-economic datasets do not include much information on health-related aspects, while nutritional surveys do not collect the full range of information on socio-economic characteristics of the individuals. According to them, there is no data set in Europe, which would incorporate individual data on nutrient intake, health outcomes, expenditure levels and input prices. BEHRMAN and DEOLALIKAR (1988: 646-648), who applied the framework of household production to the investigation of demand for health and nutrients in particular to the case of developing countries, provide a detailed discussion on a wide array of exogenous variables that may affect such demand relations, e.g., a range of exogenous processes, components of genetic, environmental and community endowments. However, they stress that it is very difficult or most often impossible to account for all the relevant variables empirically. Therefore, omitted-variable bias may arise. The problem of data unavailability is also true in respect to the inclusion of endowments (e.g., genetics, environmental dimensions). This can also lead to omitted-variable bias during the estimation of reduced-form equations, if these variables are correlated with observed ones.

Third, *errors-in-variables* problems may contribute to the biased estimates, too. Thus, nutrition and health data is often based on self-reports and available only for a short reference period (BEHRMAN and DEOLALIKAR, 988: 658). Self-reports are believed to contain measurement errors and may also be correlated with respondent's education, culture and socioeconomic status (STRAUSS, 1999). BEHRMAN and DEOLALIKAR (1988: 659) suggest that estimation of health status in the form of a *latent variable* could be a solution to reduce the bias. It is formed by multiple indicators and is believed to be able to provide a more valid and reliable measurement of a given construct (KLINE, 1998). In empirical analysis in the field of health economics, *structural equation models* is often specified to present health as a multiple-indicator (latent) model (JONES, 2000: 270). Due to the relevance of the structural equation modelling to the present study, its methodology is presented in more detail in the next section.

Another aspect relevant for the estimation of both reduced-form equations and production functions is the estimation of parameters *aggregated at the household level* (i.e., household averages). However, the relations may differ for different individuals in the same household (BEHRMAN and DEOLALIKAR, 1988: 659).

Finally, the impact of some inputs on health status can be *lagged* considerably (e.g., dietary quality) and if these lags are not specified, an estimation bias may arise (BEHRMAN and

DEOLALIKAR, 1988: 659). However, the specification of appropriate lags is often confronted with data limitations as well.

To summarise, the household production model developed by BECKER (1965) is particularly applicable to the modelling in the field of health as the latter may be viewed as a commodity or an output of the production process-taking place in the household. Moreover, health directly enters the utility function as a household or an individual as they have a direct benefit from being healthy. Further, health status of an individual has multiple determinants and is produced by a number of choices that also interact with each other. The complexity of household health production implies a need to account for the discussed aspects in order to obtain unbiased estimates. In doing so, a complex econometric model should be applied with simultaneous estimation of the postulated relations. The following section gives an overview of the estimation approaches with special attention toward simultaneous equations models.

4 Methodological approaches to health production function estimation

Chapter overview

In this chapter, the approaches used in economic literature to account for the complexity of health production in empirical analysis are discussed. The section starts with an overview of the existing estimation methods with a focus on simultaneous equations models. First, the method of instrumental variables, which is commonly used in the economic literature, is discussed, and relevant empirical examples from the health economics are presented. Further, the chapter provides a detailed discussion of the structural equation modelling approach (SEM), which can be used for the estimation of complex multi-equation models. The chapter discusses the possibilities and special features of the SEM. The fundamental issues of model specification, its identification, parameters estimation, and evaluation of model fit are outlined in detail. The chapter concludes with empirical examples of SEM in the field of health.

4.1 Methods of simultaneous equations models estimation

A common strategy in economics aimed at investigation of a particular outcome (e.g., event or behaviour) in response to some influencing factors is to specify an equation that captures the theoretical assumptions and to estimate its parameters, e.g., the ordinary-least-squares method. However, in case that the assumptions about relationships among variables have a more complex character, a simultaneous equations model may be more appropriate (BERRY, 1984: 8).

A number of methods have been developed for simultaneous equations models. They can be grouped into two main categories based on whether the equations are estimated one at a time or jointly. Table 2 provides the most common estimation methods of both groups.

These are:

a) “single-equation” methods that are also called “limited-information” approaches and

b) “systems methods”, known as “full-information” techniques.

Table 2 Estimation strategies for empirical models

Empirical modelling:	**Single-equation (limited-information) methods**		**Systems (full-information) methods**
		Simultaneous equations methods	
Estimation method:	Ordinary least squares (OLS), Probit, Logit	– Indirect least squares (ILS) – Instrumental variables (IVs) – Two-stage least squares (2SLS) (special case of IVs) – Limited-information maximum likelihood (LIML)	– Three-stage least squares (3SLS) – Full-information maximum likelihood (FIML) – Structural equation modelling (SEM) (e.g., LISREL, MIMIC models)

Source: Own presentation based on KENNEDY (2003: 186-191) and GREENE (2003: 396-413).

The single-equation (limited-information approach) foresees an estimation of a number of equations in the model, whereas each equation is estimated separately (one at a time) and the information on the restrictions is used only in the particular equation. On the contrary, the "systems" (full-information methods) allow estimating all the equations simultaneously; thereby, knowledge of all the restrictions in the model can be utilised (full-information methods) (KENNEDY, 2003: 186). An application of single-equation methods is connected with the estimation of one (or several) structural equation(s) and some reduced-form equations. On the contrary, in the "systems" methods all equations in the model are structural (CAMERON and TRIVEDI, 2005: 35)[12].

There are other methods dealing with estimation of multi-equation models. However, as stressed above, not all sets of equations are simultaneous. Thus, the frequently employed technique "seemingly unrelated regressions" (SUR or SURE) proposed by ZELLNER (1962) is a generalization of OLS for multi-equation systems. It represents a system of regression equations that are connected not because they interact, but because the error terms across the equations are correlated. Each equation in the model could be estimated separately by the OLS and would deliver consistent estimates. However, parameter estimates of the SUR method are more efficient. KENNEDY (2003: 192) gives an example of a two-equation model that presents demand functions for two different goods. In case a shock affects the demand for one good, it might be transmitted to another good. Therefore, estimation of these equations in a set may deliver estimates that are more efficient.

[12] Equations are expressed in reduced form when each endogenous variable in the model is modelled to be caused only by predetermined variables (i.e., exogenous and lagged endogenous) and an error term. Therefore, estimators from the reduced-form equations show how much each endogenous variable in the model changes in response to a unit change in each predetermined variable. In the structural equations, the endogenous variables are expressed as a function of the exogenous and endogenous variables in the model that are assumed to have a causal effect on them and error term. Thus, the structural equations display the causal interrelations in respect to the modelled process and, therefore, reveal the reason for change of endogenous variable in response to a unit change in a predetermined variable (BERRY, 1984: 28).

The full-information techniques are generally believed to be able to derive more efficient estimators compared to the limited-information methods (BERRY, 1984: 81; KLINE, 1998: 177). The drawbacks of these methods are their high computational costs. Additionally, they are very dependent on the correct model specification. Thus, in case of a wrong specification all the parameter estimates in the model are affected, whereas in estimations by single-equation methods, the impact of a wrong specification is transmitted only on parameters of the corresponding equation (KENNEDY, 2003: 190).

From the techniques listed in Table 2, the 2SLS approach finds most frequent application. It replaced the earlier, more computationally complex LIML estimation procedure. In the first stage of 2SLS, the possibly endogenous causal variables are regressed on all the predetermined variables in the model. The reduced form is estimated. In the second stage, the estimated values of the endogenous variables from the stage 1 (treated as instrumental variables) and included in the OLS equation as regressors along with the predetermined variables. The extensions of the 2SLS approach are the Two-stage Residual Inclusion (2SRI) and the Two-stage Predictor Substitution (2SPS). The latter is employed for modelling non-linear relationships (TERZA *et al.*, 2008).

Although IV procedures including 2SLS showed to be appropriate for estimations that use non-experimental data, some of the pitfalls are pointed out in the literature (WOOLDRIDGE, 2002: 101). First, this approach relies strongly on the explanatory power of the instruments employed. However, empirical analysis has shown that often the selected instruments are only weakly correlated with the potentially endogenous variables and therefore are weak and less reliable measures of these variables (ROSENZWEIG and SCHULTZ, 1983; KENKEL, 1995; BOUND *et al.*, 1995). A related potential problem that is connected with the quality of the instruments is that the standard errors tend to be "large" in these estimations and the estimated coefficients are non-significant. Additionally, multicollinearity problem may arise in the 2SLS when the newly created variables are entered as predictors together with the exogenous variables (BERRY, 1984: 69).

The systems counterpart of 2SLS is the 3SLS method. It is an extension of the 2SLS procedure that allows the incorporation of disturbances' correlations of different equations (similarly to the way how SUR extends OLS) (KENNEDY, 2003: 190). Another full-information approach to the estimation of complex multi-equation models is the SEM that is explained in more detail in the section 4.3 together with the relevant empirical examples.

The following chapter gives empirical examples of the 2SLS method as an approach frequently applied in the field of health production modelling with an aim to account for the endogenous nature of certain inputs of health production (as discussed in section 3.3.3).

4.2 Empirical examples of the two-stage estimation method

The importance of accounting for endogenous health inputs is demonstrated in two early studies of ROSENZWEIG and SCHULTZ (1983) and SCHULTZ (1984) who provided a generic approach to the estimation of health production and input equations. Based on the data from the USA and using the instrumental variables technique, they obtained parameters of a production function related to children's birth weight. Thereby, they recognised that the choice of inputs (e.g., prenatal medical care in SCHULTZ, 1984) is influenced by unobservable variables, which also have an impact on health outcomes. That is, unobservable health endowments such as difficulties prior to pregnancy may induce a higher demand for prenatal care. SCHULTZ (1984) showed that when the endogeneity of prenatal care was ignored (treated as exogenous in an estimation of production function by OLS), its effect of child mortality was positive. In contrast, in the 2SLS estimation that accounted for endogeneity of prenatal care, this health input was found to reduce the mortality significantly. Similar findings can be found in the work of ROSENZWEIG and SCHULTZ (1983). They demonstrated that not accounting for health heterogeneity leads to an underestimation of the positive effect of early prenatal care on the weight of a new-born and of the negative impact of the mother's smoking while pregnant.

In recent decades the problem of rising overweight and obesity induced active research in the health field, with a number of studies investigating the determinants of these negative health outcomes (e.g., CHOU *et al.*, 2004; CHOU *et al.*, 2008; SCHROETER *et al.*, 2005; NAYGA, 2000). Due to a frequent lack of longitudinal data (e.g., especially on prices) the estimations based on a single-period data are prevailing (STRAUSS and THOMAS, 1995). An example of a longitudinal study is the one by CHOU *et al.* (2004). Based on household production theory they investigated the determinants of BMI and obesity in the USA using the data from the Behavioural Risk Factor Surveillance System for the years 1984–1999. They estimated reduced-form equations for the BMI and the probability of being obese by the OLS method. The equations contained a number of relevant price variables, e.g., a real fast-food meal price, the number of fast-food and full-service restaurants per 10,000 persons in respondent's state of residence, the real full-service restaurant meal price, real cigarette and alcohol prices. In addition, household income, individual characteristics and environmental variables were included. The study revealed a positive relationship between the increasing per-capita number of restaurants, declining food prices, anti-smoking campaigns (higher cigarette prices) and an upward trend in weight. This is in line with results of other studies that found a relationship between higher fast-food prices and lower BMI as well as obesity among children and adolescents (see e.g., POWELL *et al.*, 2007 and CHOU *et al.*, 2008). Further, CHOU *et al.* (2004) argue that it is a priority for further research to develop a structural model of obesity with caloric intake, energy expenditure, and smoking being endogenous determinants of weight.

HUFFMAN *et al.* (2006) investigated based on household production function obesity-related mortality among 18 OECD countries using panel data for the years 1971 to 2001. The mortality rates attributed to cardiovascular diseases and diabetes were used as proxies for obesity. First, the health production function to analyse links between mortality and diet were specified. According to the results, higher intake of calories and sugar increased mortality (10% rise in consumed calories increases mortality by 7%). Conversely, higher intake of fruits and vegetables, dietary information, technical change in medicine, and a better healthcare system reduced mortality. The second model estimates the household health supply function in reduced form that depends on prices for foods and other goods, real salary, schooling, share of the employed as a dummy for health system and trend. Negative effects of food prices were found (10% decrease in the price increases mortality by 1.5%); of non-food prices, real wage and labour participation. However, the effect of education and income on obesity-related mortality was not significant.

Using the data of first, second, and third National Health and Nutrition Examination Surveys, RASHAD *et al.* (2006) investigated an influence of a number of community (e.g., gasoline tax, smoking tax, availability of restaurants) and individual characteristics (e.g., age, gender, marital status) on BMI and obesity among US citizens. The reduced equations for BMI and obesity were estimated with the exogenous variables mentioned above. It was assumed in the study that changes in the environment (such as a rise in a number of fast food restaurants) led to changes in habits. The results suggested an increase in obesity due to a higher per-capita number of restaurants and a higher BMI among females as a response to the campaign on smoking reduction.

Demand relations for health inputs and production technology are both considered in the study by RASHAD (2006). To investigate the determinants of adult obesity among US citizens he constructed a structural model of obesity among US citizens, relating individual BMI to their energy intake, activity level and smoking. First, the OLS model is estimated. Further, he treats the behavioural variables as a subject of individual choice and controls for their potential endogeneity by applying the 2SLS method. This included an estimation of reduced-form equations for behavioural variables with a set of state-level characteristics as instrumental variables. In the second stage, the parameters of the production function of BMI were estimated. In contrast to the results of the single-equation procedure, the strong effects of caloric intake and smoking disappeared (except the impact of energy intake for females) in the two-stage least squares models.

CHEN *et al.* (2002) provided empirical evidence that accounting for endogeneity in the modelling of health outcomes and its determinants can lead to changes in the direction and intensity of the postulated relations. In their study blood pressure is modelled to be dependent on the person's nutrient intake, physical activity and medication use. When the endogeneity of these inputs was controlled (by modelling these choices as dependent on prices, wages and income), the effect of sodium intake on blood pressure turned out to be negative. They argue that this result is supported by the biomedical view on this relationship.

The problem of the quality of instruments in the IV approach is discussed in the work of KENKEL (1995), who aimed to estimate the impact of a number of behaviours on adults' health. However, he evaluates the results from his two-stage model as implausible and attributes the failure to account for the endogeneity partly to the lack of explanatory power of the instruments such as money prices. He argues that prices might be of low relevance for many behavioural choices. ROSENZWEIG and SCHULTZ (1983), who used an instrumental-variable technique to examine the effect of endogenous health inputs such as medication, smoking, and fertility on birth weight, also indicated that the instruments employed in their two-stage estimation approach had little explanatory power[13].

To summarise, the first category of the estimation methods reviewed in this chapter is related to the single-equation approach, which presumes an exogenous nature of all regressors. The second type involves an estimation of the equation in several steps that allows to account for potential endogeneity of the model variables and to produce consistent estimates (e.g., 2SLS). Finally, as discussed above, the full-information estimation methods can be employed that offer a number of advantages including a possibility to test complex relationships and to estimate all parameters of the system simultaneously. In the next section SEM as one of the full-information approaches is discussed and its features and strengths are presented taking into account the goals of the study. The section discusses the nature of the method and provides a rationale for its application in the actual project.

[13] Some of the study examples presented in this chapter are also discussed in DEMYDAS (2013).

4.3 The structural equation modelling approach

4.3.1 Definition and main features

SEM belongs to the full information estimation methods. It is applied to the quantitative analysis of complex causal interrelations based on the hypotheses formulated a priori. Its development is connected with the names of K.G. Jöreskog and D. Sörbom, who in the 1970s created the first widely available computer software Linear Structural Relationships (LISREL). Since that time several alternative software packages have emerged, e.g., Equations (EQS), Mplus, Covariance Analysis and Linear Structural Equations of SAS (CALIS) and the special package "sem" of the R software. Due to its rising popularity, nowadays the SEM is available in such leading statistical programs such as STATA ("sem" module) and SPSS (special package AMOS).

SEM is a general term that incorporates numerous statistical techniques. It may be seen as an extension of general linear modelling (GLM) procedures, such as the ANOVA and multiple regression analysis (LEI and WU, 2007). Some authors refer to it as a merger of multi-equation regression models from econometrics and measurement models from psychology estimated by factor analysis (HAIR *et al.*, 1995). The SEM methodology has been constantly developed over the last decades. Three generations of SEM are described in the literature (GRACE *et al.*, 2010): 1) estimation through the decomposition of correlations going with its roots to the work of WRIGHT (1934), 2) maximum-likelihood procedures, and 3) Bayesian methods and estimation using Markov Chain Monte Carlo methods that currently are enjoying increased popularity.

As noted above, SEM is an extension of multi-equation regression analysis. Compared to the latter, SEM has a number of *additional features* that are particularly important for an actual study. One of the most important advantages of SEM is its ability to employ in the analysis not only measured variables but also non-observed theoretical constructs in the form of *latent variables*. A latent variable approach permits representing an unobservable construct (e.g., health, prestige) in terms of a number of observed indicators. First, this offers an advantage in terms of the improved measurement properties that come from multiple measures of the same construct (KLINE, 1998). Second, the relationships among latent constructs (represented in form of regression or path coefficients) can be estimated. MANNING *et al.* (1982) demonstrated empirically that a latent multidimensional construct of health status contributes significantly to a higher precision in the estimations compared to estimations when a single-item health measure is used.

Further, SEM allows *to model measurement error*[14] for each latent construct and to derive unbiased estimates for the relations between them. Measurement error is estimated and theoretical parameters are adjusted accordingly, that is, the measurement error is subtracted from parameter estimates. In contrast, regression analysis assumes perfect measurement of variables and hence their perfect reliability. The lack of observed power of predictive variables may be due to the lack of association between variables or it may be due to a poor reliability of measurement. SEM allows distinguishing between the problems of imperfect measurement (reliability of latent variables) and non-random, unexplained variance (e.g., due to model misspecification) (MUSIL *et al.*, 1998).

As discussed in chapter 2.2, a number of indicators proposing a rough description of health status are employed (GERDTHAM *et al.*, 1999; BEHRMAN *et al.*, 1988). However, these measures can represent an individual's health only approximately and measurement error may be high. The latent variable approach provides a sound option for the empirical estimation in this study that allows presenting not directly observable health via a set of its observable indicators. This approach can be found in a number of studies in health economics (JONES, 2000; GIUFFRIDA *et al.*, 2000). Some of the studies employ a special case of SEM, the *multiple-causes multiple-indicators (MIMIC) model,* in which endogenous latent variables (e.g., health) are caused by a number of exogenous observed variables that are assumed to be measured without error. Empirical examples of MIMIC models in the health economics field are given in section 4.3.4.

KENNEDY (2003: 163) discusses that modelling of unobserved "latent" variables is more common for sociological and psychological research and that these unobserved "latent" variables correspond to the economists' unobserved "measured-with-error" variables. Thus, when performing multiple regression analysis, a researcher is forced to choose among alternatives a single measure of each construct in the model. However, as noted above, any single measure is susceptible to measurement error, while a multiple indicator approach may help to reduce the overall effect of measurement error of any individual observed variable on the accuracy of the results (KLINE, 1998: 189). KENNEDY (2003: 163) claims that economists have not made much use of SEM technique due to several reasons. Among them is the unavailability of such modelling procedures in the earlier econometric software and the fact

[14] There are two types of residual terms in SEM, which are considered as independent variables in the analytical model and estimated together with other variables. *E* (error) presents a measurement error and unexplained variance of observed variables, while *D* (disturbance) depicts the unexplained variance in latent variables. Both, *E* and *D* are considered as independent variables in the analytic model and are estimated together with other variables.

that in many cases the variables are not assumed by economists to be normally distributed, which is the assumption of SEM. However, the recent developments in SEM account for the distributional characteristics of the variables (i.e., to include categorical variables) by application of specially developed procedures, e.g., Asymptotically Distribution Free (ADF) in AMOS and Weight Least Squares (WLS) methods in LISREL.

Next, a special strength lies in SEM's ability *to test both direct and indirect pathways* (i.e., through other variables as intermediaries) in the model as well as feedback relationships. This provides a way to test hypotheses about more complex relationships among variables in the model (direct, indirect and total effects) that makes this feature particularly interesting for the actual study (Figure 1).

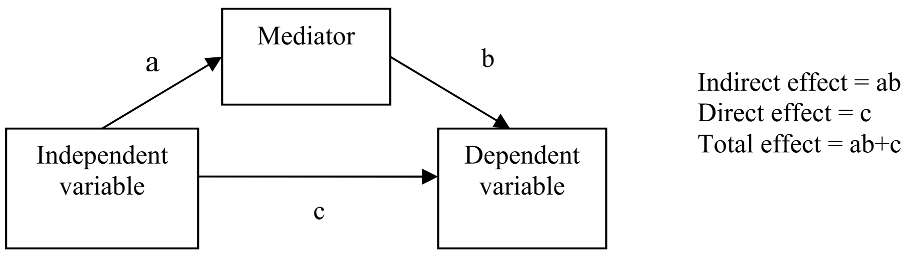

Figure 1 A three-variable mediation model

Source: MACKINNON *et al.* (2000: 174).

As shown in Figure 1, indirect effects involve a third variable (a mediator), which transmits part of the effect of one variable on another one. It is estimated as a product of direct effects. A total effect is a sum of all direct and indirect effects of one variable on another one. The test of mediation shows whether the effect of an independent variable on a dependent variable can be explained by a third variable, i.e., through an intervening (intermediate) mechanism (LEI and WU, 2007). Distinguishing between direct, indirect and total effects is called *"effect decomposition"* and is a special strength of SEM (KLINE 1998: 121). These effects can be also estimated between unobservable latent variables.

Further, in comparison with the regression analysis that implies no high correlation among independent variables in the model, the latter can be explicitly modelled and accounted for in the SEM, so that it does not present any problem for the analysis. However, very high multicollinearity (r>=0.85) may lead empirically to an under identification (KLINE 1998: 169). The problem of identification is discussed in Section 4.3.3.

Another strength of SEM to be acknowledged is the possibility to obtain *measures (indices) of overall fit* of a hypothesised model even if it involves a large number of equations.

Additionally, the overall fit measures in SEM may provide suggestions to improve the fit of the model (e.g., by adding paths between variables). However, such modifications should be based on theoretical considerations (MUSIL *et al.*, 1998). It is also possible to compare the *alternative models* that differ by their complexity. This feature is supported by the nested chi-square tests (TOMARKEN and WALLER, 2005).

Finally, SEM is a constantly developing framework that can be applied to the analysis with both experimental and non-experimental data, as well as cross-sectional and longitudinal data. However, it is suggested that models based on longitudinal data would be more appropriate for testing reciprocal relations so that the condition that causes preceding effects is satisfied (WONG and LAW, 1999). Recent innovations in SEM include latent growth modelling, multilevel models, approaches for dealing with missing data and with violations of normality assumptions, and complex survey data analysis (with Mplus software). All of these features have increased the scope and capabilities of SEM (TOMARKEN and WALLER, 2005).

4.3.2 Aim and general form

Generally, the SEM *aims* to investigate whether the hypothesised model is consistent with the actual patterns in the sample data. The estimation incorporates fitting data to a model or practically, solving a set of equations. The main aspects assessed are the adequacy of parameter estimates and the model fit as a whole.

The estimation procedure is undertaken by minimizing the difference between the actual covariances in the sample (an empirical covariance matrix) and the covariances predicted by the model (model-implied covariance matrix). The fundamental hypothesis for the SEM is that the covariance matrix of the observed variables is a function of a set of parameters (4.1). Once the model's parameters have been estimated, the resulting model-implied covariance matrix is compared to an empirical or database covariance matrix. If the two matrices are consistent with one another, then the SEM can be considered a plausible explanation for relations between the variables in the model. The difference between the observed and predicted covariances is formed by residuals (BOLLEN, 1989: 1).

(4.1) $\sum = \sum(\theta),$

where $\sum$ is a population covariance matrix of observed variables, θ is a vector of model parameters, and $\sum(\theta)$ is a covariance matrix presented as a function of θ.

All relations are usually expressed graphically by path diagrams or alternatively can be formulated by linear regression equations (BULLOCK *et al.*, 1994, FOX, 2006). SEM software applications use various sets of symbols to represent the equations to be estimated. Figure 2 presents a SEM in a general form; thereby, the LISREL terminology is used.

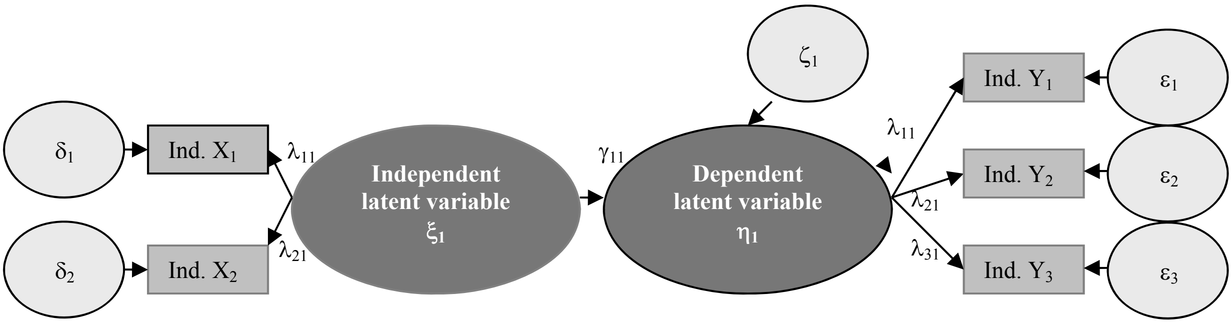

Figure 2 Full structural equations model

Source: Modified from BACKHAUS (2006: 355).
Note: Ind. is indicator; ζ corresponds to D, ε and δ correspond to E in the software language other than LISREL (e.g., AMOS).

This is a simple model. Additional variables (latent and observed) as well their interrelations, either causal (depicted by one-sided arrows) or by correlation (marked by double-sided arrows), can add significant complexity to the model.

The model includes *indicators* (X and Y) that are observed variables in the model used to form an *unobserved (latent) construct* (ξ and η). The model that specifies how well the unobserved (latent) variables are measured in terms of observed indicators is called *measurement model*. Latent variables are especially important for measurement of human behaviour and attitudes. They can be both exogenous (ξ) and endogenous (η) in the model. They allow accounting for the *measurement errors* that are usually typical for any observed measures (here depicted as δ and ε for indicators of latent exogenous and endogenous variables respectively). Whether latent variables are meaningful is tested in the SEM methodology through confirmatory factor analysis (CFA), in which the obtained *factor loadings* (λ) present a relationship between measured indicators and the respective factor. The indicators of one latent variable should be at least moderately correlated. On the contrary, indicators of different constructs should not be highly correlated ($r>0.85$, KLINE, 1998: 190). It is usually recommended to perform CFA before estimating a full structural model because the measurement model must work before the construction and evaluation of a more complex structural model. This is called two-step estimation (BROWN, 2006).

The full *structural model* presents the postulated causal relationships between all endogenous and exogenous variables in the model. The structural paths from one latent variable to another are interpreted as *regression coefficients* and denoted as γ. *Structural error terms* or disturbance terms reflect the unexplained variance in the latent endogenous variable due to the unmeasured causes (ζ).

Using the LISREL terminology introduced above, the *structural equation* for the model shown in Figure 2 can be written as follows (modified from BACKHAUS, 2006: 350):

(4.2) $\eta_1 = \gamma_{11}\xi_1 + \zeta_1$

where η is a latent endogenous variable, γ_{11} is a structural path, ξ - independent latent variable, and ζ is a structural error term.

The measurement model of exogenous latent variable has the following form:

(4.3) $x_1 = \lambda_{11}\xi_1 + \delta_1$

(4.4) $x_2 = \lambda_{21}\xi_1 + \delta_2$,

where x_1 and x_2 are indicators of the exogenous latent variable ξ_1; λ_{11} and λ_{11} are corresponding loadings of the indicators on this latent variable (factor) ξ_1.

The measurement model of endogenous latent variable is:

(4.5) $y_1 = \lambda_{11}\eta_1 + \varepsilon_1$

(4.6) $y_2 = \lambda_{21}\eta_1 + \varepsilon_2$

(4.7) $y_3 = \lambda_{31}\eta_1 + \varepsilon_3$,

where y_1, y_2, y_3, are indicators of the endogenous latent variable η_1; λ_{11}, λ_{21} , λ_{31} are corresponding loadings of the indicators on this latent variable (factor) η_1.

The above equations can be represented in a general form (BACKHAUS, 2006: 349-352):

(4.8) $\eta = B\eta + \Gamma\xi + \zeta$

(4.9) $x = \Lambda_x\xi_x + \delta$

(4.10) $y = \Lambda_y\eta + \varepsilon$,

where B is a coefficient matrix for latent endogenous variables (not present in the example above), $\mathbf{\Gamma}$ is a coefficient matrix for latent exogenous variables, Λ_x and Λ_y are matrices containing factor loadings of the latent exogenous and latent endogenous variables respectively.

The modelling process in LISREL (and other programs) includes estimation of four further matrices, i.e., a covariance matrix Φ of latent exogenous variables (ξ), a covariance matrix Ψ of residuals (ζ) of the latent endogenous variables; and the matrices of measurement errors in the model (Θ_δ and Θ_ε).

In contrast to some other software programs, the model is specified in AMOS through a graphical interface and the mathematical system of equations is generated automatically based on the hypothesised relationships presented graphically (ARBUCKLE, 2010). AMOS is used in this study. After the model is specified, the sample covariance matrix (alternatively, a raw data file, e.g., in SPSS or excel format) is entered directly into the software to perform the estimations. During the estimation procedure a number of equations are solved to estimate the parameters of the model, i.e., factor loadings and regression coefficients as well as variances and covariances of exogenous variables. The next section describes the process of SEM in more detail.

4.3.3 Steps in the modelling process

A process of SEM is demonstrated in Figure 3.

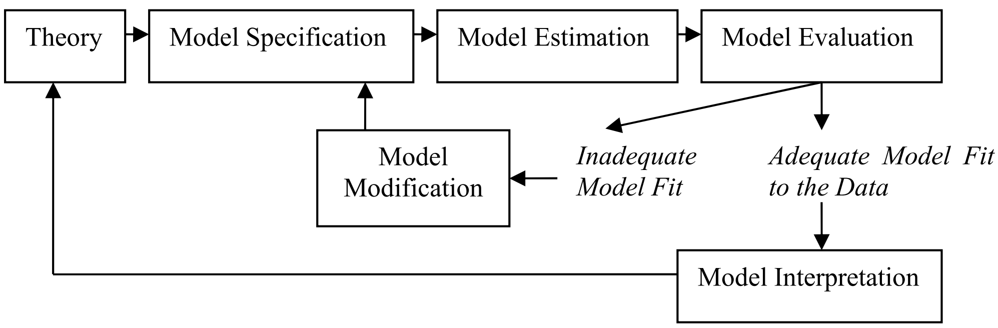

Figure 3 SEM process

Source: Own presentation based on GRACE *et al.* (2010).

A model should be based on the *theoretical knowledge* about the research problem, which is the foundation for the model. This step includes the formulation of hypotheses that are to be tested in the study.

In the following, the *model is specified*, which means the representation of postulated hypotheses about the relationships between variables in a form of a graph and/or equations. The model specification is usually based on the theory, but may also incorporate findings of previous studies. In this stage an explicit notion of causality is done, i.e., which variables are endogenously determined and which are assumed exogenous. In the graphical form, the causal relationships are presented as single-headed arrows or "paths", statistically meaning regression coefficients, while double-headed arrows indicate covariance or correlation. The latter is usually assumed and specified among all exogenous variables in SEM without any further hypotheses about the reasons for this correlation (HOX and BECHGER, 1998; KLINE, 1998: 51).

A specified model should be tested for its mathematical *identification.* This is a fundamental concept in modelling, which shows whether "[]…there is any way to obtain estimates of the parameters of the model" (GREENE, 2003: 385). Models with only one possible solution for each parameter estimate are "just-identified", those with infinite number of solutions are "unidentified", and models which may produce more than one possible estimate for each parameter are said to be overidentified. If the identification requirements are not provided (the model is underidentified) the estimation will fail and the model should be re-specified. In SEM, it is desirable to work with an overidentified model, where the number of knowns (observed variable variances and covariances) is greater than the number of unknowns (parameters to be estimated) (see examples in Table 3). Such a model has a positive number of degrees of freedom (DF) in the chi-square goodness of fit test, while DF equal sample moments minus free parameters.

Table 3 Identification in SEM

Unidentified	Just identified	Overidentified
a+b=6	a+b=6 2a+b=10	a+b=6 2a+b=10 3a+b=12
Infinite number of solutions: e.g., a=4, b=2; a=8, b= -2 etc.	A single solution: a=4, b=2.	The solution that approximates the real observations is a=3.0, b=3.3.
2 parameters (a and b) > 1 observation (6)	2 parameters (a and b) = 2 observations (6 and 10)	2 parameters (a and b) < 3 observations (6, 10, and 12)

Source: own presentation based on KLINE (1998: 108-111).

Several methods exist to test the model's identification. The two *necessary conditions* for identification are:

- The number of observations must be equal to or exceed the number of parameters (DF≥0) (*parameter-to-observations test).* The number of observations (sample moments or knowns) is computed as n=v(v+1)/2, where v is a number of observed variables in the model. Free parameters (unknowns) is a sum of "[…] variances and covariances (i.e., unanalyzed associations) of exogenous variables that are either observed or unmeasured (i.e., disturbances) plus direct effects on endogenous variables from other observed variables" KLINE (1998: 204). However, such calculations for complex models may be very tedious.

- To be able to calculate the estimates of the effects involving an unobserved latent variable, it should have a scale (metric). Therefore, the variance of a latent variable is standardised, i.e., usually set to a unity (1). Alternatively, a loading of one indicator on a latent variable may be scaled to 1, which gives a latent variable the same metric as of that indicator KLINE (1998: 204).

The identification problem is typical for *non-recursive models* (Figure 4), which do not require the assumptions typical for recursive models[15] (e.g., uni-directional relations) and therefore are much more difficult to specify and test (KLINE, 1998: 155).

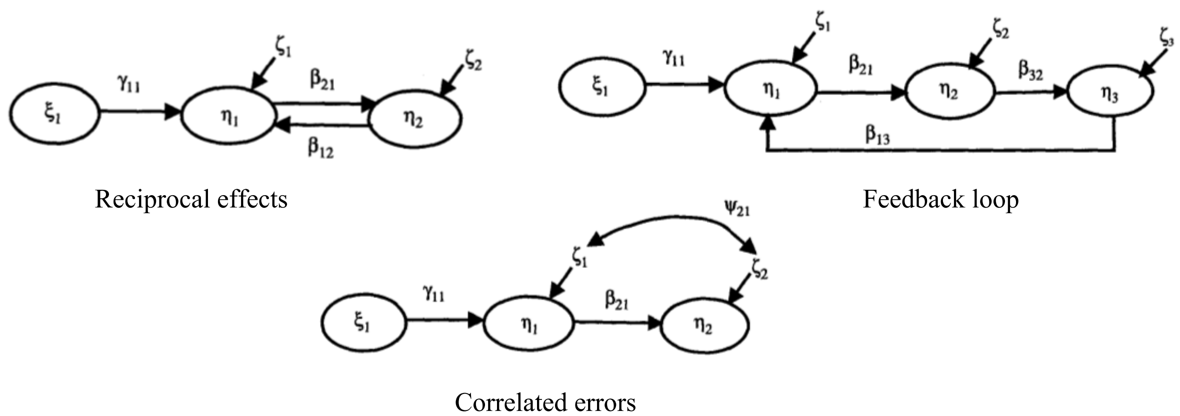

Figure 4 Types of non-recursive relationships

Source: RIGDON (1995).

Note: η represent latent endogenous variables, γ are structural paths, ξ are exogenous latent variables, and ζ correspond to structural error terms.

Thus, reciprocal effects very often lead to underidentification. In addition to the parameter-to-observations test, the order and the rank condition tests may be applied to check the identification of a non-recursive model.

[15] A recursive system presumes unidirectional relations among its endogenous variables, no feedback relations or correlated disturbances. Thereby, an endogenous variable in the first equation is regressed on exogenous variables, in the second equation it depends on endogenous variable from the first equation and all exogenous variables, while the dependent variable in the third equation is dependent on the first and second endogenous variables and the exogenous factors etc. (KENNEDY, 2003: 193).

- The *order condition* is applied to each endogenous variable in the model, meaning that the equation for this variable is underidentified if this condition is not met. It is a counting rule, implying that the number of observed variables (exogenous or endogenous) that have no direct effect on each endogenous variable (they are called excluded variables) should be equal or greater than the total number of endogenous variables minus 1 (KLINE, 1998: 160).
- The test of the *rank condition* is a more stringent test that requires the utilisation of a number of linear matrix operations leading to a construction of a complex matrix system. In general terms, it requires that "[…] each of the endogenous variables in a feedback loop has a unique pattern of direct effects on it from variables outside the loop" (KLINE, 1998: 161).

Although these procedures can be applied by hand to simple models with several variables, the calculations become very complicated for models that are more complex. Therefore, an identification test is usually included in SEM software programs and is done through a *pre-test run of a model*, which in case of an underidentification generates an error message.

An underidentification is usually a problem of model specification. It can be solved by several methods which include introduction of new exogenous variables, thereby influencing only one of the endogenous variables involved in the reciprocal relationship (like an instrumental variable) (ASHER, 1986: 58). Another method to overcome an underidentification is by imposing additional restrictions on the equations in the model. For instance, a zero-restriction can be applied, i.e., an assumption that some variables in the model can be omitted or that certain parameters of the model are equal to zero. Alternatively, an assumption that a pair of parameters in the model is equal can be introduced (BERRY, 1984: 57).

The next step in SEM is *model estimation*. The model estimation starts with the evaluation of a number of assumptions that include adequate sample size and missing data, multivariate normality, linearity and homoscedasticity, absence of outliers, of multicollinearity, and of singularity (TABACHNICK and FIDELL, 2007: 682-684; TOMARKEN and WALLER, 2005: 40-44).

- Sample size and missing data

The *sample size* is an important criterion when choosing an iterative (estimation) method. By default, the estimation of parameters is performed using the Maximum-Likelihood-Method (ML) that derives estimates which have the greatest chance of reproducing the observed data. It can be used for recursive as well as non-recursive models. The other full-information estimation methods are unweighted least-squares (ULS), generalised least-squares (GLS), and the asymptotically distribution-free method (ADF). An important feature of the ADF method is that it can be employed when the data are non-normally distributed. There is no agreement in the literature on the optimal sample size for this procedure. BACKHAUS (2006: 371) suggests a need in more than 100 cases, for good performance the ADF method needs a much higher sample size that can be calculated as 1.5*p(p+1), where p is the number of observed variables.

In case of a presence of *missing data* in the sample, several approaches can be applied. Besides the common procedures such as listwise, pairwise deletion, mean substitution, and regression-based imputation, which are often seen as less suitable, other methods of handling missing data have been developed. They have shown better performance in comparison to the traditional methods (OLINSKY *et al.*, 2003; SCHAFER and GRAHAM, 2002; BARALDI and ENDERS, 2010). These modern approaches do not concentrate solely on identifying a replacement for a missing value, but use all the available information to preserve relationships in a data set. Additionally, they produce unbiased estimates with both MCAR (missing completely at random) and MAR (missing at random) data. The ML estimation algorithms to handle missing data include *Full Information Maximum Likelihood (FIML), Multiple Imputation (MI),* and the *Estimation Maximisation (EM)* algorithm. FIML is a method that is used by default if a raw dataset (not covariance matrix), which is imputed into model-fitting programs, has missing values. Some researchers consider this procedure as being superior to the others (OLINSKY *et al.*, 2003). MI provides another useful strategy for dealing with data sets with missing values. This procedure replaces each missing value with a set of plausible values that represent the uncertainty about the right value to impute. Thus, several "complete" sets of data are generated and used in the analysis, whereas the final parameter estimates are calculated as an average of the estimates obtained from the analyses with the generated “complete” datasets. Next, the EM algorithm uses a two-step iterative procedure where missing observations are filled in, or imputed, and unknown parameters are subsequently estimated. One of the advantages of this algorithm, in comparison with FIML and MI methods, is that it delivers a single complete dataset, i.e., missing-data points are estimated and imputed at the final iteration. This feature can be important for the further stage of model evaluation, as the modification indices are available only for a complete dataset.

- Normality

One of the SEM assumptions is that sample data follow a normal distribution. Therefore, before the actual analysis, the distribution of the variables should be evaluated based on three indices: univariate skew, univariate kurtosis, and multivariate kurtosis (e.g., Mardia test in AMOS and EQS). The effect of non-normality on ML-based results depends on its extent. No consensus exists about "acceptable" values of these indices. FINNEY and DISTEFANO (2006: 272) based on the values from the literature argue that if the value of univariate skew is <2 and of kurtosis is <7, then the distribution is moderately non-normal and ML method that is fairly robust to non-normality can still be used. However, the values above these ranges are believed to indicate severe data non-normality. In the latter case, transformations (square root, logarithm, reciprocal etc.) can be considered to normalise the distribution of data. However, this should be accounted for in the interpretation of results (KLINE, 1998: 209). Additionally, the value of Mardia's normalised kurtosis greater than 3 indicates the multivariate non-normality. Although ML has been shown to produce relatively accurate parameter estimates with non-normal data, the chi-square statistics and standard errors (SE) tend to be biased with an increasing non-normality (GAO *et al.* 2008; FINNEY and DISTEFANO (2006: 273).

Approximately normally distributed continuous variables are desirable input for the SEM. However, the literature review reveals that the ML procedure is applied to the estimation of parameters also when the scale of the variables is not continuous, typically a Likert-type scaled data (BYRNE, 2001: 71). Several options exist in SEM to deal with non-normal and/or categorical data. The Mplus software has been specially developed for the analysis with categorical variables. Such analysis is also possible with the ADF procedure which does not assume normality. Moreover, several statistical procedures have been developed to improve the performance of the ML estimator with non-normal data. Among them is the *Satorra-Bentler approach* that adjusts the test statistics (i.e., chi-square and standard errors) for the degree of non-normality (SATORRA and BENTLER, 1988) to reduce bias. However, this procedure is not available in AMOS. Alternatively, *the bootstrap resampling method*[16] can be used in AMOS to perform the test of global model fit (by Bollen-Stein bootstrap option) and/or to find parameter estimates, standard errors and significance levels under non-normal data conditions (YUAN and HAYASHI, 2003). This procedure is available in AMOS for a number of estimation procedures, e.g., ML and ADF. Importantly, it requires fairly large samples with no missing values. Additionally, bootstrapping is advised as an auxiliary method to the EM procedure in order to obtain correct estimates of standard errors, which might be negatively biased to some extent

[16] Bootstrapping is related to the creation of multiple subsamples from original data, whereas the latter is treated as a whole population. The cases are selected on a random basis with replacement to create a number of other data sets. Another frequently used resampling procedure is jacknife estimation (KLINE, 1998: 310).

due to the EM approach (WAYMAN, 2003). A comparison of these two methods (i.e., Satorra-Bentler correction and bootstrapping) showed their similar performance in case of large samples (NEVITT and HANCOCK, 2001).

- Linearity and homoscedasticity

Multivariate normality implies also linearity and homoscedasticity among variables in the model. These aspects may be tested by inspection of scatter plots among pairs of variables. In case of non-linearity, the transformations may be considered (TABACHNIK and FIDELL, 2007: 613; KLINE, 1998: 84).

- Absence of outliers

Outliers can distort the results based on the classical procedures of SEM (e.g., ML) affecting the model fit, parameter estimates and SE (YUAN and BENTLER, 2001). Univariate outliers can be detected by examining the frequency distributions and computing the kurtosis and skewness indices. The extreme cases can be kept, excluded from the sample or can be substituted for a value of three standard deviations from the mean (KLINE, 1998: 80).

To find multivariate outliers, the Mahalanobis distances are calculated for each case (available in most statistical programs). This indicator shows the distance between a score of a particular case and the sample mean. Those cases with the highest distances can be considered for deletion (BYRNE; 2001: 279). Another remedy is to use a robust approach such as the ADF estimation method. YUAN and BENTLER (2001) compared the performance of the classical ML method and a robust ADF approach and concluded that the latter has a number of advantages in the presence of influential cases in the data. However, ADF estimates can be also biased due to the presence of outliers indicating a need to solve this problem.

- Absence of multicollinearity

Although the correlation between independent variables can be modelled in SEM, very high intercorrelations (i.e., multicollinearity) among some variables may result in a failure to perform estimation. The typical error message obtained in model-fitting software is "the covariance matrix is not positive definite". The correlation of >0.85 between variables in the correlation matrix is considered to be high. The remedies include removing some variables or combining them into one composite variable (KLINE, 1998: 78).

The next step is *model evaluation.* SEM aims to test how well the hypothesised model fits the sample data. In case of an inadequate fit a researcher seeks to detect the source of the model misfit and considers its modification. The main aspects assessed are adequacy of (a) parameter estimates and (b) the model as a whole.

- Parameter estimates

The estimation output provides standardised and unstandardised estimates of structural coefficients. To compare the direct effects on a particular endogenous variable in a single-group model, the standardised coefficients are used, while for comparisons across samples unstandardised values are considered. The standardised coefficients are interpreted in the same way as regression coefficients in regression analysis.

Evaluation of the *fit of model parameters* includes inspection of their signs and sizes in relation to the hypothesised values, appropriateness of standard errors, and statistical significance of the estimates. Negative variances, very large/small standard errors as well as not positively definite correlation matrices indicate the unreasonable character of the estimates. Statistical significance of individual parameters is evaluated by their critical ratio (i.e., parameter estimate divided by its SE). The absolute values of test statistics of >1.96 are considered to be statistically significant at the 0.05 level. Non-significant parameters can be considered for exclusion from the model (BYRNE, 2001: 76).

Another criterion of the reliability of parameter estimates is the *squared multiple correlation coefficient* R^2 that ranges from 0 to 1. It is computed for each observed and latent endogenous variable in the model and indicates "the fit of separate equations" in the model (BOOMSMA, 2000). The closer the coefficient to the value of 1, the more reliable the measurement. It is also called the "reliability coefficient" as it shows the reliability of the measurement of indicators, latent variables, and other endogenous variables. The *reliability of the indicators* in a measurement model is also assessed by a squared multiple correlation coefficient. It is derived by squaring a factor loading (path from each indicator to its factor, λ in Figure 2) and is also called "common variance". It shows whether the measures are meaningfully related to their latent variables (BACKHAUS, 2006: 378). There is no agreement in the literature about a threshold value. BACKHAUS (2006: 378) suggests a value of 0.4 and above. The remaining unexplained variance, which is called "unique variance", is computed as "1-common variance" and presents a measurement of an indicator's unreliability or "measurement error" (δ and ε in Figure 2). It reflects other sources of variance not explained by a factor. Importantly, indicators should relate significantly to the factor (absolute values of test statistic of >1.96).

- Model as a whole

The model chi-square with its degrees of freedom and probability value provides an overview of the overall model fit. The null hypothesis is that the model fits the data. Therefore, a significant chi-square ($p<0.05$) indicates a lack of fit. However, the usage of this test is a matter of active discussion among scientists (BARRETT, 2007; HU and BENTLER, 1999; MARSH *et al.*, 2004; HOPWOOD and DONNELLAN, 2010; STEIGER, 2007; HAYDUK *et al.*, 2007). The evaluation of the model fit based on chi-square statistics is strongly criticised as it is believed to be very sensitive to sample size (tends to be significant in large samples), to violations of normality and to a model's complexity. Therefore, a large number of goodness-of-fit indices were developed, which in their turn are less dependent on such assumptions, e.g., root mean square error of approximation (RMSEA), goodness-of-fit statistic (GFI), adjusted goodness-of-fit statistic (AGFI), root mean square residual (RMR), standardised root mean square residual (SRMR), normed-fit and non-normed indices (NFI and NNFI), or comparative fit index (CFI).

There is no agreement on which indices should be employed, but it is believed that reporting the values of multiple indices is necessary because they reflect different aspects of model fit (CROWLEY and FAN, 1997). HAYDUK *et al.* (2007) strongly advise to always report the model's chi-square, along with its degrees of freedom and associated p-value. KLINE (1998: 130) advocates the usage of the chi-square test, the CFI, the NNFI and the SRMR. HU and BENTLER (1999) proposed to always present the SRMR in combination with CFI, RMSEA or NNFI (also known as Tucker-Lewis Index). Table B2 in Appendix B gives an overview of fit indices and their thresholds taken from the existing literature.

Importantly, KLINE (1998: 130) notes that caution is advisable in model interpretation based on fit indices as their good values do not ensure meaningful results. Special attention should be given to the adequacy of values and signs of the parameter estimates. Thus, an assessment of the model fit should incorporate both statistical and theoretical criteria (BYRNE, 2001: 88).

For non-recursive models a *stability index* is also computed, which shows whether the system of linear dependencies is stable. If its values range between +1 and -1, the system is considered to be stable (ARBRUCKLE, 2007: 137).

In case of poor fit, a *model modification* can be considered. High standardised residuals and computed modification indices provide information on misspecifications in the model and may be used for its modification. The *residuals* show the discrepancy between the covariance matrix implied by the model and the sample covariance matrix. They are calculated for each pair of variables. In a well-fitted model, residuals should have small values, i.e. below 0.10

(KLINE, 1998: 131). However, they tend to be larger when the non-normality of data increases (BYRNE, 2001: 89).

Other indicators of model misspecification are *modification indices (MI).* MI is computed for each fixed parameter (i.e., those that have not been a part of the model structure before) and gives the minimum reduction in chi-square if the corresponding parameter would be freely estimated. Practically, the modification indices in AMOS point out which additional arrows (e.g., covariances between error terms, regression lines) are missing and could be added to the model.

Importantly, such modifications should always be theoretically based. Moreover, it has to be borne in mind that such post-hoc modifications change the *strictly confirmatory* SEM approach (the single model is either accepted or rejected) into a *model development approach*, which is a rather an exploratory one (BACKHAUS, 2006: 386). Although the latter is the most common procedure, another option is an *alternative-models approach*. This includes a-priori specification and testing several alternative (or competing) models to determine which one has the best fit.

The alternative models may by *hierarchical (nested)* or *non-hierarchical*. The model is nested if it can be derived from another model that has the same variables by adding or deleting constraints, therefore it is a subset of another model. The fit of nested models is compared by *chi-square difference test.* It is performed as follows:

(4.11) $\chi^2_{difference}$ = *the model* χ^2 *with the greater DF - the model* χ^2 *with the lower DF.*

If the difference is not significant, the fit of the models is considered to be comparable and the more parsimonious model may be preferred.

To compare the fit of two non-hierarchical models, the *Akaike Information Criterion* (AIC) can be applied, which is provided in the estimation output of AMOS. The lower values of AIC indicate a better fit (KLINE, 1998: 137-138).

The next step is *model interpretation*. An important principle of SEM, that is to be accounted for in model interpretation, is that the data cannot confirm a model, but only disconfirm it. It implies that there can be a number of alternative competing models that would not have been falsified (MARUYAMA, 1998: 272). Moreover, KLINE suggests that, although rare in practice, the consideration of equivalent models should be made after the selection of the final model in order to demonstrate the better fit of the chosen model. Following his definition, "[…] equivalent models yield the same predicted correlations or covariances, but they do so with a different configuration of paths among the same variables" (KLINE, 1998: 138). In other words, they are mathematically equivalent.

A number of limitations of SEM may be mentioned. These are discussed in relation to the empirical results of the study in chapter 5.3.9.

In the next section, empirical examples of SEM in health economics research are presented.

4.3.4 Empirical examples in health economics research

A number of studies that apply SEM approach to health research have specified a model with several latent variables and investigated the relationship among them and directly observed measures, e.g., WOLFE and BEHRMAN (1984), BEHRMAN AND WOLFE (1987), ERBSLAND *et al.* (1995), GIUFFRIDA *et al.* (2005), and MAZZOCCHI and TRAILL (2008)[17].

BEHRMAN and WOLFE (1987) estimate a one-period household production model using the SEM methodology. They specify health production functions for maternal and child health in Nicaragua, where besides children's and mothers' health statuses, a number of health inputs such as nutrition, medical care usage and community endowments are treated as latent constructs. Weight, height, biceps circumference, and number of sick days and diseases were used as indicators of health. Estimation of health production functions and reduced-form relations for inputs is performed using LISREL. By estimation of several alternative models, the authors demonstrated that the strong positive effect of mother's education on health and nutrition may be overstated if the mother' endowments such as her health knowledge, abilities, habits, and her health status in childhood are not controlled for.

GIUFFRIDA *et al.* (2005) using cross-sectional data developed a structural model to investigate determinants of health and health care utilisation amongst the adult population of Brazil. Health, wealth and access to health care are treated as latent variables. The health latent variable is presented by four indicators, i.e., a measure of self-rated health, the number of chronic diseases, the number of limitations in performing activities, and a variable showing whether a person was unable to perform any habitual activity due to health problems in the previous two weeks. The model incorporated a number of individual and community variables that are believed to be related to health status. Furthermore, they extended the model to a non-recursive in order to test a possible reciprocal relation between wealth (measured by indicators

[17] Some of the study examples presented in this chapter are also discussed in DEMYDAS (2013).

of income, wage and being insured) and health. Analysis was performed for men and women separately. It showed that compared to men, women's health status tended to be much more sensitive to such factors such as unemployment and race discrimination. Analysis of a non-recursive model revealed a positive impact of wealth on being healthy, which was somewhat stronger for men. On the other hand, a feedback relation from health to wealth was much smaller and non-significant. Moreover, the stability index calculated for the non-recursive model showed instability of the hypothesised model that suggests a need in its re-specification.

Using the data collected in 1986 from the German socio-economic panel, ERBSLAND *et al.* (1995) specified a two-latent variables structural model to estimate the impact of quality of environment (latent) on individual health (latent) and demand for medical care. The level of air and noise pollution as perceived by an individual were used to represent the quality of environment (exogenous in the model), whereas self-rated health, number of chronic complaints and sick days as well as the degree of handicaps were employed as indicators of endogenous latent health. Health was modelled to be determined by environmental factors and a number of other personal and community characteristics, e.g., age, income, education, community size, and doing sports. Demand for health care was a function of the quality of environment, health status and socio-economic characteristics. The results revealed a negative direct impact of environmental pollution on health and a significant positive indirect effect (via health) on health care demand, whereas its direct effect on the utilisation of health services was not significant. Engagement in physical activity was positively associated with health. However, the variable of doing sports was treated as exogenous in the model. The authors discuss that the unexpected negative sign of age variable on health care demand can be due to the fact that only a linear age term is used in the model, although it is believed that the relation between them may be convex (first increasing and thus decreasing the demand for medicines).

Another example from Germany, which among other factors focused on psychological determinants of obesity, is a recent study by KRÖMKER and VOGLER (2011). They investigated the determinants of overweight and obesity among children in five German regions using the survey data collected from 2681 children and adolescents and from 1210 parents. The specified model took into account a number of weight determinants simultaneously. Except the socio-demographic factors, they incorporated attitudes and preferences in respect to nutrition of both children and their parents. Children's diets had the largest effect on weight with overeating leading to a higher BMI. At the same time, more intensive physical activities, importance of own appearance as well as children's perceptions of an ideal body were associated with a lower weight status[18]. Furthermore, the results indicated an importance of parents' characteristics for the children's weight outcome. Thus, a higher mother's BMI was associated with a higher BMI of a child. A pattern of dieting implemented in the household was not related to a lower weight among children, but on the contrary showed a positive contribution to weight. This may be an indication of the inefficiency of self-performed dieting practices in the household.

Empirical evidence from the USA can be found in the work of CONNELL *et al.* (2001). They attempted to develop and test a comprehensive model of the relationships among a number of socio-demographic and economic factors, food insufficiency, diet quality, health behaviours and CVD outcomes for a sample of adults from the Southern United States who participated in the NHANES III. Latent constructs were used for health behaviours, CVDs risks and outcomes. However, the authors came to the conclusion that the hypothesised model had a low fit and the results were partly implausible. They point out the importance of the choice of appropriate indicators for latent variables (e.g., in the construction of measurement model of CVDs risk) and suggest a need in the analysis of the direct and indirect effects of the determinants for CVDs.

The study of MAZZOCCHI und TRAILL (2008) is of special interest. They modelled the endogenous relationships between wealth, nutrition, weight and health based on the UK National Diet and Nutrition Survey from 2000-2001. Thereby, a household production theory serves as a theoretical background. The weight, wealth and health state were presented as latent variables and SEM was applied (using the AMOS module) to test the fit of the proposed model. The authors concluded a direct positive effect of a better diet, more exercises and lower weight on health and an indirect effect of wealth on health due to a better diet. They note that the obtained positive effect of smoking on health is implausible, but state its instability in the further model specifications. This model presents an important background to the present study, although a number of modifications related to the model specification were performed (see chapter 5.3.1).

Examples of empirical studies employing a SEM in the field of health research include, e.g., WAGSTAFF (1986, 1993), VAN DE VEN and VAN DER GAAG (1982), VAN VLIET and VAN PRAAG (1987), VAN DER GAAG and WOLFE (1991), HÄKKINEN (1991), and KIISKINEN (2003).

Based on the production function approach, HÄKKINEN (1991) used the data of the representative cross-sectional Survey on Health and Social Security among adults in Finland to

[18] For further insights into individual perceptions of ideal body weight and their impact on attitudes and behaviour (e.g., food consumption, exercising, dieting), look at the study of ETILÉ (2007).

estimate the MIMIC model of determinants of health status and of the health care demand. Health was specified as a latent variable measured by three indicators: self-rated health status, number of longstanding/chronic diseases and number of complaints such as overwork, tiredness, sleeplessness etc. The model included lifestyle variables (e.g., smoking, drinking, and overweight), socio-economic variables (e.g., age, income, education) and health service utilisation. The results revealed the importance of healthy lifestyles such as decreasing smoking and reducing weight for better health. HÄKKINEN (1991) stresses that although these variables are treated as exogenous in the model, they are choice variables and, therefore, should be modelled as being endogenous. However, this would imply a specification of demand equations and, thus, a higher model complexity. Furthermore, in contrast to the other studies that consider health-care utilisation as an input into health production (e.g., KEMNA, 1987), HÄKKINEN (1991) treats medical care usage as an indicator of an adverse health status. Therefore, he models it as affected by the health status of the individual, his socioeconomic characteristics and availability of medical services. The authors estimated the direct effects of socioeconomic variables on health status, which appeared to be somewhat lower compared to the effects of lifestyles (indirect effects are not taken into account).

The focus of the research project of KIISKINEN (2003) was the role of an individual's health knowledge and the engagement in health education activities on health status. In contrast to the vast majority of existing studies using cross-sectional data (due to the lack of empirical data), he used two waves of the Finnish health examination survey data and the household production framework to test his structural equation (MIMIC) model of health. The latent health construct is measured by the following five observed indicators: self-assessed health, two indices reflecting mental health and main somatic health problems, a variable representing longstanding diseases, and a measure showing the disabling aspects of health problems (days off from work). The study aimed to separate the effect of health knowledge from a general impact of education on health. The results indicated a positive influence of health knowledge on the efficiency of health production, whereas schooling contributed to better health knowledge. Therefore, education appeared to be indirectly related to health. A detailed analysis of (in)direct relations between other variables in the model such as smoking, alcohol consumption, medical care and physical exercise is given. The study presents a comprehensive analysis of health behaviours with a specification of the model using both the one-period cross-sectional data and data from two-wave health survey.

Numerous examples of modelling health and health-related behaviours using the SEM approach can be also found in medical, epidemiological, sociological and psychological research (e.g., COBAS *et al.*, 1996; OH and SEO, 2001; SHEN and TAKEUCHI, 2001, MCALISTER *et al.*, 1984; Hays *et al.*, 2005; HÖFER *et al.*, 2005.)

To summarise, due to the complexity of interrelations among variables in the health production model, the OLS estimation cannot be employed. Section 4.1 presented the simultaneous equations methods that can be used in order to obtain non-biased estimates of model parameters. These techniques include single equation (e.g., 2SLS) and system methods (e.g., 3SLS, SEM). The SEM approach offers a number of features considered particularly important for the purpose of the actual study (see chapter 4.3 for details). Some of them are the possibility to specify and test complex model interrelations, including effects between several endogenous variables; testing of direct and indirect effects among model variables; the possibility to model the central concept of the model, health, as an unobservable latent variable and to test its appropriateness; simultaneous estimation of all relationships by a full-information approach.

Therefore, this study proposes a model of cardiovascular health that takes into account theoretical considerations discussed in the previous chapters. The empirical estimation is performed using the SEM approach.

5 Empirical analysis

Chapter overview

The first Section (5.1) of this chapter describes the dataset and provides descriptive statistics of the study sample. The empirical analysis starts in Section 5.2 with the investigation of dietary quality of the U.S. adult population. With this purpose a number of indicators are employed, e.g., person's self-assessment, structure of his/her energy supply, nutrients density and biological markers. The latter are based on the data obtained in laboratory conditions. Special focus is given in this section to F&V consumption due to the rich scientific evidence about its determinative role in a person's diet and health. The investigation of F&V intake is broadened to an important aspect, for which empirical investigations are lacking, i.e., preparation forms of consumed F&V and their nutritional quality. Section 5.3 is devoted to the model of cardiovascular health. It starts with the theoretical specification of the model (5.3.1). The next subsection (5.3.2) gives an overview of the model's variables including both endogenous and exogenous health inputs. A number of alternative indicators are presented for each variable using the data available in the NHANES 2005-2006. Thereby, the expected relations between model's variables are discussed taking into account the insights from existing studies. This supports the formulation of the study hypotheses presented in the next subsection 5.3.3. In subsection 5.3.4, the empirical specification of the full structural model of health production is done. Further, the assumptions needed for empirical estimation are tested and the descriptive statistics of the variables chosen for the model is given (5.3.5). The next subsections are focused on the results presentation and their discussion. First, the initially specified model is discussed (5.3.6). Second, the insights from the alternative structural model of health are presented (5.3.7). In addition the potential reverse causality among variables is addressed (5.3.8). Subsection 5.3.9 concludes with the discussion of the study limitations.

5.1 Dataset: The U.S. National Health and Nutrition Examination Survey 2005-2006

5.1.1 Sampling method and content of the dataset

The U.S. National Health and Nutrition Examination Survey (NHANES) 2005 to 2006 provided the data for this research. The NHANES is a program of studies of the National Centre for Health Statistics (NCHS) of the Centres for Disease Control and Prevention (CDC) that was established in 1960s. Its aim is to assess the health and nutritional status of the U.S. population aged 2 months and older. A nationally representative sample of about 5,000 persons located across the country is studied annually (CDC, 2008). Complex multistage probability techniques are used to select the study sample. There are four stages of NHANES complex sampling procedure (CDC, 2008a):

- Stage 1: The country is divided into geographical areas, known as primary sampling units (PSUs). These are usually single counties or may be also groups of counties chosen with a probability proportional to a measure of size (PPS).
- Stage 2: The PSUs are divided into segments (strata) such as city blocks. At this stage sample segments are also chosen with PPS.
- Stage 3: Each stratum is divided into a series of neighbourhoods from which the households are randomly chosen.
- Stage 4: Based on the list of the individuals living in a selected household, persons are randomly selected. These are interviewed to determine their eligibility for participation. On average, 1.6 persons are chosen in each household. Each participant represents about 50000 other U.S. residents.

Depending on the actual public health interest, NHANES may oversample some population groups, e.g., in relation to age, sex and race/ethnicity, in order to increase the reliability of the estimates. Therefore, sample weights and sample design variables that compensate for different probability of selection as well as non-response and post-stratification should be used to obtain representative results procedure (CDC, 2008a). Weighting procedures for such complex samples are available in, e.g., SAS, SPSS, STATA, SUDAN, and R. A special module of the SPSS software (SPSS for complex samples) is employed for an empirical analysis of dietary quality among US population. However, the model of health production, which is specified and tested by AMOS, is based on the unweighted sample due to unavailability of the weighting procedure in this software.

NHANES provides comprehensive data with regard to health conditions, nutrition and lifestyles, e.g., such as smoking, alcohol consumption, physical activity, which are relevant to the research questions. The main topics of NHANES include nutrition, anthropometry, mental health, risk behaviour, reproductive health, environmental exposures, and infectious diseases. Data are divided into 4 sections (CDC, 2007):

- Demographic files contain information on survey design variables and demographics.
- The examination section presents data collected by a number of standardised physical exams and dietary interviews (e.g., body measurements, vision exam).

- The laboratory part contains results from analysis of blood, urine etc. collected by trained specialists in Mobile Examination Centres (MEC) (e.g., total cholesterol and triglycerides).
- The questionnaire files contain information obtained during household and MEC interviews (e.g., alcohol use, blood pressure, drug use).

The data collection starts with an interview about the demographic characteristics of the respondents. Within the next 1-2 weeks, a physical examination of the selected individuals is performed in MEC. Further, the detailed information about foods and beverages consumed is collected through two 24-hour computer-assisted dietary recalls, where the first one is a personal interview done in MEC and the second one is a telephone follow-up interview done in 3 to 10 days after the first one. The survey data is publicly available on the web page of the CDC (CDC, 2007).

Finally, NHANES is a unique source for nutritional and health information that combines interviews with a physical examination. However, unavailability of key economic information in the dataset, e.g., expenditures or prices, limits its application to economic modelling.

5.1.2 Data preparation and study sample

In total 10348 persons were interviewed about their socio-demographic characteristics in frames of NHANES 2005–2006. Out of them, 9950 persons were chosen for physical examination in MEC (CDC, 2007). The sample used in this study was restricted to the adult population of 20 to 59 years of age, who were not pregnant and non-lactating and had reliable two-day dietary information (90 % of the NHANES 2005-2006 adult sample). Pregnant and breast-feeding were excluded due to specifics of health and nutrition for these persons. The same is applies to children, adolescents and elderly individuals. Moreover, the information on smoking and alcohol consumption among the youth is not publicly available which would be a limitation in case of inclusion of this group into analysis.

Based on the above, the total sample used in this project is comprised of 2505 adults. Table 4 delivers the descriptive statistics. Average age in the sample is 40 years. Females and males are represented equally, with the majority of the respondents being married or living with a partner. The collected data on income distribution shows that the majority of households (64 %) have disposable incomes of over $45,000 US per year. About 28% of the respondents are college graduates or have a higher degree.

Table 4 Socio-demographic characteristics of the sample (N=2505) [a) b)]

Characteristics	Mean/%	SE
Age	40.12	0.31
Gender (%)		
Male	49.51	0.89
Female	50.49	0.89
Marital status (n=2503) (%)		
Married/living with partner	68.49	1.83
Ever married (widowed, divorced, separated)	13.70	1.16
Never married	17.81	1.26
Race/ethnicity (%)		
Mexican-American/ other races	18.22	2.00
Non-Hispanic Black	11.39	2.00
Non-Hispanic White	70.39	3.01
Education (n=2504) (%)		
Less than 9th grade	4.14	0.66
9-11th Grade or 12 grades with no diploma obtained	9.51	1.08
High School graduation or equivalent	23.59	1.14
Some college or AA degree [c)]	35.01	1.22
College graduation or above	27.75	2.49
Household size (%)		
1 person	10.54	1.20
2	28.57	1.71
3	21.86	1.16
4	19.78	1.03
5 persons and more	19.25	1.38
Household income, $ US per year (%)		
Under 20.000	11.34	0.78
20.000-44.999	24.76	1.98
45.000-74.999	27.78	1.19
Over 75.000	36.12	2.57
Home tenure (%)		
Owned/being bought	71.40	2.18
Other (rented/other arrangements)	28.60	2.18

[a)] Data are weighted to be representative of the population. [b)] Sample size may vary slightly due to missing data.
[c)] AA refers to associate of arts.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

5.2 Dietary quality among adults in the USA

Methods of dietary quality analysis as well as their strength and weaknesses were discussed in Section 2.1. In this study, the dietary quality among U.S. adults is assessed based on several approaches, which allow consideration of different aspects of nutrition and verification of the obtained results.

5.2.1 Subjective (self-assessed) dietary quality

First insights about the dietary quality of the sample can be obtained from the subjective self-assessment that was conducted in the frames of NHANES 2005-2006. In the following sections, these results can be compared and verified by more objective indicators of dietary quality.

The respondents were asked to evaluate their diet on the scale from 1 “excellent”, 2 “very good”, 3 “good”, 4 “fair” to 5 “poor”. The results show that about 40% of the respondents assess their diet as “good” and 29% believe it is excellent/very good (Table 5). Around 24% of individuals believe their diet is fair and 7% think it is poor. Furthermore, females and adults with college education and above tended to give better marks to their diet (i.e. excellent or very good), while males and persons with lower education significantly more often stated to have lower nutritional quality (i.e., fair or poor).

In addition, about 32% of adults reported eating out “sometimes” and about 30% have food away from home “often” or “very often”. Eating away from home showed to be associated with an increased risk of obesity (MA *et al.*, 2003).

Table 5 Subjective dietary quality indicators (N=2505) [a)]

Description	%	SE
Own diet evaluation		
Excellent	7.21	0.93
Very good	21.76	1.12
Good	39.84	1.22
Fair	23.96	1.25
Poor	7.24	0.59
Eating out		
Never/seldom	13.44	0.96
Sometimes	32.12	2.04
Often/very often	30.23	1.25

[a)] Data are weighted to be representative of the population.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

5.2.2 Energy supply and its structure

Fats, carbohydrates, and protein are three macronutrients that provide energy to human body. A right balance of these elements is very important. Table 6 shows the structure of energy supply in the studied population. The figures are derived based on the amounts of nutrients as reported by the respondents in two 24-h recalls.

The U.S. Department of Health and Human Services and U.S. Department of Agriculture (USDA and HHS, 2010) list the nutritional goals for the population in the “Dietary

Guidelines for Americans 2010" (DGA). To evaluate the conformance of actual intakes among adults with the recommendations, two references are used: a) Acceptable Macronutrient Distribution Ranges for adults (AMDR) of the Institute of Medicine of the U.S. National Academy of Sciences (INSTITUTE of MEDICINE, 2002) presented in the DGA 2005 and 2010 and b) USDA Food Guide Plan for healthy eating based on 2,000-calorie diet available in the Dietary Guidelines for Americans 2005 (HHS and USDA, 2005). The first reference shows the ranges of macronutrients associated with reduced risk of chronic diseases, while providing sufficient amounts of nutrients. The other provides an example for healthy eating in terms of adequate intakes of these three main macronutrients.

Table 6 Structure of recommended and actual energy supply in the sample (N=2505) [a) b)]

	Recommended supply [c)]	Supply in the sample		
		All	Females (n=1256)	Males (n=1249)
	%			
Total fat	29	33.82 (0.26)	34.17 (0.33)	34.70 (0.33)
Carbohydrates	55	49.07 (0.35)	49.31 (0.42)	48.83 (0.44)
Protein	18	16.48 (0.16)	16.52 (0.19)	16.47 (0.16)

[a)] Data are weighted to be representative of the population. [b)] Standard errors are in parentheses. [c)] The references of the recommendations is the USDA Food Guide Plan for healthy eating based on 2,000-calorie diet outlined in the Dietary Guidelines for Americans 2005 (HHS and USDA, 2005).
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

Average daily calorie intake in the whole sample is estimated to be 2236 kcal, while the highest intake amounted to 6575 kcal per day. Women and men consumed on average about 1790 and 2686 kcal respectively. This is close to the estimated average needs of about 2000 and 2600 kcal for moderately active women and men of 19 to 50 years old, respectively (USDA and HHS, 2010)[19]. However, the sources of the consumed calories are not optimal. As shown in Table 6 adults tend to overconsume fat and underconsume carbohydrates and protein. Such inadequacy may lead to negative health consequences. According to scientific evidence, a high fat intake contributes to high blood cholesterol levels and therefore to the risk of cardiovascular diseases. On the other hand, the DGA stresses a positive health impact of the foods rich in fibre (HHS and USDA, 2005). As seen from Table 6, adults do not consume enough carbohydrates. Additionally, an adequate intake of protein is important due to its role in delivery of essential amino acids needed for body health and growth. The actual protein supply in the sample showed to be somewhat lower than the recommended amounts.

[19] Based on the estimated calorie needs per day by age, gender, and physical activity level provided in the Dietary Guidelines for Americans (USDA and HHS, 2010). Estimates used are relevant for moderately active men and women of 19 to 50 years old (see Table A1 in Appendix A).

5.2.3 Nutrient density and Index of Nutritional Quality

To examine adequacy of the diet in terms of consumption of important nutrients within energy needs, an index of nutritional quality (INQ) is applied. INQ is defined as ratio of nutrient density and the amount of this nutrient recommended for the maintenance of good health within a given calorie need (e.g., DREWNOWSKI, 2005). The *Dietary Guidelines for Americans* (HHS and USDA, 2005) based on evidence of public health problems stress that intake of the following nutrients may be of a particular concern for the adults: calcium, potassium, fibre, magnesium, and vitamins A, C, and E. At the same time, attention is drawn to fats, cholesterol, sugar, and salt that are generally overconsumed by Americans. Therefore, this part of the study considers supply of the above mentioned nutrients. Nutrient densities of the selected nutrients are calculated based on the two-day average intakes of a particular nutrient and are presented here either as a proportion of energy or as intake per 1000 calories (Table 7).

According to the results, the nutritional quality of adults' diets is low with respect to the considered nutrients. Thus, both genders tend to overconsume undesirable nutrients (e.g., fats, sodium) and underconsume desirable elements (e.g., fibre, vitamins). Especially high non-compliance with the recommendations is revealed for saturated fatty acids, sugar and sodium. Although women reported somewhat higher intakes of important micronutrients, these are still below the recommended amounts.

Table 7 Nutrient densities in the diet of adults from NHANES 2005-2006 (N=2505) a) b)

	Reference c)	All N=2505	Male n=1256	Female n=1259	*P*-value d)
Total fat, %	29	33.82 (0.26)	33.76 (0.32)	33.88 (0.34)	0.768
Total saturated fatty acids, %	7.8	11.23 (0.10)	11.24 (0.09)	11.33 (0.15)	0.477
Total sugar, %	25	49.61 (0.77)	48.40 (0.99)	50.80 (1.00)	0.059
Cholesterol, mg/1000 kcal	115	136.33 (2.78)	137.39 (3.07)	135.28 (3.05)	0.426
Sodium, mg/1000 kcal	890	1657.82 (19.87)	1615.60 (21.20)	1699.65 (25.00)	0.003
Dietary fibre, g/1000 kcal	15.5	7.49 (0.15)	6.87 (0.17)	8.09 (0.19)	0.000
Calcium, mg/1000 kcal	658	446.39 (5.92)	415.27 (7.20)	477.22 (7.76)	0.000
Magnesium, mg/1000 kcal	190	143.73 (1.74)	135.07 (1.81)	152.31 (2.43)	0.000
Potassium, mg/1000 kcal	2022	1296.45 (15.14)	1219.05 (16.34)	1373.14 (21.75)	0.000
Vitamin A, mg/1000 kcal	526	301.88 (6.26)	265.81 (9.24)	337.57 (10.40)	0.000
Vitamin C, mg/1000 kcal	77.5	43.63 (1.43)	38.57 (1.59)	48.64 (2.15)	0.001

a) Data are weighted to be representative of the population. b) Standard errors are in parentheses. c) Reference ranges are taken from USDA Dietary Guidelines and Food Guide Plan for Healthy Eating based on 2,000-calorie diet outlined in the Dietary Guidelines for Americans (HHS and USDA, 2005) (here recalculated per 1,000 kcal). d) *P*-value between gender groups (Wald F-test or chi-square test).
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

Further, based on the data presented in Table 7, INQs were calculated for the key nutrients[20]. The nutrient levels from the USDA Food Guide Eating Plan (Appendix 1), were used as a reference for computation. Figure 5 demonstrates a low compliance with the guidelines amongst adults. Both male and female respondents overconsume the undesirable nutrients (e.g., fat, sugar, sodium) and underconsume vitamins and important micronutrients.

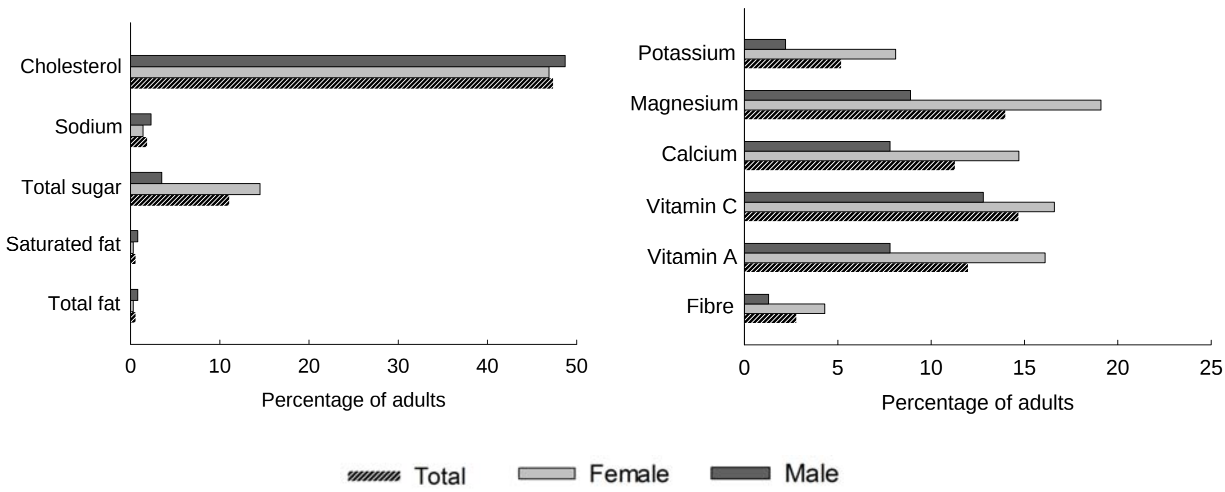

Figure 5 Share of adults from NHANES 2005-06 who comply with recommendations as measured by INQ of eleven key nutrients

Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

5.2.4 Biological markers of nutritional quality

The study makes use of the advantage of NHANES in respect to availability of data from analyses of blood related to nutritional status, which are collected under laboratory conditions. To verify the results from the previous section (derived from dietary data) the nutritional quality is assessed based on the findings from blood tests. Levels of cholesterol, glucose, triglyceride, sodium and adequacy of the intake of Vitamins D, B_{12} and C are investigated as critical indicators of the individual's nutritional and health status (WALTER *et al.* 2008; NEUHOUSER *et al.*, 2003; OVESEN and BOEING, 2002, KANT, 2002).

Due to the fact that laboratory tests were performed in frames of NHANES only for a subsample of adults, the sample size used in the following estimations varies between 1012 and 1049 persons. Additionally, those adults who were not fasting before these measurements were

[20] INQ=nutrient density/USDA Food Guide for this nutrient per 1000 kcal; where INQ<1 is desirable for fats, total sugar, sodium and cholesterol; INQ>1 is aimed for fiber, vitamins and microelements.

excluded due to the fact that non-fasting may change a level of some elements in the blood (e.g., cholesterol).

Table 8 Biological markers of nutritional status of adults from NHANES 2005-2006 (N=2505) [a) b)]

	Reference [c)]	All	Male	Female	*P*-value [d)]
Total cholesterol, mg/dL	<200	197.26 (2.38)	196.94 (2.33)	197.57 (3.16)	0.831
HDL-cholesterol, mg/dL	>60	54.81 (0.43)	49.34 (0.64)	60.16 (0.72)	0.000
LDL-cholesterol, mg/dL	<100	115.45 (2.04)	117.12 (1.76)	113.87 (2.94)	0.237
Triglycerides, mg/dL	<150	127.28 (4.95)	144.83 (7.38)	110.10 (5.56)	0.001
Glucose, mg/dL	60-110	96.25 (1.05)	97.47 (1.17)	95.06 (1.75)	0.276
Sodium, mmol/L	136–144	138.90 (0.16)	138.97 (0.16)	138.83 (0.19)	0.339
Vitamin B_{12}, pg/mL	165-1600	551.19 (33.35)	522.38 (15.23)	579.33 (62.34)	0.369
Vitamin D, ng/mL	10-40	21.79 (0.58)	21.53 (0.55)	22.04 (0.78)	0.475
Vitamin C, mg/dL	0.02-2.16	0.87 (0.02)	0.82 (0.02)	0.93 (0.03)	0.003

[a)] Data are weighted to be representative of the population. Due to the fact that laboratory tests are performed in NHANES for a subsample of adults, the sample size varies between 1012 and 1049 persons. Sample weights for this subsample are used. [b)] Standard errors are in parentheses. [c)] Reference ranges are taken from the Laboratory Procedure Manuals of the Centres of Disease Control and Prevention (CDC) for glucose, sodium, folate, Vitamin B_{12}, D, and C (CDC, 2007a-e) and the standards of the National Cholesterol Education Program for cholesterol and triglyceride of the National Institutes of Health (NIH, 2002). The ranges are valid for both sexes and all ages of individuals with fasting status. [d)] *P*-value between gender groups (Wald F-test).
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

The tendencies revealed in analysis of dietary data were generally confirmed. Based on biological specimens, adults' total cholesterol level is close to the normal on average. However, further analysis showed that about 45% of adults had an elevated blood cholesterol confirming earlier findings. Further, the majority of the respondents had low concentration of HDL-cholesterol ("good cholesterol"), which showed to be inversely correlated with coronary heart diseases, whereas the concentration of LDL-cholesterol ("bad" cholesterol) was with too high values outside of the normal range. Lowering the LDL-cholesterol is a primary target for prevention of heart diseases (NIH, 2002).

Besides a special inadequacy of HDL-cholesterol among men, this group is also characterised by a significantly higher level of triglycerides in comparison to women. High concentration of blood fats is positively associated with incidence of heart diseases. Importantly, the level of triglycerides may be elevated not only due to the particular diet, but also due to alcohol and cigarettes consumption, physical inactivity, overweight and genetic factors (NIH, 2002).

Both genders have high blood glucose levels. On average the values reached the upper borderline of normal concentration. In contrast to the finding from the dietary data, blood examination showed an acceptable level of sodium. An explanation of this result could be an overestimation of sodium intake based on self-reported dietary data.

Vitamins B_{12}, D and C play an important role in the prevention of a number of diseases including cancer and heart diseases. The concentration of these elements in blood of the adults showed to be in normal ranges. However, in the case of Vitamin B_{12} it was rather close to the lower borderline indicating that the majority of adults do not consume sufficient amounts of this vitamin. Similarly, the analysis of dietary data showed that intake of vitamin B_{12} is two times lower than corresponding recommendation (not presented in Table 6).

While comparing the results from Tables 7 and 8, the potential contribution of dietary supplements to the overall blood measurements is to be borne in mind, which might have impacted a somewhat higher compliance with recommendations for micronutrients as based on laboratory tests. Consumption of dietary supplements is quite common in the USA with over 50% of the adults in NHANES 2005-2006 stating regular supplements intake. An especially large contribution to vitamin C intake is due to fortified orange juice, the consumption of which, as showed in the following section, is an important compound of adults' diet.

5.2.5 Fruit and vegetable consumption

The dietary guidelines for Americans (HHS and USDA, 2005) provide recommendations for nutrients as well as food group intakes. Moderate consumption of fats, oils and sweets is emphasised, and higher intakes of fruits and vegetables and grains are promoted. F&V intake is believed to be an indicator of healthy nutrition, which is due to scientific evidence on their preventive effect in relation to a number of diseases. This section investigates F&V consumption among adults in the USA. Special focus is given to the degree of processing of consumed F&V. The full discussion of the findings, which are presented here in brief, can be found in DEMYDAS (2011).

A number of studies have investigated F&V consumption in the population and especially its correspondence to the existing recommendations such as the "5-a-day" message[21] (CASAGRANDE *et al.*, 2007; SERDULA *et al.*, 2004; DONG and LIN, 2009; KREBS-SMITH *et al.*, 1995). Usually the intakes of F&V are considered in one category or differentiated by botanical characteristics, e.g., berries, citrus fruits, legumes or dark green vegetables. However, the way in which this produce is prepared and in what form it is incorporated into the diet may also contribute to the diet healthiness. For instance, deep-fat frying of some vegetables or fruits as well as serving them with high-fat dressings or sauces greatly increases the total energy and fat

[21] The USDA Food Guide Pyramid (FGP) encourages Americans to eat 2 to 4 servings of fruit and 3 to 5 servings of vegetables daily as well as to have a variety in consumption (USDA, 2005).

of the consumed dish (LIN and MENTZER MORRISON, 2002). High content of sugar and salt are typically found in canned F&V. Further, juices provide much less satiety than when F&V are eaten as a whole.

An advantage of the NHANES dataset, which allows conducting this analysis, is unique and very detailed information about the consumed F&V including their amounts, form (i.e. whole, juice), processing degree (i.e. cooked, canned) and additional ingredients accompanying an intake. Data are available for two non-consecutive days and is collected in frames of 24 h dietary recalls. The raw dataset includes all F&V consumed by each individual during these two days. They are marked with unique codes of the Food and Nutrient Database for Dietary Studies (HHS and CDC, 2005a). Using these codes and the respective descriptions of F&V consumed, the reported intakes were aggregated by the author into seven subgroups indicating degree of their processing. Created subgroups are showed in Table 9.

Table 9 F&V classification by degree of processing

Groups	Subgroups	Examples of foods in subgroup classification
Fruits		
	Raw	Orange; papaya; plum; fruit salad without dressing.
	Juice	Apple juice, fresh; lemon juice, bottled; tangerine juice canned.
	Canned/frozen/ dried/desserts	Grapefruit, canned or frozen, in light syrup; apricot, cooked or canned, in heavy syrup; cherry pie filling; mango, pickled; blackberries, frozen; banana chips; pear, dried, cooked with sugar; fruit salad with salad dressing or mayonnaise.
Vegetables		
	Raw	Broccoli, raw; spinach salad, no dressing; cucumber salad with creamy dressing; artichoke salad in oil.
	Cooked	Beet greens, cooked, fat not added in cooking; tomatoes, from fresh, broiled; mushrooms, stuffed; white potato, baked, peel not eaten; green plantains, boiled.
	In mixed dishes	Vegetable combinations, cooked, with pasta; carrots, tomato beef rice soup, prepared with water; potato from Puerto Rican beef stew, with gravy; corn, cooked, from fresh, with cream sauce, made with milk; bean and rice soup.
	Fried	Potato pancake; eggplant, batter-dipped, fried; white potato, french fries, from frozen, deep fried.

Source: DEMYDAS (2011). Refer to this study for a more detailed explanation of creation of the subgroups.

As explained before, the study sample included non-pregnant and non-lactating adults of 20-59 years of age with reliable two-day dietary information (2505 persons). Out of them, 2444 individuals reported consumption of F&V during the analysed period.

On average, adults consumed 359 g of F&V per day, taking fruit juice into account, and 285 g/person if juice is excluded from calculation (Table 10). This is below the WHO recommendations of a minimum of 400 g per day[22].

[22] The WHO recommendation of minimum 400g of F&V per day excludes potatoes and other starchy produce.

Women have somewhat higher total F&V intake than men. Fruit juice with 237 g/person is the largest contributor to the total fruit consumption, followed by raw fruits (139 g/person). Female respondents report significantly higher intake of raw fruits in comparison to males ($p<0.01$).

As to vegetables, they are mostly consumed in cooked (105 g/person) or in raw form (91 g/person). Females had a significantly higher density of vegetables eaten in all preparation forms in their diet (i.e. raw, cooked and vegetables from mixed dishes) with an exception of fried vegetables.

Table 10 F&V intakes by degree of processing in the sample of adults from NHANES 2005-2006 (n=2444) [a) b)]

	Total intakes		Intakes per 1000 kcal by gender [c)]				
	All		Male		Female		
	Mean	SE	Mean	SE	Mean	SE	*P*-value [d)]
Fruits							
Raw	139.3	6.5	60.65	4.42	80.59	5.05	0.005
Juice	236.5	8.9	114.39	5.33	114.10	16.71	0.976
Canned/frozen/dried/ desserts	56.9	5.0	25.88	4.30	27.25	2.68	0.811
Vegetables							
Raw	90.9	3.6	34.66	2.18	57.33	2.49	0.000
Cooked	105.2	4.1	46.09	2.19	55.35	2.08	0.010
In mixed dishes	79.7	4.3	31.07	1.74	45.66	3.31	0.000
Fried	52.7	1.8	23.01	1.04	22.28	0.90	0.577
Total F&V	359.4	10.6	105.09	6.34	115.68	6.83	0.293
Total F&V, excluding fruit juice (n=2420)	285.1	8.9	59.94	4.30	79.46	4.87	0.003

[a)]Data are weighted to be representative of the population. [b)] Multiple answers were possible; persons who reported no consumption of a particular subgroup were not considered during mean calculation. [c)]To compare the F&V consumption between the male and female subsample, the intakes per 1000 kcal were considered. [d)] *P*-value among groups (two-sided t-test). Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

The variety of F&V intakes in the whole sample in terms of preparation methods is showed in Figure 6. Special attention is drawn to the fact that about 20 % of the interviewees incorporated fruits into their diets only in the form of juice, which shows its importance in the adults' diet.

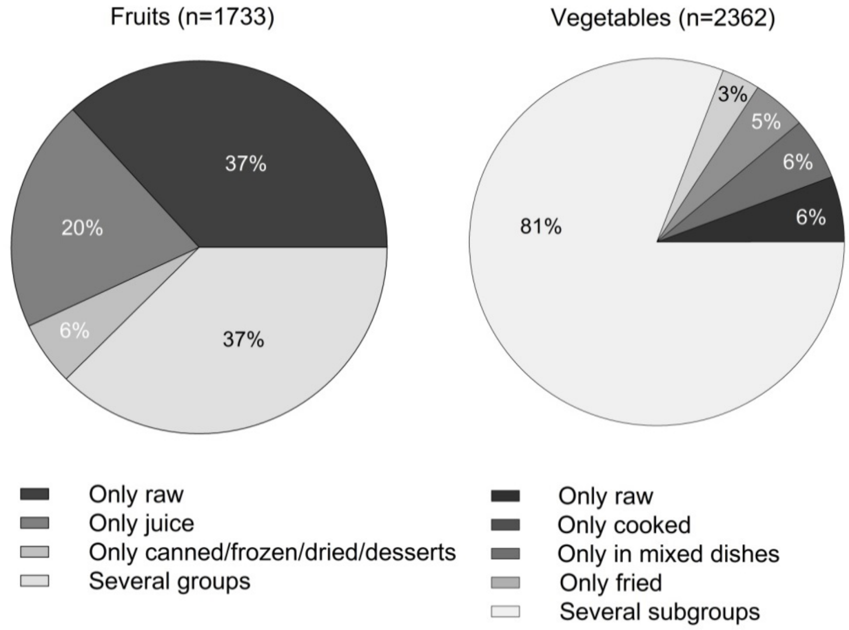

Figure 6 Share of adults consuming exclusively one fruit/vegetable subgroup (n=2444)

Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007). The Figure is also presented in DEMYDAS (2011).

In DEMYDAS (2011), the analysis is followed by an identification of consumer segments with similar F&V intake patterns in respect to the degree of processing of the F&V. The created F&V subgroups (Table 9) are used as input variables into cluster analysis [23].

Briefly, three adult segments with distinctly different F&V intake patterns were identified and typified as *"Low-intake F&V consumers"* (74 % of respondents), "*Intensive fruit juice consumers"* (13 %) and *"Consumers of healthier F&V options"* (13 %). The derived groups differed in terms of their F&V consumption patterns as well as socio-demographic and behavioural characteristics.

The study discusses that while the majority of adults consume very low amounts of F&V (occasional intake as a compound of another dish, e.g., salad leaf in a sandwich), a specific part of the population intakes F&V predominantly in the form of juice. Although the diet of these *"Intensive fruit juice consumers"* showed a higher adequacy in terms of vitamin C intake, it was highest across the segments in terms of sugar. Thereby, a small share of the respondents (13%) was found to have higher F&V intakes and at the same time to consume them in healthier preparation forms. Although all three consumer segments showed to have a low dietary quality, the latter cluster had a somewhat better nutritional profile in comparison to the others. A contribution of F&V intake to this finding was discussed. Finally, the study raises

[23] Cluster analysis presents a methodological approach widely used for identification of dietary patterns as it groups individuals with similar characteristics into homogeneous, mutually exclusive segments (POPKIN *et al.*, 2005; WIRFÄLT *et al.*, 1999; BAILEY *et al.*, 2006).

a discussion about a need for more attention to the way F&V are incorporated into the diet and in more specific F&V promotion messages that would include clear advisory statements on healthier preparation methods.

To summarise, this chapter assessed the dietary quality of the American adult population, who participated in the NHANES 2005-2006. A self-evaluation showed that the majority of individuals seem to be satisfied with their own diet. About 70% of the respondents consider their diet to be excellent, very good or good. However, a number of dietary indicators employed at the next steps indicated the contrary, i.e., a low nutritional status of the majority of adults. Thus, the estimations based on the self-reported diet showed an inconsistency between recommendations and actual intakes of fats, sodium and cholesterol as well as important micronutrients such as minerals and vitamins. These negative trends were further confirmed by analysing the data obtained from laboratory blood tests. Here, a contribution of supplements intake to the diet was revealed. Such intakes are typical for US adults, however, as stressed in the dietary guidelines a primary source of nutrients should be food, not supplements (HHS and USDA, 2005). The chapter concludes with the analysis of F&V consumption among adults, which is showed to be generally lower than recommended. Moreover, an extreme importance of fruit juice was revealed with about 20% of the sample reporting consumption of fruits only in the form of juice on both recall days. Therefore, there is a need for attention to the ways F&V are incorporated into the diet and more clear recommendations.

5.3 A model of cardiovascular health and its determinants

5.3.1 Theoretical specification of the model

The household production theory outlined in chapter 3.3 provides the theoretical basis for this study. For the empirical estimation, the SEM is chosen due to the fact that it offers a number of features particularly important for the purpose of the actual study (see chapter 4.3 for details). The most important of them are:

- Possibility to specify and test complex model interrelations, including effects between several endogenous variables.
- Simultaneous estimation of all relationships by a full-information approach.
- Testing of direct and indirect effects among model variables.

- Possibility to model the central concept of the model, health, as an unobservable latent variable and to test its appropriateness.
- Testing of the measurement model of a latent construct simultaneously with the structural model.
- Possibility to test reverse causality.

Taking into account the theoretical background and outlined methodological aspects, this study proposes and tests a health production model of cardiovascular health, which aims to take into account a) the demand relationships related to the individual's choice of health inputs constrained by input prices, available resources and individuals' personal characteristics (the reduced-form input demand functions) and b) the relationship among the chosen inputs and health outcome in the form of a health production function[24].

The present study is an attempt to specify a full structural model incorporating these two stages simultaneously, although some simplifying assumptions are necessary. First, in the absence of longitudinal data, the potential long-term effects of some inputs are not accounted for. Thus, a one-period model is constructed. Second, as in previous studies, the estimation is confronted with the unavailability of information on exogenous market prices and wage rates that should enter the demand functions of health inputs, but had to be omitted here[25]. It should be noted that prices are often assumed to be fixed when cross-sectional data is used (BLAYLOCK *et al*., 1999).

Taking the theoretical model of BECKER (1965) as a theoretical background and considering its empirical applications (e.g., in MAZZOCCHI *et al*., 2009; CHEN *et al*., 2002), the stock of health is assumed to be produced according to the following health production function:

(4.12) $H = H(F, Q, S, A, P, M, W, x_i), \qquad i=1, \dots ,7.$

The above function corresponds to the general representation of health production function in equation 3.9.

Health *H* is related to the food intake *F* as well as nutritional quality of the consumed foods *Q*. Further consumption items, such as cigarettes *S*, alcohol *A*, physical activity *P*, and

---

[24] The discussion presented in this section can be found in a somewhat more concise form in DEMYDAS (2013).

[25] BECKER (1965) discusses a "full-income" constraint that combines the income and time constraints. The income constraint presents a money income equal to the sum of earnings from wages and non-labour income, while time constraint is a sum of all time inputs into production of commodities including time for work and leisure. Due to data limitations, input prices, individual wages, and time input variables had to be omitted from estimations of demand equations. Therefore, the model proposed here incorporates only the information on household money income that is treated here as exogenous variable.

medical care M may also have a direct health impact. It is expected that weight W is related to the person's health state as overweight and obesity have shown an association with a number of adverse health conditions including CVDs. Finally, x_i is a vector of individual exogenous characteristics such as age, age^2, gender, race, education, household size and income. A person's age reflects the health depreciation function (direct health effect) and induces behavioural changes over the lifetime, e.g., decreasing physical activity (indirect relation). Household size represents "possible scale and congestion effects" (BEHRMAN and DEOLALIKAR, 1989: 641) and income is connected with the affordability of inputs. A person's exogenous characteristics are believed to affect the demand for health inputs as well as the efficiency with which individual's health is produced (CHEN *et al.,* 2002; VARIYAM, 2003). More detailed discussion of model variables is given in section 5.3.2.

Each person is believed to have a unique health production function. Moreover, the chosen inputs may either improve one's health (e.g., nutritious food, medicines and exercising) or reduce it (e.g., smoking). Individuals may also have very different perceptions about the impact of these inputs to their health that may also affect their choices.

Special focus in the health production model is given to the endogenous variable of weight. It is seen as an intermediate health input that is affected by the amount of food consumed F, quality of the diet Q, physical activity P, smoking S[26], and exogenous characteristics x_i:

(4.13) $W = W(F, Q, P, S, x_i)$

Further, dietary quality Q is hypothesised to be affected by the total amount of the consumed food F, by knowledge of nutrition-related aspects K and individual exogenous characteristics x_i:

(4.14) $Q = Q(F, K, x_i)$

Importantly, nutritional knowledge K is specified as endogenous too. It is believed to play an intermediary role in the relation between education and diet. Education may induce better knowledge of nutrition-related aspects and therefore contribute to a more balanced diet indirectly.

The health production function (4.12) is estimated together with equations of weight (4.13) and dietary quality (4.14) as well as the demand functions of the other health inputs K, F, S, A, P, and M. The latter are modelled as functions of an individual's observed personal

[26] E.g., CHOU *et al.* (2004), FLEGAL *et al.* (1995). HU *et al.* (2002) showed a negative interrelation between weight and smoking.

characteristics x_i. Furthermore, nutritional knowledge K enters the equation of the overall overall energy intake F:

(4.15) $K=K(x_i), F=F(K, x_i), S=S(x_i); A=A(x_i); P=P(x_i); M=M(x_i)$

Estimation of the both stages (health production and demand for inputs) simultaneously has been performed in economic studies before (e.g., CHEN *et al.*, 2002). This study delivers several empirical developments and additional insights.

First, as discussed before, cardiovascular health will be presented as a *latent variable* including tests of its appropriateness. Second, the model suggests additional *links among endogenous health behaviours* (equations 4.13-4.15). Thus exercising may influence a health state directly as well as indirectly through weight, i.e., exercise lowers weight, thus lowering the health risks. Smoking has been shown not only to be directly and negatively related to health, but also to have an association with a person's weight (CHOU *et al.*, 2004). Moreover, not only could smoking affect health but also a *feedback relation* seems to be plausible, where a person would adjust his smoking behaviour in case of a worsening of health status. Such potential reverse causality between health and its determinants adds further complexity. GROSSMAN (2004) discusses the relation between health and education, which can also have a reverse direction with better health causing more schooling. Similarly, overconsumption may lead in the long run to weight increase; however, overweight may also affect food choices. At the same time, it can also be that a person would adjust his own consumption behaviour depending on the actual weight status or his desired body weight (e.g., reduce energy intake). This idea can be found in other studies. RASHAD, who tested an impact of caloric intake on BMI, stresses "[…] caloric intake not only influences BMI but is also likely to be influenced by BMI, especially if caloric intake is habituating" (RASHAD, 2006: 278).

Although SEM methodology allows incorporation of such types of relations (direct, indirect, reciprocal), due to the potential complexity, this study focuses on the selected specific relationships in the health production model (as presented in the equations above). Another reason for not testing reciprocal relations is the cross-sectional character of the data. Reciprocal causality should be investigated based on longitudinal data as behaviours within the same period have weaker effects than those accumulated over longer periods. BEHRMAN and DEOLALIKAR (1989: 642) stress that "[…] it is important to realise that our knowledge of technical relations determining health and the nature of interactions and lags are quite primitive".

In addition to the simultaneous modelling of two stages of health production (inputs demand and production function) the study provides an extension of the empirical estimation of the health production model by specifying and testing several interrelations between health behaviours. Thereby, all hypothesised relations are estimated simultaneously with consideration of all available information due to the application of the full information estimation procedure.

The *full structural model* to be tested in this study can be summarised as following:

(4.16) $H = H(F, Q, S, A, P, M, W, x_i), \qquad i=1, \dots ,7$

(4.17) $W = W(F, Q, P, S, x_i)$

(4.18) $Q = Q(F, K, x_i),$

(4.19) $F=F(K, x_i),$

(4.20) $K=K(x_i), Q=Q(x_i); S=S(x_i); A=A(x_i); P=P(x_i); M=M(x_i).$

The first equation is a production function of health, whereas the next three equations show the hypothesised relationships among endogenous health inputs. Equations (4.20) are the demand functions relating demand for health inputs to exogenous personal characteristics that include income. Further determinants such as prices and wage rates had to be omitted.

5.3.2 Definition of model variables and expected signs

5.3.2.1 Health status

A variety of health status indicators have been used in the empirical investigations (see chapter 2.2 for further details). As discussed in section 4.3, studies employing a SEM estimation approach use several health indicators to form a latent variable "health status". These measures might include, e.g., self-assessed health status, a number of chronic diseases and additional limitations (GUIFFRIDA *et al.*, 2005; KIISKINEN, 2003; HÄKKINEN, 1991). To form latent variables, they may be chosen a posteriori via exploratory factor analysis procedure (e.g., KIISKINEN, 2003), or a priori that is followed by confirmatory factor analysis to test whether the factor (latent construct) is meaningful (e.g., GUIFFRIDA *et al.*, 2005).

In the frames of NHANES a number of health status indicators are collected including respondents' self-reports about own health and related problems as well as the measures collected by trained health technicians. Table 11 shows an overview of the selected variables.

Table 11 Summary statistics of the selected health indicators [a)]

Description of variables	N	Mean	SE
Self-assessed health (max. 5): 1=excellent, 2=very good, 3=good, 4=fair, 5=poor	2361	2.57	0.04
Systolic blood pressure, mmHg	2416	120.12	0.49
Diastolic blood pressure, mmHg	2416	72.21	0.35
Total cholesterol, mg/dL	2380	198.17	1.23
Direct HDL-cholesterol, mg/dL	2380	53.50	0.40
LDL-cholesterol, mg/dL	1012	115.45	2.04
Triglyceride, mg/dL	1044	139.71	4.47
# of days when physical health was not good during the past 30 days	2358	3.18	0.17
# of days when mental health was not good during the past 30 days	2356	3.91	0.20
# of inactive days due to physical or mental days during the past 30 days [b)]	2356	1.63	0.18
# of working days missed during the past year days due to illness	2104	5.77	0.78

[a)] Data are weighted to be representative of the population. [b)] During the past 30 days, for about how many days did poor physical or mental health keep you from doing your usual activities, such as self-care, work, school or recreation? During the past 12 months, that is since of last year, about how many days did you miss work at a job or business because of an illness or injury {do not include maternity leave}?
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

As discussed before, an actual concern of public health in the USA is the high prevalence of CVDs among the adult population. The health state in this study is related to the risk of this disease. It is presented as a latent variable measured by *diastolic blood pressure, systolic blood pressure, and total cholesterol level*. These are important indicators of diverse health risks, in particular of CVDs, and have been used previously (KENKEL, 1995; MAZOCCHI and TRAILL, 2008; CHEN *et al.*, 2002).

High blood pressure is defined as systolic blood pressure ≥ 140 mm Hg and or diastolic blood pressure of ≥90 mm Hg (LLOYD-JONES, 2010). Although the population averages estimated for the adults and reported in Table 11 are in normal ranges, about 11% of the sample had high systolic BP and 8% had high diastolic BP. Moreover, 45% of the sample had elevated total cholesterol level (≥200 mg/dL), 17% had too low HDL cholesterol (≤40 mg/dL) and 32% were diagnosed with too high LDL-cholesterol level (≥130 mg/dL) (normal ranges for these variables are summarised in Appendix B, Table B1). Thereby, about 57% of the respondents reported a family history of 1 to 2 chronic diseases related to the heart (out of 4 considered).

5.3.2.2 Dietary quality

Diet is a significant factor in the risk of heart disease, stroke, certain types of cancer, obesity, diabetes and other leading chronic diseases. Analysis of dietary quality of the American adult population performed in Section 5.2 suggested a poor quality of diet among adult Americans. This is in line with the findings from the previous NHANES, which also indicated that food consumption habits of the majority of Americans needs substantial improvement. E.g., the analysis based on the data from the NHANES 2003-2004 (ERVIN, 2011) showed the HEI-2005 total score for adults of 20 years and over to be at the level of 57.2 out of 100 indicating a need in improvement.

As discussed before, a number of indicators of dietary quality exist. The actual model of cardiovascular health uses F&V intake as the measure of dietary quality. This is due to rich scientific evidence about the preventive effect of F&V against cardiovascular diseases (WHO, 2005; VAN DUYN and PIVONKA, 2000). Empirical evidence of this relationship can be found in HUFFMAN *et al.* (2006), who showed a negative link between higher intake of F&V and prevalence of cardiovascular diseases in 18 OECD countries using panel data for the years 1971 to 2001.

In the previous section the importance of fruit juice intake in the total F&V intake was demonstrated (Table 10) as well as a negative impact that it might have (e.g., sugar over-consumption). Therefore, the presented model incorporates F&V intake excluding fruit juice as an indicator of dietary quality. Higher F&V consumption is hypothesised to contribute to better health status, i.e., to lower blood pressure and cholesterol level.

5.3.2.3 Weight

Overweight is a major risk factor for coronary heart disease, stroke, some cancers, diabetes, and hypertension (WILSON *et al.*, 2002). The *body mass index* (BMI) (kg)/height (m^2)) is a widely used marker of obesity and predictor of coronary heart disease risk. Adults (aged 18 years or older) with a BMI of 25 or more are considered to be at risk for premature death and disability, while the higher the BMI is, the higher the health risks (ROGER *et al.*, 2012). *Waist circumference* is another obesity indicator that is a measure of abdominal visceral adipose (BUCHHOLZ and BUGARESTI, 2005). Men with a waist measurement greater than 102 cm and women with a measure of over 88 cm are considered to be in a risk group. The majority of the studies suggest that waist circumference is a better predictor of cardiovascular disease compared to BMI or waist-to-hip ratio (DOBBELSTEYN *et al.*, 2001; BUCHHOLZ and BUGARESTI, 2005). Therefore, waist circumference serves in the model as a *weight* indicator. Further, weight is assumed to be an intermediate health determinant, which is affected by personal exogenous characteristics and other lifestyles (e.g., diet, exercising), and is a determinant of health status.

Following the discussion by MAZZOCCHI and TRAILL (2008), the study aims to test whether a higher weight still has additional negative health impacts after accounting for effects of other unhealthy behaviours such as low diet quality or physical activity. MAZZOCCHI and

TRAILL (2008) argue that if the relationship between higher weight and poorer health can not be confirmed in the presence of other unhealthy lifestyles (and accounting for them), the health policy should focus predominantly on promotion of other healthier behaviours rather than body weight reduction. Table 12 presents a summary of weight indicators available in NHANES data.

Table 12 Summary statistics of the weight measurements [a)]

Description of variables	N	Mean/%	SE
BMI [b)] (self-reported)	2405	28.18	0.33
BMI (measured)	2482	28.67	0.33
BMI by groups (%):	2482		
Underweight/normal (<24.99)	756	33.35	1.13
Overweight (25.00-29.99)	821	31.64	1.57
Obese (≥30.00)	905	35.01	1.92
Waist circumference (WC) (cm) (measured)	2444	96.89	0.83
Respondents with WC of normal range (%)	1240	51.53	2.07
Tried to lose weight in past year (%)	2173	44.32	1.13
Consider yourself to be (%):	2501		
overweight	1464	60.89	1.93
underweight	112	4.02	0.54
about right	925	35.13	1.74
Respondents who would like to weight (%):	2505		
more	186	6.43	0.49
less	1664	70.12	1.75
same	655	23.59	1.60

[a)] Data are weighted to be representative of the population. [b)] BMI refers to Body Mass Index; BMI=kg/m^2.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

According to the estimations, about 67% of US adults are overweight or obese as measured by the BMI and only about half of them have waist circumference lying in the normal range. About 61% of the respondents consider themselves to be overweight and the prevailing majority (70%) would like to have a lower weight. Around 44% reported an effort to lose weight during the preceding year.

Body weight was found to be related to a number of socio-economic and lifestyle characteristics of an individual. HUFFMAN and RIZOV (2010) in their study of the Russian population showed that higher education may contribute to lower obesity. RÖMLING and QAIM (2011) estimated a model of direct and indirect determinants of obesity in Indonesia and demonstrated a direct contribution of less healthy consumption patterns as well as low levels of leisure-time and work activities to higher body weight. Thereby, socioeconomic variables (income, education, and other household demographics) were showed to affect BMI indirectly via their impact on diet and physical activity. For further empirical examples of obesity determinants, see, e.g., the studies of RASHAD (2006) and RASHAD *et al.* (2006) presented in chapter 4.2. An association between less healthy diets and higher weight has been shown in the studies of HAVEMAN-NIES *et al.* (2001) and GREENWOOD *et al.* (2000).

5.3.2.4 Smoking

According to the American Heart Association (LLOYD-JONES *et al.*, 2010) *smoking* is associated with an increased risk of heart attack and stroke. Therefore, it is an important variable for the actual model. NHANES collects the data on cigarette use, history of use, age when started smoking, current use, smoking history during the past 30 days, number of cigarettes smoked and their brand as well as usage of other tobacco products (e.g., pipe, cigar). In this project we considered only cigarette smoking due to large amounts of missing data on the use of other tobacco products in the NHANES survey. The indicators of smoking behaviour are presented in Table 13.

Table 13 Summary statistics of the indicators of smoking [a)]

Description of variables	N	Mean/%	SE
Smoked at least 100 cigarettes in life (%)	2505	46.65	1.50
Current smokers (%)	2505	26.12	1.13
Average number of cigarettes per day during past 30 days [b)]	648	15.58	0.68
Average number of days smoked cigarettes during past 30 days [b)]	652	26.65	0.35

[a)] Data are weighted to be representative of the population. [b)] Averages are given for the sample of smokers.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

Around 47% of the adult population reported to have ever smoked, while 26% are classified as current smokers. On average, smokers consumed about 16 cigarettes per day and smoked on 27 days during the past month.

The reliability of self-reported data on cigarette smoking is questioned in the literature. It is argued that such information is likely to contain errors due to difficulties related to reporting accurate data on daily consumption as well as a typically negatively biased reporting in the presence of other household members during the interview (CLARK and ETILÉ, 2002). This may have contributed to the mixed results of empirical studies on direct linkages between smoking and health (HÄKKINEN, 1991; CONTOYANNIS and JONES, 2004; OH and SEO, 2001). BLAYLOCK and BLISARD (1992) estimated a model of simultaneous relationships between health status and smoking status of a person (current smoker, former smoker, and the number of cigarettes consumed). Being a current smoker was associated with lower health status, while the persons who had never smoked and ex-smokers had somewhat better health. At the same time, the health status showed no impact on the decisions on (non)smoking or quitting.

Smoking is related to other lifestyles and health behaviours and, therefore, may have an indirect health impact. The majority of previous studies have shown a negative link between smoking and body weight (RÖMLING and QAIM, 2011; AKBARTABARTOORI *et al.*, 2005; FLEGAL *et al.*, 1995; HU *et al.*, 2002; CHOU *et al.*, 2004). However, there are also studies that show a positive association between these variables (e.g., MAZZOCCHI and TRAILL, 2008; MOLARIUS *et al.*, 2001). AKBARTABARTOORI *et al.* (2005) discusses a number of factors that may have contributed to the existing inconsistencies. These are misreporting by respondents of their smoking habits as well as not accounting for other health-averse behaviours such as physical inactivity. Further, epidemiological studies have outlined that adult smokers tend to consume unhealthier diets comprised of higher energy-dense foods (DALLONGEVILLE *et al.*, 1998). This may with time result in a higher body weight. Moreover, health behaviours are not only interrelated but are also affected by sociodemographic factors (e.g., age and income).

Similar to previous work (e.g., CONTOYANNIS and JONES, 2004), we use a binary variable (smoker), which equals to 1 if a person reported smoking over the period of last 30 days and 0 if otherwise. A direct negative health impact of smoking on health is hypothesised and tested. To verify the results from previous studies, the effect of smoking on weight is modelled (expected to be negative). Furthermore, direct effects of personal exogenous characteristics on smoking are tested.

5.3.2.5 Alcohol consumption

While moderate alcohol consumption is believed to have a protective effect against CVDs and mortality overall (O'KEEFE et al., 2007), heavy drinking showed to be related to chronic diseases, including CVDs and cancer (USDA, 2005). Estimation results based on the NHANES 2005-06 data show that on average respondents had about two alcoholic drinks per day on the days when they consumed alcohol in the past 12 months. About one fifth of the sample reported consuming four drinks or more, i.e., the quantity that may have a negative health impact (Table 14).

Alcohol consumption has shown to be related to obesity and other negative behaviours. Thus, in the work of BRESLOW and SMOTHERS (2005), who used the pooled data from the 1997–2001 National Health Interview Surveys, those persons who reported consuming the highest quantity of alcohol per drinking day had the highest BMIs. CONTOYANNIS and JONES

(2004) found no significant effect of alcohol on the state of health, while in the study of KENKEL (1995) moderate alcohol consumption was beneficial to health.

Table 14 Summary statistics of the indicators of alcohol consumption [a)]

Description of variables	N	Mean/%	SE
Average number of alcoholic drinks per day during past year (%)	2356	2.23	0.10
0 drinks	628	23.56	1.99
1 drink	482	22.40	0.89
2 drinks	494	22.92	0.99
3 drinks	284	11.74	0.96
4 drinks and more	468	19.39	1.24

a) Data are weighted to be representative of the population.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

An average number of alcoholic drinks consumed per day during the past year is incorporated in the model as an indicator of alcohol intake. A negative health impact is assumed.

5.3.2.6 Physical activity

A large share of deaths from coronary heart disease, colon cancer, and type 2 diabetes in the United States are attributed to sedentary lifestyle and physical inactivity (BERLIN and COLDITZ, 1990; BLAIR and MORROW, 1998). The role of physical activity in reduction of a risk of many adverse health outcomes is stressed in the official guidelines for Americans (HHS, 2008). Scientific reviews show that active persons have lower rates of CVDs in comparison to less active individuals (e.g., SHIROMA and LEE, 2010). CONTOYANNIS and JONES, 2004; ERBSLAND *et al.*, 1994) discuss in their studies that overall, exercising reduces the rate of health depreciation and thus has a direct impact on the state of health.

Most studies in the systematic review by FOGELHOLM and KUKKONEN-HARJULA (2000) confirm an inverse association between physical activity and weight gain (in the long run). A higher level of physical activity in leisure time has been shown to be associated with a lower BMI in empirical work of RÖMLING and QAIM (2011). Thus, exercising has an indirect health effect via higher energy expenditure, which in the long run helps to control/reduce weight and is, therefore, beneficial to health.

NHANES collects information on three domains of physical activity: leisure time (e.g., doing sports or physically active hobbies), domestic (e.g., homework and yard work), and transport (e.g., walking or bicycling to get to the workplace). The dataset includes detailed information about all leisure time physical activities during the past 30 days: times a person did vigorous or leisure sport activity, its average duration in minutes, and intensity in metabolic equivalent (MET) score. In addition, NHANES 2005-06 included the physical activity monitor (PAM) survey component that recorded information on physical activity over 7 days by a special device (ActiGraph AM-7164) able to detect and record each movement of a person and its intensity, except such activities as swimming as the device is not waterproof (CDC, 2007). Because of the special emphasis on the benefits of leisure time physical activity and its relation to CVDs and obesity (HHS, 2008), this study focuses on these parameters.

In the USA, adults are advised to engage in at least 150 minutes of moderate-intensity or 75 minutes of vigorous leisure physical activity per week or combination of both[27]. To measure the activity intensity, MET scores are used[28]. Following these recommendations and depending on the activity's intensity, adults can achieve about 500 to 1000 MET-minutes of exercises per week that would have a substantial positive impact on their health. Higher amounts of activity (above the recommended minimum ranges) are believed to bring larger health benefits (HHS, 2008).

To calculate the total MET minutes in a particular period, first the MET score of each activity is multiplied by the reported frequency of this activity and its duration. The outcomes are summed up to receive the total MET minutes. The obtained total MET score can be divided by 30 (to obtain the MET minutes per day) and multiplied by 7 to get the total MET minutes of exercise per week (WANG *et al.*, 2010; FORD *et al.*, 2010).

(5.1) Total MET minutes of exercise/week= ((∑ MET scores * frequency of activity per week * duration of activity in hours)/30) * 7

Using the cut points suggested in the *2008 Physical Activity Guidelines for Americans* HHS (2008), it is possible to group the participants according to their level of leisure-time physical activity during the week into 4 categories: no activity, low (0 to <500 MET-minutes/week), moderate (500 to <1,000 MET-minutes/week), or high (over 1,000 MET-minutes/week) (WANG *et al.*, 2010). Table 15 gives an overview of the main indicators of physical activity available in NHANES.

---

[27] Moderate activities are activities that lasted for at least 10 minutes and caused only light sweating or a slight to moderate increase in breathing or heart rate, e.g., brisk walking, bicycling for pleasure, golf, and dancing. Vigorous activities are activities that lasted for at least 10 minutes and caused heavy sweating, or large increases in breathing or heart rate, e.g., running, lap swimming, aerobics, and fast bicycling (US DEPARTMENT OF HEALTH AND HUMAN SERVICES, 2008).

[28] A metabolic equivalent, or MET, is used to express a rate of energy expenditure by individual during a specific activity. It presents a ratio of the amount of energy expended during an activity to the amount of energy spent while resting (AINSWORTH *et al.*, 1993 and 2000; HHS, 2008: 54).

Table 15 Summary statistics of the main physical activity measurements [a)]

Description of variables	N	Mean/%	SE
Usual daily activity (%):	2503		
Sitting, almost no walking	530	21.29	1.30
Standing or walking a lot, but do not have to carry or lift things very often	1222	48.30	1.24
Lifting or carrying light loads/climbing stairs or hills often	484	20.61	0.87
Doing heavy work or carrying heavy loads	267	9.81	0.92
Compared with most women/men of the same age, respondent considers him/herself (%):	2480		
more active	805	33.41	1.71
less active	616	25.02	1.11
about the same	1059	41.69	1.09
MET min week 4 groups (%):	2505		
0 MET minutes = no activity	826	28.61	1.96
0.01- 500 MET minutes = low activity level	1013	44.37	1.52
501-1000 MET minutes = moderate activity level	402	17.37	1.02
1001 and more MET minutes = high activity level	263	9.65	0.63
Hours per day watched TV or videos past 30 days (%):	2505	2.04	0.05
0 -1h	880	38.87	1.25
2h	702	29.61	0.95
3h	404	19.07	1.25
4h	247	17.80	0.70
5h	272	29.61	0.95
Walked or bicycled over past 30 days (%)	2490	27.3	1.39

[a)] Data are weighted to be representative of the population.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

The results show that about 21% of adults have a completely sedentary lifestyle with almost no walking during their usual day. About 42% of adults perceive to have a similar activity level as most of other persons of their age and 25% think that they are less active compared to the others. Calculated MET scores show that leisure physical activity of only about 27% of adults can be characterised as moderate or high, while 73% of the respondents have a no or low activity level.

Furthermore, over 47% of the adults dedicate four hours or more to viewing TV and videos. Previous studies demonstrated a positive association between this indicator and overweight and obesity (EISENMAN *et al.*, 2002; FOSTER *et al.*, 2006; JEFFERY and FRENCH, 1998). Moreover, TV viewing is believed to be related to an increased prevalence of diabetes and risk of cardiovascular disease (GRØNTVED and HU, 2011). The actual study employs this variable in the health production model and hypotheses that adults spending less time on TV viewing are less likely to be obese and to have a risk of CVDs.

5.3.2.7 Medical care utilisation

Medical care usage has an impact on the state of health of an individual. NHANES collects information about utilisation of health care providers, access to care during the previous 12 months and usage of medications prescribed by a doctor (Table 16).

Table 16 Summary statistics of the indicators of medical care utilisation [a)]

Description of variables	N	Mean/%	SE
Is there a routine place to go for health care? (%)	2505		
no place	491	17.01	1.18
at least 1 place	2002	82.44	1.17
more than 1 place	12	0.55	0.15
Number of times received professional health care over past year (%):	2504		
0 times	533	18.96	0.75
1 time	546	21.95	1.03
2-3 times	621	25.67	0.89
4-9 times	467	19.83	0.99
10-12 times	134	5.46	0.50
13 times or more	203	8.13	0.66
Number of prescribed medications taken over the past year [b)] (%):	2468		
0 medications	1415	53.01	1.01
1-3 medications	799	35.90	0.72
4 medications or more	254	11.09	0.08

[a)] Data are weighted to be representative of the population. [b)] Prescription medications do not include dietary supplements.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

As shown above, about one fifth of the sample had no routine place to go for health care and did not receive professional medical care during the past year. Empirical evidence of the relationships between higher availability and more intensive utilisation of medical inputs and health status is conflicting (OR, 2000). While some studies support a positive relationship between health outcome and health care (JOYCE, 1987), the others show only a small or negative association (NEWHOUSE and FRIEDLANDER, 1977; AUSTER *et al.* 1969). Some studies treat utilisation of medical care as endogenous variable being affected by a specific health state. Thus, HÄKKINEN (1991) and ERBSLAND *et al.* (1995) specified structural equations for medical care as dependent on socio-demographic variables (a direct but small effect) as well as on lifestyles such as smoking and overweight (negative indirect impact via state of health).

It is stressed in the literature that medical care cannot fully explain observed health differences and that personal lifestyles[29] play an important role in determining the health outcomes (AUSTER *et al.* 1969, FUCHS, 1986; OR, 2000). Moreover, it can be considered as an

[29] OR (2000: 58) provides a definition of lifestyle as "[…] all the factors over which individuals have some control, such as alcohol and tobacco consumption, physical exercise, personal hygiene, etc."

intermediate factor in health production as, for instance, education (and income) may contribute to more intensive health care utilisation that in turn might have positive health effects. A variable depicting how many times a respondent received professional health care over the past year is included in the actual model.

5.3.2.8 Energy intake

Energy intake presents a measure of the quantity of nutritional inputs into health production (MWABU, 2007). It can be seen as an intermediate health input affecting health outcome via other measures, e.g., body weight.

During 1971-2000, a significant increase in energy intake occurred among the US population, which is mainly attributed to increased carbohydrates and fat intake (BRIEFEL and JOHNSON, 2000). Excessive energy intake has been linked to overweight and obesity. Although physical activity can help avoid weight gain, other health-related behaviours as well as genetic makeup and metabolic efficiency play an important role, too (HILL and PETERS, 1998).

Despite these facts, empirical evidence on the linkages between energy intake and obesity incidence is inconsistent (PARSONS *et al.*, 1999). It is argued that this may be related to the difficulties in diet measurement as well as to the character of analysed data. Thus, short-term cross-sectional data may not show this effect (or it might be very small), so it is better accumulated over time, i.e., small variations in calorie intake may not lead to being overweight immediately, but rather over a longer time period (AGRAS *et al.*, 2004).

As discussed before, NHANES records information on all types of food items and beverages (including tap, bottled water and non-alcohol drinks) and their amounts consumed by the surveyed individuals in frames of two 24-h recalls. These data are used to estimate for each food item its corresponding amounts of energy, nutrients, and other components. The calculations are performed by NHANES specialists based on the USDA's Food and Nutrient Database for Dietary Studies, 3.0 (FNDDS 3.0). Nutrients obtained from dietary supplements are presented separately. Estimation of energy intake of the study sample is given in chapter 5.2.2.

5.3.2.9 Exogenous socio-demographic and economic factors

FUCHS (2004) discusses the main socio-economic determinants of health such as income, education, occupation, age, sex, marital status, and ethnicity and stresses potential difficulties when deriving conclusions on causality and policy implications due to existing correlations among these factors: "[…] even when a causal connection appears to be particularly robust, the mechanism of action is usually unknown" (FUCHS, 2004: 654). One way to avoid the multicollinearity among these variables is to combine them into one, e.g., often income, education and occupation are grouped under the name of "socio-economic status" (SES)[30]. This, however, limits the derivation of individual implications. The actual study is looking for individual effects of socio-economic variables in the model.

Of special interest in the economic literature has been the impact of education and income on health.

Education

The Healthy People 2020 report (INSTITUTE OF MEDICINE, 2011: 23) states that "Education is associated with longer life; improved health status; lower infant mortality; more favourable social and economic determinants of health, including better occupations, higher income, increased wealth, and higher social standing; and positive health behaviours".

The level of education showed to be negatively related to a number of diseases such as cardiovascular disease, hypertension, and diabetes. A detailed overview of the studies investigating associations between socioeconomic status and CVDs is available in KAPLAN and KEIL (1993).

A number of health economics studies confirm an association of education with better health state suggesting that higher education increases the efficiency of household health production (FU *et al.*, 2004, AUSTER *et al.*, 1969, GROSSMAN, 1972). A positive impact of education on health remained after controlling for the other variables, e.g., income or family background (KEMNA, 1987; EGERTER *et al.*, 2009). However, inference about causal relation between education and health remains to be a challenge due to unclear underlying mechanisms of this linkage, potential reverse causation[31] and bias due to omitted confounding variables (e.g., time preference) (KAWACHI *et al.*, 2010).

A number of mechanisms can be responsible for the relationship between education and health status (see e.g., KAWACHI *et al.*, 2010; CUTLER and LLERAS-MUNEY, 2010). EGERTER *et al.* (2009) suggest that education and health are linked through three interrelated pathways: a) higher education can positively affect health knowledge and, thus, lead to healthier behaviours; b) education is positively related to employment and income, thus, contributing to better health,

[30] See e.g., MAZZOCCHI and TRAILL (2008) who created a latent variable of wealth combining person's social status, income and education.
[31] Fuchs (2004) argues that the reverse causation between health outcome and education is less likely than between health and income. See also the related discussion in GROSSMAN (2004).

e.g., through healthier environment or better nutrition; c) education is connected with social and psychological factors such as sense of control, social standing and support, which can be beneficial for health, e.g., via reducing stress.

FU *et al.* (2004) argue that persons with a higher educational level are likely to be more productive and efficient in maintaining health through choosing better lifestyles and health care utilisation. On the other hand, health heterogeneity may be partly explained by different time preference of individuals with different education levels, i.e., the more educated individuals are more willing to invest into their health (FUCHS, 1982, 2004). KEMNA (1987) and LEIGH (1983) suggest that better educated individuals choose healthier working conditions (through "healthier" jobs) and are therefore healthier. FUCHS (1982) states there might also be unobservable variables causing both, health and education.

Nutritional knowledge

In the focus of health economics has been the role of *nutritional information and nutritional awareness* in the relationship between education and health. VARIYAM *et al.* (1998) discussed that positive effects of education and income on dietary choices found in previous studies are actually due to the positive effects of these factors on nutrition knowledge. Moreover, they note that an important drawback of previous studies, which may have contributed to the inconsistencies in results, is that they treat the nutrition information as exogenous. In the model of VARIYAM *et al.* (1996), strong direct and indirect effects of education, income, and other exogenous variables on the demand for fibre among U.S. citizens were revealed. Thereby, they showed that educational attainment affects nutrient intake through its contribution to nutrition information, which is treated as endogenous in the model. NAYGA (2000) estimated a two-equation simultaneous model and showed that the part of the relationship between schooling and obesity was explained by differences in health knowledge of the U.S. population. ADELAJA *et al.* (1997) showed that diet-disease knowledge may contribute to a healthier diet and stressed a need for nutritional education.

KENKEL (1991) estimated the effect of schooling on cigarettes consumption, drinking and exercising with and without inclusion of an effect of health knowledge on these variables. He showed that the effect of schooling decreases by 5 to 20% when health knowledge is accounted for.

Various measures of health and nutrition knowledge have been employed (see e.g., KENKEL, 1991; VARIYAM *et al.* 1996; NAYGA, 2000). KENKEL (1991) and NAYGA (2000) created a measure of health knowledge by summing the correct answers given by the respondents to the questions about health problems related to cigarette smoking, heavy drinking and taking into account their knowledge about an appropriate level of physical activity.

The measure of *nutritional knowledge* used in the actual study is a composite variable based on the answers to seven questions related to the awareness of existing nutritional guidelines and usual usage of available nutrition information. Thus, in the frames of NHANES 2005-06, individuals were asked whether they: heard about 5-a-day program; heard of dietary guidelines; heard of food guide pyramid; use the nutrition facts panel on food labels; use the ingredients list on food labels; use serving size information on food labels; and whether they use health claims on food packages (Table 17). For each positive answer one point was given. Therefore, the variable ranges from 1 (lowest) to 7 (highest knowledge).

It is hypothesised in the model that education affects diet quality indirectly through nutrition knowledge. Individuals who possess greater knowledge are believed to make better choices and thus contribute positively to the state of health. To account for the potential endogeneity of nutritional knowledge, it is modelled as determined by a number of personal characteristics simultaneously with dietary and health-related decisions. Such an approach allows the estimation of separate effects of education and nutritional knowledge on the demand for health inputs as well as direct and indirect effects of these variables on dietary quality, other health behaviours and health overall.

Table 17 Summary statistics of the questions related to nutritional knowledge [a)]

Description of variables	N	Mean/%	SE
Nutritional knowledge, 1 (lowest) to 7 (highest) [b)]	2500	4.02	0.08
Heard about 5-a-day program (%)	2492	55.18	1.99
Heard of dietary guidelines (%)	2488	54.10	1.60
Heard of food guide pyramid (%)	2499	83.87	1.40
Share of respondents, who always, most of the times or sometimes use:			
…nutrition facts panel on food label	2501	63.67	1.09
…ingredients list on food label	2501	53.09	1.31
…serving size info on food label	2501	48.22	1.01
…health claims on food packages	2501	44.10	0.89

[a)] Data are weighted to be representative of the population. [b)] Nutritional knowledge, 1 (lowest) to 7 (highest): 1 point was given if the respondent answered “yes” to the questions: Heard about 5-a-day program? Heard of dietary guidelines? Heard of food guide pyramid? and if he/she answered “always”, “most of the times”, or “sometimes” to the questions: Use nutrition facts panel on food label? Use ingredients list on food label? Use serving size info on food label? Use health claims on food packages? No points was given if the answers were “rarely”, “never” or “never seen”.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

Other personal characteristics

Age, gender, race/ethnicity, occupation and marital status are the personal characteristics that can be found in health models (FUCHS, 2004). They may affect health directly as well as via demand for nutrients and health-related behaviours. VARIYAM *et al.* (1998) discusses that personal and household characteristics can be used as proxies for unobservable tastes and preferences of a person.

A person's *age* is directly related to health status due to biological processes and indirectly via behavioural changes over the lifetime, e.g., decreasing physical activity. Empirical evidence suggests a positive association of age with BMI, whereas BMI tends to lower at the highest age levels (RÖMLING and QAIM, 2011). Also, a risk of CVDs increases with age (U.S. DEPARTMENT of HEALTH and HUMAN SERVICES, 2001). Further, according to the report of the American Heart Association (LLOYD-JONES *et al*., 2010), the CVDs risk for men compared to the risk for women is higher at younger age (20-39 years), about equal at the age of 40 to 80 years, and lower in comparison to females at older ages (after 80 years). In the study of CHEN *et al.* (2002), older persons and males had a higher blood pressure.

Ethnicity/race is highly correlated with other socio-economic factors and may also be considered as a genetic marker (FUCHS, 2004). A significant racial disparity in health status in the USA has been demonstrated in empirical studies (e.g., FU *et al.*, 2004) and is supported by official statistics (LLOYD-JONES *et al*., 2010). The prevalence of CVDs is higher among African American females and males compared to individuals of other races. There are also linkages between these personal characteristics and engaging in health-related behaviours. African American and Hispanic populations showed to have higher rates of physical inactivity compared with Caucasians. Adult men engage more often in regular leisure time physical activity compared to women. However, the share of smokers as well as overweight and obese persons amongst men is higher in the USA. At the same time, the highest share of female smokers are Caucasian, while among males, African Americans tend to smoke more in comparison to persons of other races (LLOYD-JONES *et al*., 2010).

BEHRMAN and DEOLALIKAR (1988) discuss that *household size* may also enter the health production function as it represents "possible scale and congestion effects". It has been shown that large families tend to use less medical care (VAN DE VEN and VAN DE GAAG, 1982). Inclusion of this variable is important as we employ the measure of total household income in the actual study.

Other demographic factors accounted for in empirical analyses are marital status and occupation. In relation to *marital status***,** the results are mixed. FUCHS (2004: 659) discusses that being married is associated with better health across the countries as "[…] the presence of a spouse is assumed to make a positive contribution to the household production of health". While there is evidence supporting this notion (e.g., GERDTHAM and JOHANNESSON, 1999), the others show the opposite results. RÖMLING and QAIM (2011) showed a relation between marital status and a higher risk of overweight and obesity among women. In the work of CHOU *et al.* (2004) being married was associated with higher BMI among both genders. *Occupation* may be also related to health, as it may be connected with e.g., less/more healthy or risky working environment, and psychological stress. Unemployment was linked to a lower probability of good health in GERDTHAM and JOHANNESSON (1999). Difficulties with the application of occupation variables are due to a need for its meaningful categorisation and often the unavailability of data on previous occupations that may be important as well (KAPLAN and KEIL, 1993; FUCHS, 2004). Respondent's occupation was not the part of the demographic part of the questionnaire in NHANES 2005-06.

Income

Health-risk behaviours such as smoking and alcohol consumption have been found more often among lower socioeconomic groups indicating that individuals with lower incomes may be investing less in production of own health (SMITH, 1999).

Although poverty is often associated with obesity, a review based on the NHANES data 1971-2002 shows that obesity has increased at all income levels in the USA during the recent decades (CHANG and LAUDERDAL, 2005). However, the relationship between income and health status is inconsistent in the empirical studies and tends to vary across different age groups, diseases and countries (e.g., it is stronger in the poorer states) (FUCHS, 2004).

A negative link between income level and obesity was showed by e.g., CHOU *et al.* (2004). FLEGAL *et al.* (2002) investigated trends in this relationship over several decades in the USA and found a stable positive association among U.S. men and a decreasing inverse relation amongst women.

Similar to the relationship between education and health there might be a number of various mechanisms by which income affects health. A detailed discussion on this is given in ADLER and OSTROVE (1999) and SMITH (1999). It is stressed that a possible reverse causation in this relationship with the health status affecting one's earnings may bias the empirical results (KAWACHI, 2010; SMITH, 1999). MOCAN and TEKIN (2011) showed that in comparison to their normal-weight counterparts, obese adults are likely to suffer more from lower self-esteem, which may partly explain their lower incomes.

There can be a number of indirect effects of income on health. Affluence may be associated with consumption of healthier foods and thus better health. At the same time, as income rises, individuals can afford eating out more often, and restaurant meals are showed to contribute greatly to the total energy intake (JEFFERY and FRENCH, 1998). MCINTOSH *et al.* (2001) provide an overview of the studies relating income to nutrient intakes and concludes that intake of fat and saturated fats among adults tends to increase with higher incomes. Besides the decisions related to diet, individuals are also faced with other choices with regard to own income distribution. E.g., a person may use own income to join a gym or he may buy a car and eventually exercise less. While testing these relations, it is important to bear in mind that there might be omitted behavioural and psychological factors as well as unobserved genetic heterogeneity among individuals, which may confound the results.

This study contributes this research by testing the direct and indirect relationship among income, health-related behaviour, and health state. First, similar to education, income is believed to contribute to the dietary quality indirectly through better nutritional knowledge rather than directly as a higher income may make information more accessible for a consumer. Second, higher income can also have a positive effect on health via healthier lifestyles (indirect effect). Although the endogeneity of income is possible, it is usually treated as exogenous in health production studies. This approach is also adopted for the actual study.

5.3.2.10 Prices, wages and endowments

As discussed earlier, the health of an individual depends on his personal characteristics, genetic predisposition and on a number of health-related behaviours, which in turn are influenced by economic variables. However, empirical studies that account for multiple health determinants including a full range of economic factors such as wages, food prices, and incomes are rare due to dataset limitations (see e.g., studies of CHEN *et al.*, 2002 and CHOU *et al.*, 2004 discussed in Section 4.2.).

Prices

LAKDAWALLA *et al.* (2005) investigate the effect of food *prices* on macronutrients intake in the USA. They link the 1988-1994 National Health and Nutrition Examination Survey (NHANES) to the data collected by the American Chamber of Commerce Researchers' Association (ACCRA), containing the local food prices of 24 items purchased for consumption at home. The results of the analysis revealed that increase in food prices (e.g., for fruits and juices) contributes to underconsumption of macronutrients (e.g, folate and Vitamin C).

SCHROETER and LUSK (2008) based on the household production theory specify a model aimed to explain the prevalence of high blood pressure in the USA. They show that economic factors including prices have an effect on the health risk factors and health conditions such as obesity and diabetes. They differentiate between the food at home price and prices for food away from home and show that an increase in the latter is associated with lower probability of risk factors and health conditions. GOLDMAN *et al.* (2009) studied a short-term and a long-term effect of prices on obesity. In this study, a raise of a price per calorie showed to have little effect in the short run, but might have an effect over a very long time period (4.2% of BMI increase after 30 years with 10% lower price). Addressing the obesity epidemic by imposing taxes on selected "less healthy foods" has been under discussion related to employing economic instruments to control weight gain (JACOBSON and BROWNELL, 2000; POWELL and CHALOUPKA, 2009).

Empirical studies are usually faced with the non-availability of a data set with a full range of economic, health, and lifestyle information. A majority of health production studies, especially those based on cross-sectional data, treat prices as stable, i.e., they are assumed not to vary among individuals (e.g., NAYGA, 2000; GERDTHAM *et al.*, 1999; YOU and NAYGA, 2005).

Wages

In the health model of GROSSMAN (1972), the wage rate measures opportunity costs of time. GERDTHAM and JOHANNESSON (1999) stress that to avoid the endogeneity problem between income and health (health may affect labour income), non-wage income and the wage rate should be separately incorporated into analysis. However, due to data limitations, this condition is usually difficult to satisfy. GERDTHAM and JOHANNESSON (1999) employ in their analysis a continuous measure of gross income, as well as dummies for non-wage income (1 if the individual has some declared taxable property), and the gross wage rate per hour measured by three dummy variables. The results demonstrated a positive impact of all three variables on probability of having good health.

CHEN *et al.* (2002) is one of the few studies that includes not only foods prices but also individual wages (generated from another dataset) and incomes in their model of health production. The results of the study showed that these economic variables affect the individual choices of food and their lifestyles. Higher wages were associated with higher intake of potassium and lower physical activity and medication use. The authors discuss that these outcomes are connected with higher opportunity costs of time and the notion that individuals with higher wages are believed to be healthier and therefore demand less medicine.

The NHANES does not provide information on a person's wage. Combining the NHANES 2005-06 with an external dataset of wage information, e.g., as in CHEN *et al.* (2002) or usage of average wage rates, was not possible as geographic and community characteristics of the survey's participants were not available (this information is protected within NHANES).

Community variables and biological endowments

According to the INSTITUTE of MEDICINE (2011: 58) "The conditions in which people live determine, in part, why some Americans are healthier than others and why Americans are generally not as healthy as they could be. Lack of options for healthy, affordable food or safe places to play in some neighbourhoods makes it nearly impossible for residents to make healthy choices. In contrast, people living in neighbourhoods with safe parks, good schools, and high employment rates." Therefore, type of area (rural or urbanised), region and such community-level information as type and condition of infrastructure, availability of health services etc. may be important for demand of health inputs and health outcomes. Such information can be used as instruments in demand equations. An example is the study of RASHAD (2006), who studied obesity determinants in the USA and incorporated in the first-stage regressions (demand equations for caloric intake and smoking) such instruments as fast-food and full-service restaurant meal price in respondent's state of residence, state cigarette tax, private workplaces in respondent's state of residence etc.

However, the geographic information on respondents, which is collected by NHANES has not been available for public usage since 1999, due to the protection of participants' confidentiality (DUFFY *et al.*, 2009). This significantly reduces the possibilities of statistical analyses as these characteristics often serve as instruments for underlying health behaviours (e.g., cigarette tax in a particular US state for smoking behaviour). The geographic information can be obtained on a commercial basis from CDC after approval of a corresponding proposal (see e.g., the study of FLETCHER *et al.*, 2010 that employs this information).

Similar to previous studies, there also might be a number of unobservable genetic endowments of a person that could not be included in the model, but may be related to his health input choices.

5.3.3 Main hypotheses

Based on the discussion of the previous sections, the main hypotheses (Hyp) of the study are:

Hyp1: The proposed measurement model for health is reasonable; the chosen indicators, i.e., systolic and diastolic blood pressure and total cholesterol, effectively measure the latent construct of cardiovascular health.

Hyp2: Larger weight not only transmits negative effects of unhealthy lifestyles on health, but is also an important health determinant itself. Thus, larger weight still has an additional direct negative health impact after accounting for effects of other negative health-related behaviours such as low physical activity or poor diets.

Hyp3: Smoking is negatively associated with body weight.

Hyp4: The relation between higher education and better diet is not direct but partly explained by differences in nutrition knowledge.

Hyp5: "Being wealthy helps to be healthy": higher income contributes to better health through healthier lifestyle choices.

Hyp6: A number of reciprocal relations exist in the model, e.g., state of health and health-related behaviours, diet and weight; to measure is their strength.

5.3.4 Empirical specification and analytical procedure

The model specification follows the theoretical framework discussed in section 3 and its application to the research questions presented in section 5.3.1. The SEM methodology is used for empirical estimation (see chapter 4). Essentially, the SEM aims to investigate whether the hypothesised model is consistent with the actual patterns in the sample data. Estimation incorporates fitting data to a model or practically, solving a set of equations. The main aspects assessed are the adequacy of parameter estimates and the model fit as a whole.

Figure 7 gives a schematic representation of the hypothesised relationships in the model, which consists of one unobservable theoretical concept (H) and 18 observed variables. The model is comprised of *measurement and structural* parts. The measurement part of the model relates an unobserved (latent) variable health (H) to its observable indicators systolic blood pressure (SBP), diastolic blood pressure (DBP) and total cholesterol (TC), whereas a structural part presents the postulated relations between all endogenous and exogenous variables in the model.

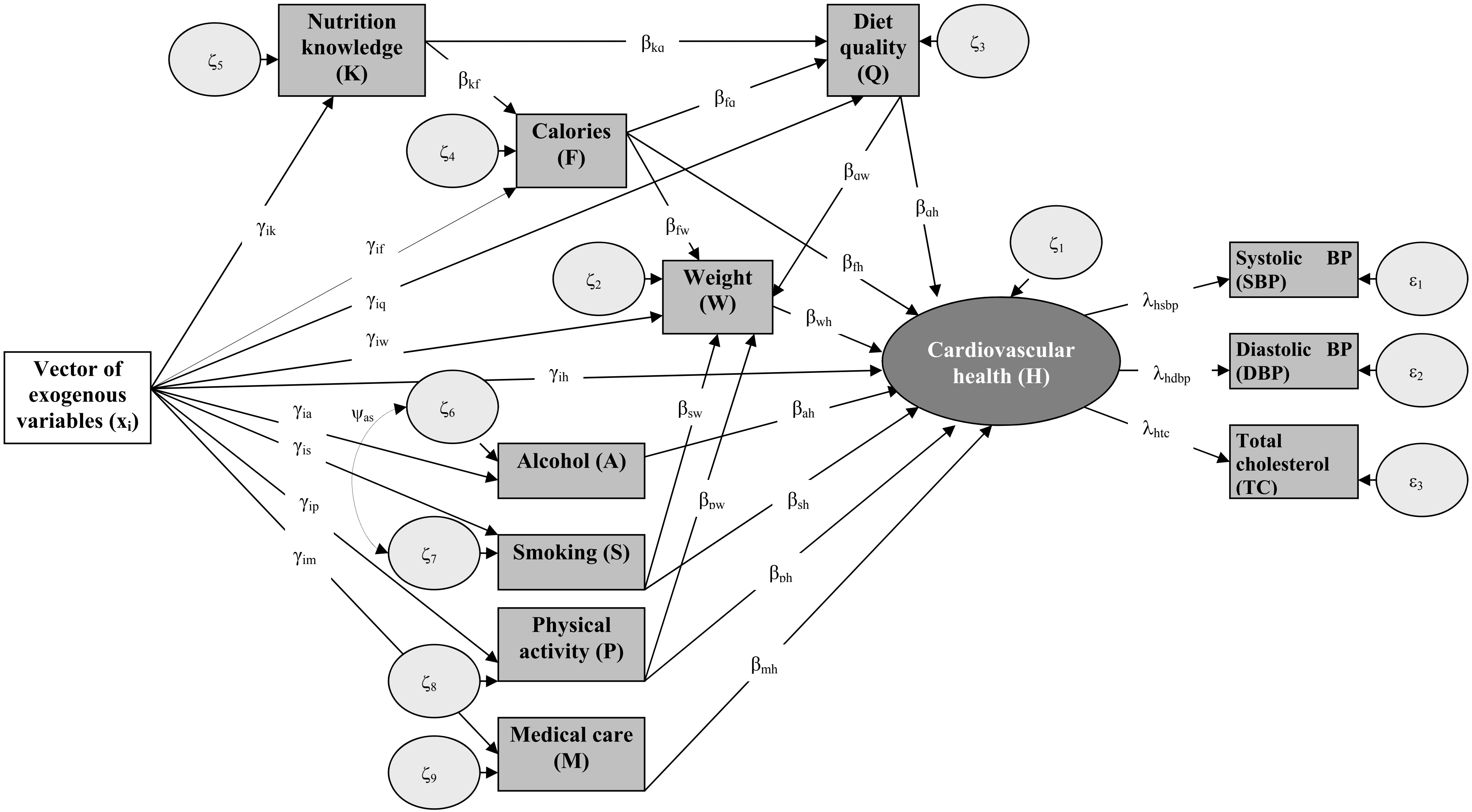

Figure 7 Graphical presentation of the structural model of cardiovascular health [a)]

[a)] β's are parameters indicating the relations between endogenous variables, λ's are loadings of indicators on factor "health", γ's show the effects of exogenous variables on endogenous, ζ's and ε's are error terms of endogenous and exogenous variables, respectively; ψ is error correlation between alcohol and smoking. BP refers to blood pressure.
Source: Own presentation with the NHANES 2005-2006 data (CDC, 2007). The figure is also presented in the author's publication (DEMYDAS, 2013) in somewhat more schematic way.

The *latent health construct* is depicted in the right-hand part of the model as an ellipse; the directly observable variables are in rectangles. The application of a latent variable approach allows modelling measurement errors (ε), which are typical for any observed variable, and to account for them in the estimation. The adequacy of the latent variable (measurement model) is assessed by confirmatory factor analysis (CFA), in which the obtained *factor loadings* (λ) express the relationship between each indicator and the factor (i.e., latent variable).

The left-hand part of the depicted model contains a set of *exogenous variables* (x_i), which for the ease of presentation are showed here in a form of a vector. It consists of age, age^2, gender, race, education, household size and income. Similar to the previous studies (e.g., CHEN *et al.*, 2002), the quadratic term of age is included to account for its possible non-linear effect in the model.

Single-headed arrows outcoming from exogenous variables are causal paths in the model and are interpreted as structural (regression) coefficients. Thus, *γ's* are the structural coefficients (effects) of exogenous on endogenous variables and *β's* indicate the estimated relationship between two endogenous variables. Exogenous variables in the model are assumed to be measured without error (similar to predictors in a regression equation). In contrast to regression analysis, SEM allows accounting for correlations among exogenous variables in the model. Thus, all exogenous variables in SEM are usually specified as correlated, unless there is a reason for the opposite. The presumption is that exogenous constructs may have common antecedents which are not part of the model. Such correlations are depicted by double-headed arrows (not showed in the Figure 7 due to its complexity) and are modelled explicitly. However, no complete multicollinearity between independents should exist (GARSON, 2011).

Variables receiving the arrows are *endogenous* in the model. There is a structural equation for each endogenous variable. As seen from the graphical presentation, endogenous variables may affect one another mutually, i.e., they may also appear as explanatory variables in other structural equations. The ζ's, which are seen in circles beside each endogenous variable, are structural errors or disturbances. Each structural equation has a disturbance term representing the omitted causes of the endogenous variable as well as the measurement error connected with it (FOX, 2006). Thus, the disturbance of a latent variable shows its unexplained variance due to unmeasured causes.

After the first run of the full model, a minor modification was performed based on the modification indices in AMOS, which suggested adding an error correlation between alcohol consumption and smoking (ψ_{as} in Figure 7). The estimated correlation coefficient is 0.15, p<0.001). Such model modifications can be performed via SEM if they are in line with the theoretical knowledge (KLINE, 1998). The disturbances of endogenous variables may be modelled as correlated when it is assumed that there are unmeasured (omitted) determinants of these variables and that they are correlated (GARSON, 2011). This seems to be plausible for the relation between smoking and alcohol as there may be factors not included in the model but which are related to both of these negative health behaviours. Thus, CONTOYANNIS and JONES (2004) discuss that (un)healthy behaviours tend to "cluster together" due to observed and unobserved individuals' characteristics. This modification did not change the magnitude of parameters in the model and their signs, but improved the goodness-of-fit measures very slightly. Similarly, MAZZOCCHI and TRAILL (2008) included a number of error correlations in their model, e.g., between exercise and diet, exercise and smoking, calorie intake and diet and calorie intake and smoking.

Linkages between variables depicted in Figure 7 correspond to the relationships showed in equations 4.16 - 4.20. Based on the notations discussed above and the links showed in Figure 7, the model can be formulated in terms of the following equations:

Measurement model:

(5.1) $HI_j = \lambda_{hj}H + \varepsilon_j, \qquad j=1, 2, 3$

(5.2) $SBP = 1 \times H + \varepsilon_1$

(5.3) $DBP = \lambda_{hdbp}H + \varepsilon_2$

(5.4) $TC = \lambda_{htc}H + \varepsilon_3$

where (5.1) is a general representation of the latent variable model. HI stands for "health indicators" and incorporates three measures of latent health (H): SBP, DBP, and TC. Equations (5.2-5.4) are individual equations for each indicator of latent health. λ's are factor loadings showing an interrelation between the factor "health" (subscript "h") and its corresponding indicator (subscripts "dbp" and "tc"). In order to scale the dimension of the latent H, the SBP was chosen as a reference indicator and its parameter (λ_{hsbp}) was restricted to be unity. ε are measurement errors of the indicators of the latent variable.

Based on equations (4.16 - 4.20), the *structural part* of the model can be specified as follows:

(5.5) $H = \beta_{fh}F + \beta_{qh}Q + \beta_{sh}S + \beta_{ah}A + \beta_{ph}P + \beta_{mh}M + \beta_{wh}W + \sum_i \gamma_{ih}x_i + \zeta_1,\ i=1, \dots ,7$

(5.6) $W = \beta_{fw}F + \beta_{qw}Q + \beta_{sw}S + \beta_{pw}P + \sum_i \gamma_{iw}x_i + \zeta_2$

(5.7) $Q = \beta_{fq}F + \beta_{kq}K + \sum_i \gamma_{iq}x_i + \zeta_3$

(5.8) $F = \beta_{kf}K + \sum_i \gamma_{if}x_i + \zeta_4$

(5.9) $K = \sum_i \gamma_{ik}x_i + \zeta_5$

(5.10) $A = \sum_i \gamma_{ia}x_i + \zeta_6$

(5.11) $S = \sum_i \gamma_{is}x_i + \zeta_7$

(5.12) $P = \sum_i \gamma_{ip}x_i + \zeta_8$

(5.13) $M=\sum_i \gamma_{im}x_i + \zeta_9,$

where H, W, Q, F, K, S, A, P, M correspond to health, weight, diet quality, food consumed (in calories), nutritional knowledge, smoking, alcohol, physical activities, and medicines respectively. Equation (5.5) is presented in a simplified form, whereas F, Q, S, A, P, M, W are functions of the corresponding health inputs. The vector x contains seven individual exogenous characteristics such as age, age^2, gender, race, education, household size and income.

5.3.5 Evaluation of the model assumptions and descriptive statistics of the variables

Examination of data distribution showed deviations from *normality*. However, indices of univariate skew and kurtosis indicated at most a moderate non-normality (skew is <2 and of kurtosis is <7) (FINNEY and DISTEFANO, 2006: 272). The highest deviation from normality (kurtosis of 5.9) was detected for the variable “total cholesterol”. The estimated value of Mardia's coefficient of multivariate kurtosis was 26.9, whereas values of over 10.0 indicate severe data non-normality. Two multivariate outliers were detected based on the Mahalanobis distance available in AMOS 19.0 and were excluded from the further analysis (BYRNE, 2001). This step resulted in a reduction of Mardia's coefficient to the value of 19.9 and, therefore, normalised the data distribution to some extent. Although ML has been shown to produce relatively accurate parameter estimates with non-normal data, the chi-square statistics and standard errors tend to be biased with increasing non-normality (GAO *et al.* 2008; FINNEY and DISTEFANO, 2006: 273). Therefore, to account for data non-normality and categorical character of several model variables, the ADF estimation procedure was used. ADF includes no assumptions about data normality. Moreover, the degree of data kurtosis is taken into account and the estimation results are adjusted respectively (KLINE, 1998: 144). ADF estimation requires a large sample (over 1000 cases according to KLINE, 1998: 145), which is satisfied in this study. The final sample is comprised of 2503 persons.

Missing values analysis was performed in the Missing Values algorithm of SPSS 19.0. The share of missing values was not high, accounting for 0.1 to 5.9% across the variables. To obtain a complete dataset, missing data points were estimated and imputed by a two-step iterative procedure "Expectation Maximisation (EM)" available in the SPSS Missing Values 19.0. Little tests performed prior to analysis showed that data is not missing completely at random (MCAR). However, no evidence of a non-ignorable missing data pattern was detected and the EM procedure can be employed with an assumption that data is missing at random (MAR). The EM approach is advised to be performed in conjunction with *bootstrapping* to ensure the stability of standard errors that might be biased to some extent under this imputation procedure (WAYMAN, 2003). Therefore, bootstrapping with 2000 replications (i.e., 2000 bootstrap samples) was performed to increase the trustworthiness of parameter estimates, standard errors and significance tests for individual parameters. Both conditions for bootstrapping such as large sample size and no missing data were satisfied.

The inspection of the residuals' distribution did not reveal a clear pattern of lack of *homoscedasticity* in the data. After the examination of scatter plots for linearity, the quadratic term of age was included in the model (similarly to previous studies, e.g., BEHRMAN and WOLFE, 1987; HÄKKINEN, 1991). There were no very high correlations (>0.85) among variables in the model, implying the absence of *multicollinearity* (KLINE, 1998: 78).

The data file was prepared in SPSS 19.0 and used as the input into AMOS 19.0 software (ARBRUCKLE, 2010), which served to verify fit of specified hypothetical model to the sample data. The correlation matrix is available in Appendix C. Table 18 provides descriptive statistics of the model's variables.

Due to the fact that the AMOS software does not provide an option to utilise the sampling weights and thus to take into account a *complex sampling design* of NHANES, the analysis is performed for an unweighted sample, which limits the possibilities of generalisations for the whole population[32]. However, to ensure the stability of the estimates as discussed earlier, the bootstrapping procedure was performed with 2000 iterations. All results presented in this chapter are obtained using the bootstrap procedure, i.e., these are the means of the parameter estimates from 2000 bootstrap samples.

Table 18 Definition, means and standard deviations of variables in the model (N=2503) [a)]

Variables	Description	Mean[b)]
Endogenous Cardiovascular health (latent), H	*Indicators:*	
	Systolic blood pressure (1st measurement)[33], mmHg	120.30 (15.51)
	Diastolic blood pressure (1st measurement), mmHg	71.69 (12.19)
	Total cholesterol, mg/dL	195.65 (39.63)
	Triglyceride, mg/dL[34]	131.16 (82.58)
Dietary quality, Q	F&V consumed (excluding juice), g	260.82 (207.90)
Caloric intake, F	Average energy intake based on two 24-h recalls, kcal	2213.36 (278.63)
Weight, W	Waist circumference, cm	97.01 (15.97)
Smoking, S	Number of days on which smoked cigarettes during past 30 days; a range from 0 to 30	6.75 (12.16)
Alcohol, A	Average number of alcoholic drinks per day during past year; a range from 0 to 4	1.78 (1.42)
Medical care, M	Number of times received professional health care over past year; a range from 0 (0 times) to 5 (13 times and more)	1.89 (1.48)
Nutritional knowledge, K	Number of positive responses related to respondent's awareness and usage of nutrition information; a range from 0 to 7	3.68 (2.22)
Physical activity, P	Television viewing as an indicator of sedentary leisure time activity. Hours per day of TV or videos watching over past 30 days; a range from 0 (less than 1 h) to 5 (5h and more)	2.16 (1.54)
Exogenous, x_i		
Age	Age of respondent; a range from of 20 to 59	39.09 (11.17)
Age^2	Age of respondent squared; a range from 400 to 3481	1652.81 (877.16)
Male	Dichotomous variable that equals 1 if respondent is male, 0 otherwise	0.50 (0.50)
Non-Hispanic white	Dichotomous variable that equals 1 if respondent is Non-Hispanic white, 0 otherwise	0.47 (0.50)
Household size	Number of people living in household; a range from 1 to 7 and more persons	3.41 (1.63)
Education level	Level of education reached by respondent; a range from 1 (less than 9th grade) to 5 (college education and above)	3.48 (1.20)
Household income	Total annual household income; a range from 1 (lowest income group of up to $5,000 US) to 11 (highest income of over $75,000 US)	7.69 (2.87)

[a)] NHANES sampling weights are not applied; missing values are imputed by the EM method. [b)] Standard deviations are in parentheses.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007). The table can be also found in the author's publication: DEMYDAS (2013).

[32] SEM software packages Mplus and LISREL have an option to use sampling weights in the model fitting procedure. For further discussion of analysis of complex sample data in SEM see, e.g., MUTHEN and SATORRA (1995).
[33] Four blood measurements were performed during NHANES 2005-2006. Due to a large share of missing data in the 2nd, 3rd and 4th measurements, the estimates from the 1st tests are used.
[34] A triglyceride variable is used in the alternative structural model (see Chapter 5.3.7).

5.3.6 Results and discussion: the structural model of cardiovascular health

Estimations of measurement and structural parameters of the model were performed simultaneously (results are shown in Table 21). For the sake of simplification, the outcomes of these two parts are discussed separately.

5.3.6.1 The measurement model of cardiovascular health

In the empirical specification of the measurement model, health is treated as a latent variable that can be adequately described in terms of the selected indicators. It is tested in the SEM through CFA, which has a primary goal to explain the covariances/correlations between a number of observed variables (here health indicators). The three observed variables chosen to present the cardiovascular health construct are diastolic and systolic blood pressure and total cholesterol.

The condition of at least moderate correlation between indicators of the common construct is satisfied (Table 19). Thereby, the correlation between TC and other BP indication is somewhat lower than between the latter two.

Table 19 Correlation matrix of the indicators of the measurement model for health (N=2503) [a)]

	Systolic BP	Diastolic BP	Total cholesterol
Systolic BP	1	0.52***	0.13***
Diastolic BP	0.52***	1	0.17***
Total cholesterol	0.13***	0.17***	1

[a)] *** indicate statistical significance at the 99.9% level. BP refers to blood pressure.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

Higher values of the chosen health indicators reflect a worse health status (i.e., higher blood pressure is associated with higher cardiovascular risks). For convenience of interpretation and in order to provide a scale for the latent variable, the coefficient of systolic blood pressure was fixed to -1 (λ_{hsbp}=-1)[35]. This makes latent health a variable of "good cardiovascular health", i.e., the value of health increases as values of indicators decreases (lower blood pressure and cholesterol level indicate better cardiovascular health). Similarly, a positive coefficient of an independent variable (e.g., dietary quality) is related to a positive health effect (will be discussed later).

The CFA model should be tested for its *identification.* It has three observed variables (DBP, SBP and TC), six observations (3(3+1)/2) and six parameters, including four variances

[35] A metric is assigned to each unobserved (latent) variable in SEM by constraining one of the indicators' paths a value of 1.0 (a reference item). Given the measurement range of this item, the other paths can be estimated.

(of factor Health and of measurement errors of observed variables: ε_1, ε_2, and ε_3) and two factor loadings λ_{hdbp} and λ_{htc} (λ_{hsbp} is fixed to -1). Consequently, the degrees of freedom are equal to zero (number of observations (6) minus number of model parameters (6)) Therefore, the model is just-identified. In additional to the satisfied necessary condition (parameters ≤ observations), the sufficient for identification condition is also met as a factor has at least three indicators.

Estimation results for all parameters of the full structural model are presented in Table 21. Results from the measurement part can be found in Figure 8 and Table 20. First, the results of the latent variable model are discussed.

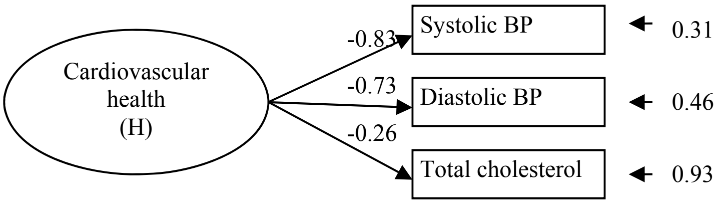

Figure 8 Measurement part of the structural model of cardiovascular health (N=2503) [a)]

[a)] Standardised coefficients are presented. All three are statistically significant at the 99.9% level. In an unstandardised solution the factor loading of SBP equals -1. BP refers to blood pressure.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

Table 20 Estimates from the health measurement model (N=2503) [a)]

	Health (H)		
Indicators	Unstandardised coefficient	Standardised coefficient	Variance explained (R^2)
Systolic BP	-1.00[b)]	-0.83***	0.69
Diastolic BP	-0.67 (0.03)***	-0.73***	0.54
Total cholesterol	-0.77 (0.08)***	-0.26***	0.07

[a)] *** indicate statistical significance at the 99.9% level. Standard errors are in parentheses. Parameter estimates, standard errors and significance levels are estimated by bootstrapping with 2000 iterations. BP refers to blood pressure.
[b)] Set to be a reference indicator.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007). The table and its discussion can be also found in the author's publication: DEMYDAS (2013).

All three indicators are negatively related to the latent construct of cardiovascular health, i.e., a better health state is associated with lower values of blood measurements. Factor loadings show the impact of the factor on each indicator. These can be interpreted as standardised regression coefficients[36]. The magnitude of the regression coefficients (-0.83 and -0.73 respectively) and their high significance (p<0.001) confirm the validity of the indicators SBP and DBP. Furthermore, the proportion of explained variance of these indicators equals

[36] Unstandardised coefficients are more applicable for model comparisons across different samples. Therefore, in the following only standardised coefficients are discussed.

69 and 54% respectively, which indicates their adequate reliability. Thus, improvement in a health state by 1 standardised score is associated with a decrease in systolic blood pressure by 0.83. The R^2 of the indicator systolic blood pressure (0.69) is a common variance indicating its reliability. It means that about 69% of the variance in this indicator is explained by its underlying factor (health), whereas the measurement error[37] of 31% (showed in the right-hand part of the Figure 8) is an error-variance reflecting other sources of variation in systolic blood pressure not explained by the factor of cardiovascular health. When measurement error is high, the estimated regression coefficients remain unbiased statistically, but may be less reliable (GARSON, 2011).

The estimated loading of total cholesterol on cardiovascular health is highly significant, but lower in magnitude (-0.26) compared to the loadings of the blood pressure measures. Only 7% of the variance in TC is explained by the factor. MAZZOCCHI and TRAILL (2008) who specified a health measurement model in a similar way (instead of TC they used the TC to HDL cholesterol ratio) demonstrated similar findings concerning total cholesterol. This may be seen as an indication that cholesterol does not reflect the latent variable of cardiovascular health well enough.

To further test the quality of indicators and their contribution to an underlying common factor, the coefficient proposed by HANCOCK and MUELLER (2001: 195) can be employed. They discuss a number of advantages of this measure[38] in comparison to the commonly used Cronbach's alpha, which in turn only gives an indication on the measures' reliability.

The index is calculated according to the following formula[39]:

$$HM = \sum_{i=1}^{p}\left[l_i^2/(1-l_i^2)\right]/\left(1+\sum_{i=1}^{p}\left[l_i^2/(1-l_i^2)\right]\right)$$

where l_i is the standardised loading of the *i*-th indicator variable on a single latent construct and *p* is the number of indicators.

The calculated coefficient HM_1 (corresponds to the latent variable with three indicators) equals to 0.774, while HM_2 (latent variable with two blood pressure indicators) equals to 0.771. Therefore, the difference between HM_1 and HM_2 (ΔHM) is 0.003, meaning

[37] As discussed in Chapter 4.3, unlike in regression models that assume that the variables are measured without errors, the error terms are modelled in the SEM and parameters are adjusted accordingly (errors are subtracted from the coefficients) thus making them unbiased by error terms.

[38] For more information see HANCOCK and MUELLER (2001: 207).

[39] The original index from HANCOCK and MUELLER has a notation "H". To exclude the misunderstandings (health is denoted as H in the model) it is given the notation "HM".

that the indicator of total cholesterol contributes very little additional information in defining the latent construct of cardiovascular health.

Taking into consideration that an elevated level of cholesterol is an accepted indicator of CVDs risk, the results of the measurement model may be an indication of a more complex character of the cardiovascular health construct. It might have several (latent) dimensions, one of which is related to blood pressure measures and another to the cholesterol level. In other words, total cholesterol may reflect another distinct aspect of CVDs. Furthermore, these two dimensions of the same disease could be also explained in a different manner by the other variables in the model.

To summarise, the three selected indicators of the health status, although not perfectly, are meaningfully related to the cardiovascular health construct (Hyp1). However, the obtained results suggest that cardiovascular health may have a more complex (multidimensional) structure. Therefore, at a later stage, the measurement model will be respecified in order to test the hypothesis about its multidimensionality (Hyp1.1).

In the next section the results from the full structural model depicted in Figure 7 are presented and discussed according to the postulated research questions and hypotheses. Afterwards, an alternative measurement health model will be specified in order to test a more complex structure of the cardiovascular health construct, where the cholesterol level is to be considered as an indicator of another distinct dimension of the CVDs (Hyp1.1). Furthermore, the estimates from the alternative structural model with a two-factor health construct will be presented and compared with the results of the initial structural model.

5.3.6.2 Findings from the full structural model

Results of the parameter estimates from the full structural model (Figure 7) are reported in Table 21. The model is over-identified with df=57[40]. To evaluate the overall fit of a model, traditionally the chi-square statistics, which is based on a comparison of the predicted and observed covariance matrices, has been used, with non-significant values indicating a good model fit.

[40] The model is overidentified, i.e., the number of knowns (observed variable variances and covariances) is greater than the number of unknowns (parameters to be estimated): df=171-114=57, where the number of observations is 171=18(18+1)/2; 18 is the number of observed variables in the model and 114 is the number of model parameters. The AMOS test for model identification is employed.

Table 21 Estimation results of the structural model of cardiovascular health (N=2503) [a)]

	Dependent variables											
	Health	**Weight**	**Diet**	**Calorie**	**Know**	**Smok**	**Alc**	**Med**	**TV**	**SBP**	**DBP**	**TC**
Health										-0.83***	-0.73***	-0.27***
Weight	-0.24***											
Diet	0.05$^{\$}$	-0.05$^{\$}$										
Calorie	-0.11***	0.01	0.27***									
Know			0.14***	-0.04$^{\$}$								
Smok	0.01	-0.07**										
Alc	-0.07**											
Med	0.02											
TV	-0.04$^{\$}$	0.11***										
Educ	0.03	-0.05*	0.01	0.07**	0.34***	-0.16***	-0.10***	0.08**	-0.05$^{\$}$			
HH inc	-0.02	-0.06**	0.04	0.02	0.07**	-0.13***	0.05*	-0.01	-0.10***			
Age	-0.46*	0.69***	0.16	0.14	0.26*	0.23	0.004	-0.34	-0.83***			
Male	-0.09**	0.14***	-0.05$^{\$}$	0.48***	-0.30***	0.08***	0.25***	-0.23***	0.06**			
White race	0.04	0.05$^{\$}$	0.01	0.07**	0.12***	0.18***	0.11***	0.08**	-0.10***			
HH size	0.05$^{\$}$	0.02	0.02	0.002	-0.03	-0.07**	-0.06**	-0.06**	-0.11***			
Age^2	0.10	-0.46**	0.02	-0.26$^{\$}$	-0.18	-0.25	-0.26	0.48**	0.85***			
R^2	0.26	0.10	0.11	0.27	0.30	0.08	0.14	0.10	0.06	0.69$^{\&}$	0.53$^{\&}$	0.07$^{\&}$

χ^2	575.33	CFA	0.93
df	57	RMSEA	0.060
N	2503	NFI	0.92
p-value	<0.001	AGF	1.00
AIC	803.33	GFI	1.00

[a)] ***, **, *, $ indicate statistical significance at the 99.9%, 99%, 95%, 90% level respectively. Parameter estimates (standardised coefficients) and significance levels are estimated by bootstrapping with 2000 iterations. Know - nutritional knowledge, Smok - smoking, Alc - alcohol, Med - medical care, TV - television viewing, Educ - education, HH inc - household income, SBP - systolic blood pressure, DPB - diastolic blood pressure, TC - total cholesterol, TRI - triglyceride. The coefficient of determination (R^2) for the health indicators represents the proportion of the total variance of the indicator explained by the latent variable health.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

The chi-square test of the actual model implies a difference between the estimated and observed relationships in the data (χ^2=575.33, df=57, N=2503, p<0.001). However, as previously discussed, the model's chi-square tends to increase with sample size. Fit indices employed as additional measures of model fit suggest an acceptable fit of the hypothesised model with CFI=0.93, RMSEA=0.06, NFI=0.93, GFI=1.0 and AGFI=1.0 (see Appendix B, Table B2 for acceptable thresholds of fit indices). In total, 26% of the variance in the state of health is explained. Although the R^2 is not high, it is typical for empirical studies in health economics that use cross-sectional data (see e.g., RASHAD, 2006; MAZZOCHI and TRAILL, 2008; CHEN *et al.*, 2002; GIUFFRIDA *et al.*, 2005). The R^2's of the endogenous health inputs were in the range from 0.06 for leisure physical activity (presented by a variable of TV viewing) to 0.30 for nutritional knowledge. CHEN *et al.* (2002) reported the variance explained in the endogenous health inputs at the level of 0.06 to 0.20.

The standardised estimates are presented in Table 21. They indicate the amount of change in the dependent variable due to one standard deviation change in the independent variable. The associations among variables showed to be in line with expectations and were mainly statistically significant. Several coefficients did not reach statistical significance or demonstrated small effects. This might be related to the nature of the data (cross-section). It may be argued that the effect of behavioural is stronger when it is accumulated over a longer period of time, which cannot be satisfied by cross-sectional data (DEMYDAS, 2013).

In the following, the model results related to the main study hypotheses are discussed.

Determinants of the state of health

The first column of Table 21 presents the *estimates of the health production function*. As hypothesised, the health status is positively related to *fruits and vegetables* consumption (0.05, p<0.10) and strongly negatively related to *energy* intake (-0.11, p<0.001). HUFFMAN *et al.* (2006) has demonstrated the positive impact of F&V consumption on the incidence of CVDs using the panel data. In contrast to CONTOYANNIS and JONES (2004), who found no significant effect of alcohol consumption on health, in the actual model demonstrated the negative impact of this variable (-0.07, p<0.01). *Sedentary leisure time activity* (the time devoted to the viewing of TV and videos is used as an indicator) has a negative association with one's cardiovascular health (-0.04, p<0.10). The latter confirms the outcome of the empirical review done by SHIROMA and LEE (2010).

The expected negative effect of *smoking* on health is not confirmed. The coefficient is close to zero and not statistically significant (0.01, p>0.10). Similarly, the direct effects of medical care utilisation also showed to be insignificant and very small in magnitude (0.02, p>0.10). These results may be related to the short-term data character as the impact of (un)healthy lifestyles on health is not immediate, but is rather being accumulated over time. The empirical evidence related to these two variables and their direct relation to the state of health is conflicting, while none, negative and positive effects have been reported (OR, 2000; BLAYLOCK and BLISARD, 1992; HÄKKINEN, 1991).

A strong and direct negative effect of *weight* on cardiovascular health is found with larger weight being associated with worse health state, i.e. higher cardiovascular risks (-0.24, p<0.001). This confirms the hypothesis (Hyp2) and the finding of MAZZOCCHI and TRAILL (2008). The authors demonstrated that weight is not only the outcome of negative lifestyles, but also an important determinant of the health status itself. Thus, it has an important direct health impact also when the other unhealthy lifestyles are accounted for. They argue that obesity and its consequences should be in the focus of health policies together with promotion of healthier diets, no smoking and less alcohol intake etc.

In contrast, in their later study (MAZZOCCHI and TRAILL, 2011) obesity did not show to be significantly related to heart diseases and the sign of the coefficient was “wrong”. They explain this result partly by the fact that the effect of obesity on health is not to be revealed immediately, stressing the limitations of short-term data and discussing the need to include lagged variables in the model.

Further, being *older* and *male* is associated with poorer health (the coefficients are significant and equal to -0.46, p<0.05 and -0.09, p<0.01 respectively) in terms of larger risks of CVDs. These findings are in line with the review done by the American Heart Association (ROGER *et al.*, 2012)

The model revealed a small but positive impact of living in a *larger household* on cardiovascular health (0.05, p<0.10). Thereby, indirect effects of household size via lifestyles on health status contributes to this result, as larger households are also characterised by less smoking, less frequent alcohol consumption and less time devoted to TV viewing. One of the reasons of healthier lifestyles in larger households could be connected with presence of children[41]. Also, the number of household members has a negative association with utilisation

[41] Effect of presence of children in the household could not be tested as this information is not available in NHANES 2005-2006.

of professional medical care (-0.06, p<0.01). This is in line with findings of CHEN *et al.* (2002) and VEN VAN DE and GAAG (1982) who report that large families tend to use less medical care that might be related to the resources constraint they face.

An important role of *education* in raising technical efficiency of health production is suggested in the economic literature (GROSSMAN, 1972; BERGER and LEIGH, 1989). As shown in Table 21, education and household income did not have a significant direct health effect in this study. In contrast, in the study of SCHROETER and LUSK (2008) these variables were related to a lower risk of having high blood pressure. KIISKINNEN (2003) argues that in cross-sectional studies this effect may not be captured. Indirect effects of education and income on health and other variables in the model are discussed in the following subsections.

Determinants of weight

The second column in Table 21 shows the estimates of the weight equation in the full structural model. Almost all the variables assumed to affect an individual's weight were statistically significant in this equation. About 10% of the total variance in weight status could be explained by the model. This is similar to the results of other studies on obesity determinants (e.g., RASHAD *et al.*, 2006).

The results of the model indicate that a better *diet* in terms of greater F&V intake is associated with lower weight. However, the coefficient is rather small (-0.05, p<0.10). This relationship has been a focus of previous research, but findings are contradictory[42]. One of the reasons for inconsistencies may lay in the various specifications of the category F&V, i.e., specific forms and preparation methods of the consumed produce that (as discussed in Chapter 5.2.5) may contribute to the dietary quality and weight in a negative or positive way. Therefore, investigation of the links between F&V intake and body weight is a subject for further research.

The findings of the model confirm the results of the previous studies that have demonstrated a negative impact of sedentary leisure time activities (TV viewing) on a person's weight (FOSTER *et al.*, 2006; JEFFERY and FRENCH, 1998). The estimated coefficient is highly significant (0.11, p<0.001).

The relation between *smoking* and weight showed to be negative and statistically significant (-0.07, p<0.001). This is in line with our expectations (Hyp3) and a confirmation of results from previous studies (e.g., CHOU *et al.*, 2004; LOUREIRO and NAYGA, 2005; HU *et*

[42] Detailed literature review on relationship between weight and F&V intake in available in TOHILL *et al.* (2004).

al., 2002). However, empirical evidence suggests a variation in the direction and strength of this association, which has been shown to vary by sex, age group, race, socio-economic status and smoking duration (AKBARTABARTOORI *et al.*, 2005). Moreover, the exact linkages between being a smoker and having a lower weight remain unclear and are a subject for further exploration. There is evidence that especially adolescents tend to consider smoking as a weight control/loss method (FULKERSON and FRENCH, 2003). Some epidemiological studies showed that smokers tend to have a more energy-dense diet, while others discuss that smoking rather increases body metabolism than modifies the total caloric intake or physical activity patterns (DALLONGEVILLE *et al.*, 1998; PERKINS, 1992). Furthermore, PERKINS (1992) states that the impact of smoking on metabolic rate depends on the specific smoking situation, e.g., smoking during exercising may raise it, while having a cigarette after a meal may have an opposite effect on metabolism. Finally, while considering this relation, it should be kept in mind that cigarette smoking is often a subject to misreporting due to "socially desirable" behaviour. Thus, due to complexity of this relation further investigations would gain from interdisciplinary approaches.

No effect of *caloric intake* on weight was found. The cross-sectional character of the data used for the empirical analysis could be the reason for this result. Thus, it has been demonstrated in the literature that an increase in calories consumed can lead to substantial changes in a person's weight over time (CUTLER *el al.*, 2003).

Older respondents are at higher risk of being overweight (the regression coefficient of "Age" equals to 0.69 with $p<0.001$). Thereby, a "U-shaped" relationship is observed, with "Age^2" being negative and statistically significant (-0.46, $p<0.01$). The latter implies that while weight does increase with age, at some point the direction becomes opposite with the decreasing weight among the oldest subgroup. Being *male* showed to be positively associated with weight (0.14, $p<0.001$). Furthermore, persons with higher household *income* and a better *educational* level tend to have lower weight (coefficients are -0.05, $p<0.05$ and -0.06, $p<0.01$ respectively). These findings confirm the results of previous studies (RASHAD *et al.*, 2006; SUBRAMANIAN *et al.*, 2011). HUFFMAN and RIZOV (2010) based on the extensive data from Russia also demonstrated a negative relation between education and obesity in the country.

Determinants of dietary quality

According to the model estimates, *nutritional knowledge* of an individual significantly contributes to a better diet in terms of F&V intake (0.14 $p<0.001$). Being *male* is negatively related to F&V intake (-0.05, $p<0.10$). Similarly, in the analysis based on the data from the

NHANES 2003-2004, females had slightly higher compliance with dietary guidelines compared to males (ERVIN, 2011). Estimated coefficients of the other demographic variables in this equation did not reach statistical significance.

Effects of education and income on the variables in the model

As education and income are considered to be important factors in decision-making related to the choices of health inputs, their effects on the other model variables are discussed in more detail in this subsection. For the sake of simplicity, Figures 9 and 10 focus on the specific parts of the full structural model depicted in Figure 7 and demonstrate the *direct and indirect effects* of education and income on model variables.

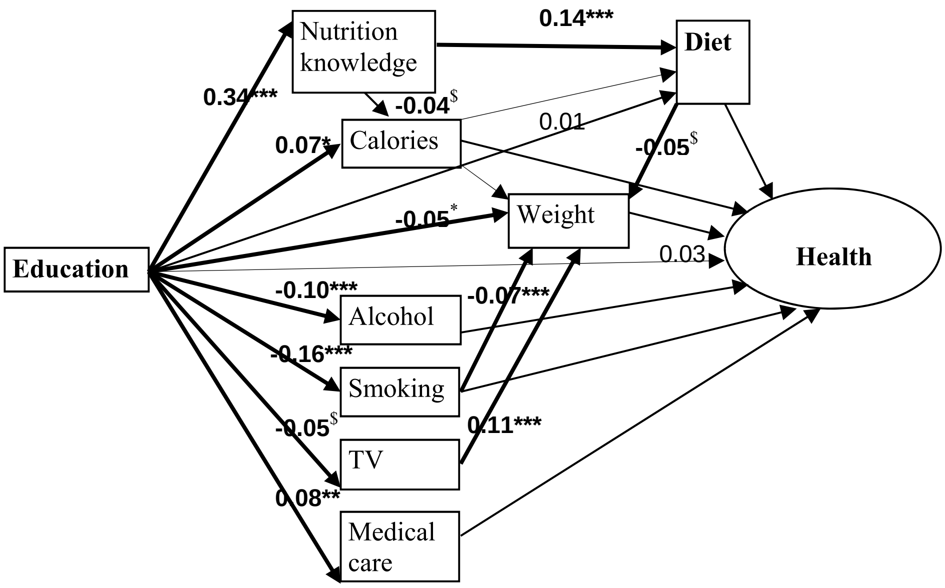

Figure 9 Direct and indirect impact of education on health and health-related behaviour (N=2503) a)

a) ***, **, *, $ indicate statistical significance at the 99.9%, 99%, 95%, 90% level respectively. Parameter estimates are obtained from the full model depicted in Figure 7. All model parameters are shown in Table 21. For the ease of presentation only effects of education are depicted.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007). The Figure (somewhat modified) can be found in DEMYDAS (2013).

Values above the arrows are the direct effects (regression coefficients) showing the expected amount of change in the variable at the end of the arrow produced by a one-unit change in the variable at the beginning of the arrow. The indirect effects may be mediated by one or more intervening variables. The total effects are estimated as a sum of direct and indirect effects (DEMYDAS, 2013).

Higher education is negatively associated with alcohol intake (-0.10, p<0.001), smoking (-0.16, p<0.001) and sedentary leisure time activities (-0.05, p<0.10). Moreover, persons with higher education tend to receive professional medical care on a more regular basis (0.08, $p<0.01$). Additionally, a small but significant and negative association between education and weight is observed (-0.05, $p<0.10$).

As hypothesised (Hyp4), nutrition knowledge showed to be an important intervening variable in the relation between education and dietary quality. As shown in Figure 9, higher education contributes greatly to better knowledge about nutritional aspects (0.34, $p<0.001$). Nutritional knowledge in its turn leads to better dietary choices (0.14, $p<0.001$). At the same time, there was no significant direct effect of education on diet quality with a coefficient being very close to zero (0.01, $p>0.10$). This is in line with the study of VARIYAM *et al*., (1998), who also revealed the importance of nutrition knowledge in this relationship. In the study of NAYGA (2000) the impact of schooling on body weight turned out to be insignificant when the health knowledge was included into estimations. BLAYLOCK *et al*. (1999) demonstrated that a mother's education is beneficial to her child's overall diet due to the fact that higher education leads to more knowledge about health and nutrition aspects. At the same time, KENKEL (1991), who confirmed an impact of health knowledge on a number of health-related behaviours (e.g., smoking, alcohol intake, and exercising), showed that a part of schooling effect still remains when the differences in health knowledge of individuals are taken into account.

Thus, Hyp5 ("*Being wealthy helps to be healthy")* is confirmed only partly, i.e., although affluence is associated with less smoking and sedentary activities, no direct effect on nutrition was observed.

Indirect effects of education can be calculated using the obtained estimates. Thus, the *indirect effect* of education on weight via less sedentary activities is: $-0.05\times0.11= -0.01$; and via better diet is: $0.01\times(-0.05) = -0.001$. Therefore, although the magnitudes of the effects are low, they indicate that higher education contributes to lower weight via less sedentary activities rather than via a better diet. The coefficient of -0.01 may be interpreted as follows: a person's weight is expected to decrease by -0.01 standard deviation given a change of 1 full standard deviation of education via its positive impact on physical activity.

The impact of *income* on other variables in the model is depicted in Figure 10. Higher income is related to better nutritional knowledge (0.07, $p<0.01$), less smoking (-0.13, $p<0.001$), and less frequent TV viewing (-0.10, $p<0.001$). However, affluence showed to be related to higher alcohol consumption (0.05, $p<0.05$). Further, higher earnings showed to be related to lower weight (-0.06, $p<0.01$). This is in line with the findings of RASHAD (2006), who estimated a structural model of the determinants of adult obesity in the US. In contrast, the research done by SUBRAMANIAN *et al.* (2011) with data from fifty four low and middle-income countries showed a higher BMI and overweight concentration among women of higher socioeconomic groups.

Similar to education, income contributes to a better diet rather indirectly via better nutritional knowledge. At the same time, its direct effect on nutrition showed to be insignificant. THIELE *et al.* (2004), who studied only a direct association between diet quality and income found it to be positive and significant. In the study of MAZZOCCHI and TRAILL (2008) wealth was also associated with healthier diet. However, the authors modelled wealth as a latent variable that incorporated indicators of income, education and social status.

Further, there are a number of indirect pathways of how affluence impacts persons' weight and overall health. E.g., an indirect effect of income on weight (although it is very small in magnitude) is somewhat higher due to engaging in more active leisure activities (-0.10×0.11=0.011) rather than choosing healthier diet (0.04×(-0.05)=0.002).

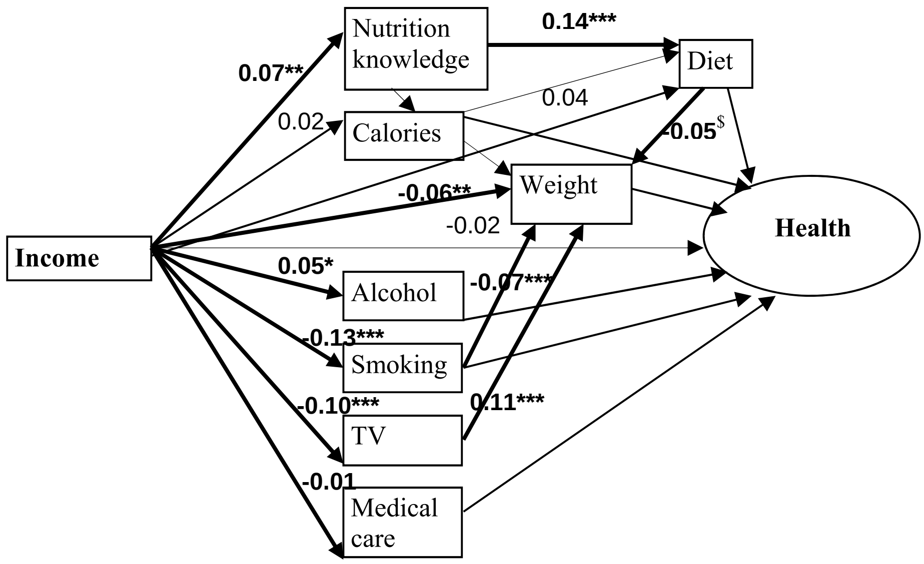

Figure 10 Direct and indirect impact of income on health state and health-related behaviour (N=2503) [a)]

a) ***, **, *, $ indicate statistical significance at the 99.9%, 99%, 95%, 90% level respectively. Parameter estimates are obtained from the full model depicted in Figure 7. All model parameters are shown in Table 21. For the ease of presentation only effects of income are depicted.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007). The Figure (somewhat modified) can be found in DEMYDAS (2013).

Direct, indirect and total effects of *exogenous socio-demographic characteristics* on the endogenous model variables are shown in Table 22. This approach to effects estimation is called **effects decomposition.** Table 22 presents estimates of the relationships between those model variables, for which the indirect effects were hypothesised by the model. Thus, no estimates for the relationships between socio-demographic characteristics and nutritional knowledge, physical activity, smoking, alcohol intake and medical care are presented here because no indirect effects were modelled between these variables, but only direct effects, which can be found in Table 21.

Table 22 Effects decomposition: direct, indirect and total effects of socio-demographic variables on endogenous health inputs (N=2503) [a)]

		Independent variables						
	Effect [b)]	HH size	Age^2	White race	Male	Age	HH inc	Educ
Calorie	*Direct*	0.006	-0.274$^{\$}$	0.070**	0.478***	0.150	0.015	0.072**
	Indirect	0.002	0.010	-0.007	0.016*	-0.014	-0.004*	-0.019*
	Total	0.008	-0.264$^{\$}$	0.063**	0.490***	0.150	0.006	0.053*
Diet	*Direct*	0.008	-0.009 [c)]	0.020	-0.042	0.190	0.035	-0.007 [c)]
	Indirect	-0.002	-0.094*	0.033***	0.092***	0.073	0.010	0.058***
	Total	0.006	-0.103	0.053	0.043**	0.263	0.045	0.051*
Weight	*Direct*	0.017	-0.438**	0.038	0.140***	0.666**	-0.048	-0.045$^{\$}$
	Indirect	-0.011*	0.103***	-0.022	0.003	-0.110**	-0.007	-0.003
	Total	0.006	-0.335*	0.016	0.153***	0.556**	-0.056*	-0.048$^{\$}$
Health	*Direct*	0.056*	0.079	0.041	-0.087**	-0.432	-0.038	0.027
	Indirect	0.003	0.095	-0.005	-0.108***	-0.112$^{\$}$	0.014	0.015
	Total	0.059	0.174	0.036	-0.198***	-0.544$^{\$}$	-0.024	0.042

[a)] ***, **, *, $^{\$}$ indicate statistical significance at the 99.9%, 99%, 95%, 90% level respectively. Parameter estimates (standardised coefficients) and significance levels are estimated by bootstrapping with 2000 iterations. Educ – education and HH inc - household income. [b)] Indirect effect is the total indirect effect on the corresponding variable. [c)] These two coefficients have a negative sign, which is the opposite to the results shown for these relationships in Table 21. However, it has to be mentioned that the signs for these relationships were very unstable during the estimation of several alternative models; moreover, the coefficients were always very low in magnitude and insignificant.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

According to the results presented in the table, educational level has a positive total impact on energy intake. This total effect is comprised of a positive direct effect and a negative indirect effect. This means that, although a higher educational level is directly associated with more calories consumed, it has also a negative impact on energy intake via its influence on other model variables (i.e., indirect effect of education). Thus, based on the results presented in Figure 9, higher education leads to better nutritional knowledge, which in turn contributes to a lower level of energy intake.

A strong and significant effect in Table 22 is seen between health state and being male; male gender is associated both directly and indirectly with an adverse health condition. The emergence of the indirect negative effect of the gender variable on health state can be explained by other estimates presented in Table 22. Thus, being male is associated with a number of negative health choices, e.g., higher energy intake, greater weight, more frequent smoking, alcohol consumption, sedentary leisure time activities and lower level of nutritional knowledge. A sum of these direct interrelations between being male and behavioural choices produces an overall negative indirect effect of male gender on health state. Furthermore, summing up the indirect and direct gender effects on CVDs results in a strong negative total effect of this variable on health.

The SEM approach additionally allows estimating *specific indirect effects* of one variable on another via selected intermediary variables (as briefly discussed above as well as shown graphically in Figures 9 and 10). In Table 23, *effects decomposition* of the two key sociodemographic variables for this study, *income and education,* are shown. Thereby, direct, specific indirect, total indirect effects and total effects of these variables *on health* are calculated. To demonstrate: income has a small direct (-0.038) as well as indirect (0.014) effect on health (see Table 22). Further, the total indirect effect of income on health (0.014) can be decomposed into specific indirect effects (Table 23) using the coefficients presented in Table 21.

As shown (Table 23), the largest indirect effect of income on health is weight (0.014), i.e. higher income is associated with better health due to its (positive) impact on a person's weight. A similar finding exists for the indirect impact of education on health. Although in this particular example the coefficients are very small in magnitude, this approach offers a possibility to obtain very detailed insights into model relationships.

Table 23 Direct, indirect (specific and total) and total effects of income and education on health (N=2503) [a)]

Income on Health		Education on Health	
Direct effect	-0.038	*Direct effect*	0.027
Specific indirect effects via:		*Specific indirect effects via:*	
Diet: (HH Inc→D × D→H)	0.002	Diet: (Educ→D × D→H)	0.001
Weight: (HH Inc→W × W→H)	0.014	Weight: (Educ→W × W→H)	0.012
Alc: (HH Inc→Alc × Alc→H)	-0.004	Alc: (Educ→Alc × Alc→H)	0.007
Smok: (HH Inc→Smok × Smok→H)	-0.001	Smok: (Educ→Smok × Smok→H)	-0.002
TV: (HH Inc→TV × TV→H)	0.004	TV: (Educ→TV × TV→H)	0.002
Med: (HH Inc→Med × Med→H)	0.001	Med: (Educ→Med × Med→H)	0.002
Calorie: (HH Inc→Cal × Cal→H)	-0.002	Calorie: (Educ→Cal × Cal→H)	-0.007
Total indirect effect (sum of specific indirect effects)	0.014	*Total indirect effect* (sum of specific indirect effects)	0.015
Total effect (direct+total indirect)	-0.024	*Total effect* (direct+total indirect)	0.042

[a)] All coefficients are not statistically significant. Parameter estimates (standardised coefficients) and significance levels (not presented here) are estimated by bootstrapping with 2000 iterations. Smok - smoking, Alc - alcohol, Med - medical care, TV - television viewing, Educ - education, HH inc - household income, Cal - calorie, D - dietary quality, W- weight, H - health. Arrows show a direction of the effect. E.g., to find the indirect effect of income on health via dietary quality, the direct effect of income on diet is multiplied by a direct effect of diet on health.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

5.3.7 Results and discussion: the alternative structural model of cardiovascular health

5.3.7.1 The two-factor measurement model of cardiovascular health

The aim of this section is to test the hypothesis about the multidimensionality of cardiovascular health[43] due to the insights obtained previously (see Section 5.3.6.1). This step will be followed by estimation of the accordingly respecified full structural model (alternative model). Further, the outcomes of the initial full structural model with a single latent construct will be compared with the alternative structural model with a multidimensional health status.

The following hypothesis (Hyp 1.1) is tested:

"The latent variable of cardiovascular health is a multidimensional construct, with blood pressure indicators presenting its one dimension (hypertension) and cholesterol level underlying its another dimension (lipids risk)."

To validate this hypothesis, the initial one-factor measurement model of health is respecified into a two-factor model (Figure 11). One latent variable is assumed to present a hypertension dimension of health state ($Health_{hyp}$) with two blood pressure indicators. Another factor has one indicator of total cholesterol and is believed to represent a dimension of cardiovascular health risk related to the elevated lipid level ($Health_{lipids}$). However, this measurement model is unidentified. There are three observed variables and six observations (3(4)/2=6), but seven parameters are to be estimated (including two variances of the factors and three measurement errors, one unanalysed association between factors and one factor loading). Thus, df=-1 and the model is empirically underidentified.

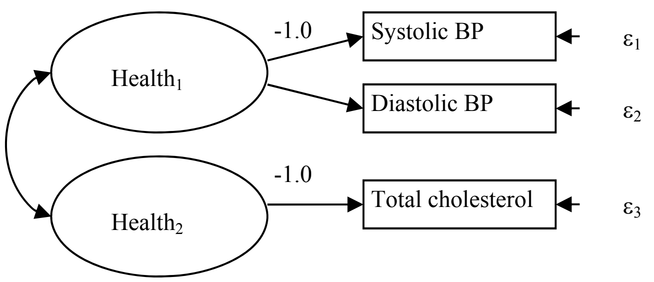

Figure 11 Unidentified two-factor measurement model of cardiovascular health [a)]

[a)] BP refers to blood pressure.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

[43] The discussion presented in sections 5.3.6.1 and 5.3.6.2 here can be found in a more concise form in DEMYDAS (2013).

To reach an identifiability of the model, one more observable indicator can be added to the health measurement model, which is the *serum triglyceride level*[44]. The rationale of this step is as follows: elevated levels of cholesterol and triglycerides are known lipid risk factors of cardiovascular diseases. A positive link between these measures and hypertension has been reported in medical literature. Moreover, a high triglycerides level is believed to be related to obesity, smoking, alcohol and nutrition (NIH, 2002).

Total cholesterol and triglycerides are used to represent a risk dimension of cardiovascular health related to elevated level of blood fats (lipids), while blood pressure measurements reflect the hypertension risk dimension. A two-factor measurement model of cardiovascular health is depicted in Figure 12. It is to be tested how well this measurement model represents the unobservable health construct.

Each of the two latent constructs have two indicators. The latent variables are assumed to be correlated. It is a unidimensional measurement as each indicator loads on a single factor and measurement errors of indicators are uncorrelated (KLINE, 1998: 203). Similar to the one-factor model, to give a scale to latent constructs, the factor loading of SBP and TC are each fixed to -1.

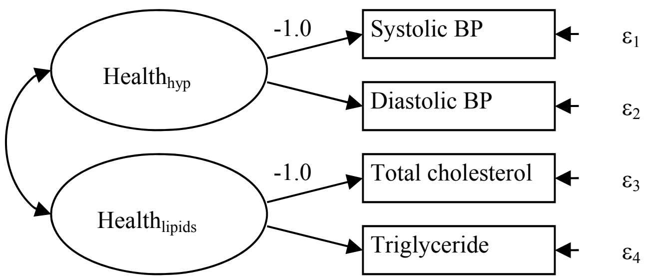

Figure 12 Modified two-factor measurement model of cardiovascular health [a)]

[a)] $Health_{hyp}$ shows a dimension of CVDs risk, which is related to hypertension; $Health_{lipids}$ reflects a dimension of elevated lipids level in the blood. BP refers to blood pressure.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007). The Figure can be also found in DEMYDAS (2013).

The two-factor model shown in Figure 12 is overidentified (df=1). There are four observed variables, ten observations (4(5)/2) and nine parameters including six variances (of 2 factors and the four measurement errors), one unanalysed association between the factors, and two factor loadings. The model meets not only the necessary but also the sufficient conditions for identification as each factor has at least two indicators.

[44] Triglycerides measurements were available for about a half of the adult subsample. Therefore, an imputation of missing values was performed by a 2-step iterative method (EM). There was no large discrepancy detected between the mean triglycerides level in the obtained full sample and the original sample.

Due to the fact that the initial one-factor measurement model was just identified (section 5.3.4.1), no separate goodness-of-fit test could be performed. Therefore, one-step estimation was done with a simultaneous test of measurement and structural parts of the model.

The alternative measurement model is overidentified, and, therefore, its goodness of fit can be assessed separately from the full structural model. Such two-step modelling is recommended by some researchers (e.g., KLINE, 1998). It includes first a test of the pure measurement model and second, if its fit is found to be acceptable, the test of the structural model.

In the following, first the CFA is used to validate the multifactorial health model (outcomes can be found in Table 24). Second, an estimation of the full structural model, including its measurement and structural parts is performed. The results from the alternative measurement model in the context of the full structural model are shown in Table 25.

Table 24 Estimation results of the two-factor health measurement model (N=2503) [a)]

Indicators	$Health_{hyp}$		
	Unstandardised coefficient	Standardised coefficient	Variance explained (R^2)
Systolic BP	-1.00[b)]	-0.66***	0.44
Diastolic BP	-0.92 (0.12)***	-0.77***	0.60
	$Health_{lipids}$		
Total cholesterol	-1.00[b)]	-0.65***	0.43
Triglyceride	-1.19 (0.22)***	-0.38***	0.15
χ^2	0.90	CFI	1.000
df	1	RMSEA	0.000
N	2003	NFI	0.999
p-value	0.342	AGF	0.999

[a)] *** indicate statistical significance at the 99.9% level. Standard errors are in parentheses.
Parameter estimates, standard errors and significance levels are estimated by bootstrapping with 2000 iterations.
BP refers to blood pressure. [b)] Set to be a reference indicator.
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007). The Table can be also found in DEMYDAS (2013).

The overall fit of the two-factor measurement model is very good, both in terms of the chi-square test (χ^2=0.90, p>0.10) and fit indices (e.g., CFI=1.0, RMSEA=0.00). All four indicators are significantly related to the corresponding latent constructs, whereas lower values of these indicators are associated with a lower risk of CVDs and thus better health. All measures have substantial factor loadings, although for triglyceride this value is somewhat lower (-0.38). The variance of the indicators explained by the two-factor model ranges from 15% for the triglyceride up to 60% for diastolic blood pressure. The estimated correlation coefficient between the factors is 0.32. As this value is not high, this suggests discriminant validity between the factors.

To summarise, the two-factor measurement model of cardiovascular health showed a good fit to the data, thus confirming the hypothesis about multidimensionality of cardiovascular health (Hyp 1.1).

In the following subsection the results from the full structural model with the two-factor measurement model of health status are presented and discussed in terms of their comparability with the outcomes of the initial structural model of cardiovascular health.

5.3.7.2 Findings from the alternative full structural model

The alternative full structural model incorporates all the relationships hypothesised by the initial model. Due to the multidimensionality of the latent health in this model, the health inputs are assumed to impact both health dimensions (see schematic representation in Figure 13). Results of the parameter estimates from this model including statistical tests of its fit are reported in Table 25.

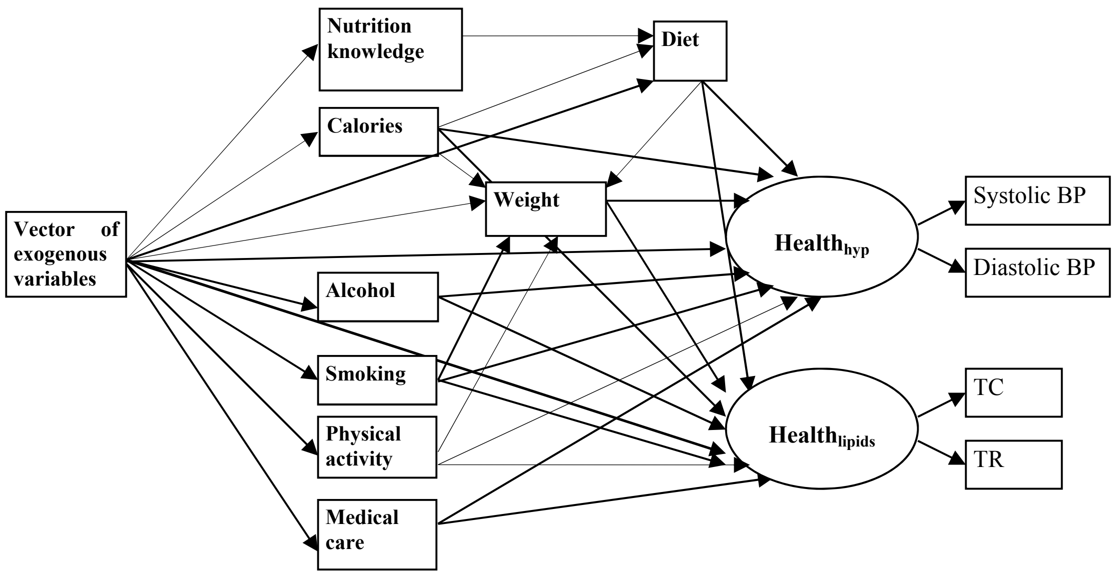

Figure 13 Schematic representation of the alternative full structural model of cardiovascular health (N=2503) [a)]

[a)] This is a simplified schematic representation. Health$_{hyp}$ shows a dimension of CVDs risk, which is related to hypertension, while Health$_{lipids}$ reflects a dimension of elevated lipids level in the blood. TC is total cholesterol and TR is triglyceride. BP refers to blood pressure.
Source: Own presentation with the NHANES 2005-2006 data (CDC, 2007).

Table 25 Estimation results of the alternative full structural model of health production with multidimensional health status (N=2503) [a)]

	$Health_{hyp}$	$Health_{lipids}$	Weight	Diet	Calorie	Know	Smok	Alc	Med	TV	SBP	DBP	TC	TR
$Health_{hyp}$											-0.85***	-0.75***	-0.59***	-0.44**
$Health_{lipids}$														
Weight	-0.22***	-0.23**												
Diet	0.06**	$0.06^{\$}$	-0.05*											
Calorie	-0.10***	-0.04	0.03	0.27***										
Know				0.13***	$-0.05^{\$}$									
Smok	0.02	-0.09*	-0.08***											
Alc	-0.06**	-0.09**												
Med	0.01	0.01												
TV	-0.04	-0.08*	0.10***											
Educ	-0.01	0.14**	-0.06*	0.01	0.05*	0.35***	-0.17***	-0.11***	0.09**	$-0.05^{\$}$				
HH inc	0.01	-0.04	-0.06*	0.04	0.03	0.06**	-0.13***	0.05*	-0.01	-0.08**				
Age	-0.31	-0.79**	0.80***	0.19	0.20	0.19	$0.37^{\$}$	0.08	$-0.31^{\$}$	-0.80***				
Male	-0.12***	-0.02	0.11***	-0.03	0.48***	-0.30***	0.06**	0.24***	-0.24***	$0.04^{\$}$				
White	0.07**	$-0.05^{\$}$	0.06*	0.01	0.08***	0.11***	0.20***	0.12***	0.06*	-0.09***				
HH size	0.05*	-0.06	0.01	0.03	-0.01	-0.04	-0.06**	-0.06*	-0.06*	-0.10***				
Age^2	-0.01	$0.49^{\$}$	-0.54***	-0.01	-0.31*	-0.12	$-0.36^{\$}$	-0.32	0.46**	0.83***				
R^2	0.23	0.24	0.10	0.10	0.26	0.30	0.08	0.13	0.11	0.05	0.72	0.56	0.34	0.20

χ^2	505.61	CFA	0.940
df	59	RMSEA	0.055
N	2503	NFI	0.934
p-value	<0.001	AGF	1.00
AIC	767.61	GFI	1.00

[a)] ***, **, *, $^{\$}$ indicate statistical significance at the 99.9%, 99%, 95%, 90% level respectively. Parameter estimates (standardised coefficients) and significance levels are estimated by bootstrapping with 2000 iterations. The latent health construct is specified as a two-factor model with two indicators per factor. The coefficients of two-factor measurement model of health in the context of the full structural model may differ slightly from those obtained in a separate CFA model (Table 24).
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007). The table and its discussion can be found in DEMYDAS (2013).

As for the initial model, the ADF estimation procedure that accounts for data non-normality was used to estimate the alternative structural model. The model is overidentified with df=59. The chi-square statistics equals to 505.61 (N=2503, $p<0.001$) indicating a difference between the estimated and observed covariance matrices. As discussed before, this is probably due to a large sample size. Fit indices suggest an acceptable fit of this model (CFI=0.940, RMSAE=0.055, NFI=0.934, GFI=1.0 and AGFI=1.0).

As discussed in Section 4.3.3, various methods can be used *to compare a fit of alternative models,* which depend on whether the models are *hierarchical (nested)* or *non-hierarchical (non-nested).* As the initial structural Model A and an alternative Model B are non-hierarchical (the latter has an additional variable of triglyceride level), the AIC statistics can provide an indication of the better fitting model. Additionally, RMSEA values of the two alternative models can be compared (MARUYAMA, 1998: 246). Lower values of these indices suggest a better fit. As shown in Table 26, the alternative model incorporating the multidimensional health status has a slightly better fit.

Table 26 Non-nested model comparison (N=2503)

	AIC	RMSEA
Initial full structural model	803.33	0.060
Alternative full structural model	767.61	0.055

Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

As shown in Table 25, 23% of the variation in the blood pressure dimension and 24% of the lipid dimension of the cardiovascular health were explained by the model. Parameter estimates of the alternative model B indicate a stability of the hypothesised interrelations with no significant changes in the estimated parameters. Thus, no changes in signs or large increase/decrease of parameter coefficients were revealed in comparison to the initial model (estimates can be found in Table 21).

The hypothesised multidimensionality of cardiovascular health provides further important insights into model relationships. As seen in Table 25, two dimensions of the same disease are explained differently by the other model variables. Higher weight negatively and significantly impacts both health dimensions. However, dietary quality (diets rich in FV) is strongly related to the blood pressure factor, thus lowering the risk of hypertension. The latter is in line with existing scientific evidence.

Negative health inputs such as alcohol consumption and sedentary leisure-time activities have a stronger relation to the lipid dimension of cardiovascular health.

Moreover, while the effect of smoking on health in the initial model was non-significant, in the alternative model smoking had a significant negative impact on the lipid dimension of cardiovascular health. This finding should be further explored by the medical field.

Another interesting outcome is regarding the role of education in the model. Higher education contributes to lower blood fat measurements and, thus, to lower health risk. However, no significant relation was found between education and the risk of hypertension. This finding may be an indication that more educated individuals possess higher awareness of the risks related to an elevated cholesterol level than about the risks related to high blood pressure. Thus, consideration of the potential complexity of the measure of health status contributes to obtaining deeper insights in the existing interrelations.

5.3.8 Discussion of reciprocal relations in the model

The structural models of cardiovascular health tested in this study (initial and alternative) are recursive. As discussed before, a number of reciprocal relations among variables in the model could also take place. Thus, while health behaviours affect one's health, a potential reverse causality may arise when a person might adjust his behaviour in respect to health inputs as a response to his current health state.

SEM approach offers a convenient way to model complicated relations, including reciprocal effects, and to test these relations simultaneously[45]. Practically, an alternative non-recursive model (e.g., with reciprocal effect) is specified and its fit is compared to the fit of a baseline recursive model (see chapter 4.3.3 for more information about non-recursive effects). Model comparison between a baseline recursive and an alternative non-recursive model is performed in SEM using a nested-model comparisons approach, which is based on the comparison of the chi-square fit statistics, where a model with significantly lower chi-square is considered to be superior. Additionally, a stability index is computed for a non-recursive model, which indicates whether the system of linear dependences is stable. If its values range between +1 and -1, the system is considered to be stable (ARBUCKLE, 2007: 137).

As discussed in section 4.3.3, non-recursive models are much more difficult to test compared to recursive models, typically due to an identification problem. Methods to overcome this difficulty were discussed before. The most common approach includes the

[45] For a discussion on the application of the two-stage least squares technique to testing the reciprocal relations with cross-sectional data, see, e.g., MARUYAMA (1998: 103) and JAMES and SINGH (1978).

introduction of additional exogenous variables (instruments). An instrument of one of the reciprocally related variables influences only one of the endogenous variables involved in this reciprocal relationship, and is not related to any unmeasured causes of another variable. Moreover, it is affected by any of these two (ASHER, 1986: 58; FRONE *et al*., 1994)[46].

This study aimed to test several potential reciprocal relations in the framework of the model of cardiovascular health, e.g., between diet and health, smoking and health, exercising and weight, and calorie and weight. Consequently, the alternative models were specified for each of the potential reciprocal relations. However, an empirical estimation of these models was not successful due to the underidentification problem.

A modification of the specified non-recursive models to overcome an identification problem could not be performed due to the unavailability of adequate instruments to be included in the model. Also, a discussion on the suitability of non-recursive models for cross-sectional studies was taken into account.

WONG and LAW (1999) discuss in their literature review that although such analyses can be performed mathematically, their validity is questionable. A critical argument is that a reciprocal relationship is not observed at the same time point as a cause should precede an effect, i.e., a certain amount of time (time lag) is needed for the consequences of causation to occur. Therefore, longitudinal models or experimental study design can be more appropriate to test reciprocal relations. An alternative way suggested in the literature for testing the reciprocal relations between two constructs is based on the panel data and called a cross-lagged panel modelling (HUNTER and GERBING, 1982; WONG and LAW, 1999; MARUYAMA, 1998). However, longitudinal measures are not available in the NHANES data. Such analysis should be a subject for further research.

5.3.9 Critical consideration of the empirical analysis

This dissertation project investigates the relationship between cardiovascular health and its main behavioural determinants: dietary quality, a person's weight, leisure time physical activity, smoking, alcohol intake and medical care utilisation. Cardiovascular health is presented as a latent variable measured by observed indicators. Health-related behaviour is treated as endogenous and modelled as function of education, income, age, gender and

[46] The introduction of new variables in a model would need application of other methods of model comparisons, i.e., non-hierarchical approaches.

race/ethnicity. Moreover, additional links among endogenous variables are tested, e.g., between physical activity and weight, diet and weight, nutrition knowledge and diet, while knowledge variable is treated as an intermediary between education and diet. The SEM methodology is employed to test the hypothesised complex linkages between health inputs and health outcome as well as to disentangle the direct health effects of the exogenous variables from their indirect impact on health via lifestyle choices. A number of aspects can be a subject of critical discussion as well as be considered for future research.

As discussed in sections 3.3 and 5.3.1, health state of an individual is believed to be determined by a unique production function, which is formed by a number of health inputs, socio-demographic characteristics, own time, genetic endowment and characteristics of the environment. It is argued that a choice of health inputs is influenced by economic variables such as wages, prices and non-labour income. Although these variables are suggested to be good *candidates for instruments of endogenous health behaviour*, they often have to be omitted from estimations of demand equations due to data limitations, which was also the case in the actual work. Thus, the model proposed here incorporates only the information on household income that is treated as exogenous variable, whereas the prices are considered to be fixed due to a cross-sectional data character. Although rather rare, there are studies that did employ the above-mentioned exogenous variables as instruments for endogenous health behaviour. The approach of CHEN *et al.* (2002), who investigated the impact of nutrient intake, exercise and medication on blood pressure of the US population, was as follows: the NHANES sample was limited to the adults living in 1976-78 in the pre-selected 11 sites in the USA. They used the information of the US Bureau of Labour Statistics about the prices for the chosen 10 food groups that were recorded in these regions during 1976-78. Wage estimates were generated using the findings of the wage equation from the 1978 Current Population Survey in the USA[47]. Finally, these data were merged with the NHANES data[48]. The combination of the NHANES data with an external dataset on prices was not possible in the actual study as geographic and community characteristics of the survey's participants were not available to the author. The geographic information can be obtained from the CDC only on a commercial basis after a corresponding proposal is approved, which faced the time and financial constraints of this work.

[47] For more information see CHEN *et al.* (2002: 993-994).

[48] The authors mention that according to their best knowledge this is the only work that merges any NHANES data with price information.

An important issue to be mentioned is a potential omitted-variables problem and the *presence of unobserved heterogeneity* in the model. Thus, such characteristics as unobserved time preferences, cognitive abilities, and health endowments (i.e., genetic predisposition) could not be incorporated into the analysis, which may have caused a bias in the estimation. A good deal of empirical work in the health-economic literature is devoted to the education-health relation and biases if one fails to control for individual time preference[49] (hypothesis proposed by FUCHS, 1982).

Another limitation concerns the *potential reverse causality* in the model that was discussed but not analysed. Thus, those individuals which are already in poor health may tend either to more risky health behaviour or, on the contrary, adjust their lifestyle in favour of healthier choices. Although SEM allows testing such interrelations, they are very complex and often lead to the difficulties in model identification (as in the actual study). To resolve this problem, adequate instruments for each variable in a reciprocal relation should be found. Unfortunately, the lack of instruments hindered such analysis[50]. Furthermore, as discussed, tests of reciprocal causality should be performed using longitudinal data as such effects are unlikely instantaneous. Longitudinal SEM procedures may provide better research opportunities, although they are rare (BULLOCK *et al.,* 1994). If longitudinal measures of both variables are available, a cross-lagged panel data model can be used, which is believed to be appropriate for measuring such relations (FRONE *et al.,* 1994). This type of analysis could be a subject of further research.

Making causal inferences from the analysis could be a subject of critical discussion, too, due to the fact that it is based on one-period data. SEM allows testing causal hypotheses. However, similar to any other statistical approach, particular conditions should be met to establish causality such as temporal precedence, association between variables, isolation of independents and directionality from cause to effect[51]. Cross-sectional models are dominating the literature, which by their nature cannot satisfy the requirement about temporal ordering (NETEMEYER and BENTLER, 2001; CLIFF, 1983). Inferences about directionality can also be seen as difficult. However, when making causal claims, the importance of theoretical reasoning and accumulated scientific knowledge is stressed (NETEMEYER and BENTLER, 2001;

[49] GROSSMANN (2004) provides an overview of the attempts to account for unobserved heterogeneity when estimating health equations. He discusses the usage of instrumental variables, which are assumed to be correlated with schooling but uncorrelated with time preference, e.g., compulsory education laws and measure of college availability.

[50] A good option of instruments available in longitudinal data, in comparison to cross-sectional, is the prior measures of the variables.

[51] See, e.g., LEI and WU (1997) and HOYLE and SMITH (1994) for a more detailed discussion about causality.

PEARL, 2012). Thus, "[…] the determination of directionality is not solely a statistical judgement. Directionality judgments can be enhanced by logical reasoning and a thorough understanding of accumulated theory and research…" (NETEMEYER and BENTLER, 2001: 83). Longitudinal SEM procedures are suggested to be more appropriate when a direction of causation is searched for.

In addition to causal inferences, it is important to bear in mind that although a confirmation of the hypothesised model proves its fit to the data, *alternative models* may exist that could offer an equally good fit. Therefore, a comparison of equivalent models[52] or alternative non-equivalent model is recommended (BULLOCK *et al.*, 1994; TOMARKEN and WALLER, 2003). In this study the alternative structural model of health (with multidimensional latent health) is proposed and tested and its fit is assessed in comparison to the initial model (one-factor health construct), which appeared to have a more appropriate fit to the data and delivered additional important insights.

Finally, the reports on smoking, alcohol intake and awareness of nutrition-related information could be not completely accurate due to the social desirability factor. At the same time, a definite strength of this work is that objectively measured health and weight indicators were used, which reduced a chance of measurement error bias in these key variables.

To summarise, if SEM-based research is theory-driven and the model is correctly specified taking into account existing scientific knowledge, it may offer important insights into causal links of interest (MARUYAMA, 1998: 277, BULLOCK *et al.*, 1994). Thus, in spite of the discussed limitations, we believe that the results of this project provide interesting insights into the researched interrelations.

[52] According to KLINE (1998: 138): "[…] equivalent models yield the same predicted correlations or covariances, but they do so with a different configuration of paths among the same variables". In other words, these models are mathematically equivalent.

6 Summary

This dissertation project contributes to the research devoted to the relationships between a person's health, his health-related behaviour, and personal endowments. Due to the fact that CVDs present a major health risk faced by U.S. population today, cardiovascular health and its determinants are in the focus of the research.

Definitions and approaches to measuring dietary quality and health

Dietary quality of an individual is believed to be one of the major health determinants. Therefore, the dissertation work starts with the discussion of the *existing approaches to the assessment of dietary quality*. The presented methods include, e.g., the subjective self-evaluation, structure of energy intake, biological markers of nutritional quality and dietary indices. Due to the existing scientific evidence on a positive relation between F&V intake and CVDs, this study pays special attention to this measure as an indicator of the dietary quality.

Further, the central concept of the study "health" is discussed with regard to a number of existing *health definitions and measurement approaches*. It is argued that the choice of the health conceptualisation is dependent upon a particular health problem relevant to the study goals as well as methodological considerations. This project is devoted to cardiovascular health and therefore considers its relevant indicators and determinants. Similar to dietary quality, a number of measures for the health state can be found in the literature. In contrast to the majority of the existing studies that commonly use a single health indicator (often self-assessed health state), a *latent variable approach* is employed to conceptualise cardiovascular health. This approach provides a possibility to utilise multiple measures to describe the state of health, and is believed to deliver a more accurate representation. The observable indicators of latent health are selected based on thorough theoretical considerations. The adequacy of the latent health construct can be assessed and, if appropriate, its modification is performed. Another advantage of this study is the fact that the indicators selected to present the latent health status are considered to be objective as they are derived in laboratory conditions rather than based on self-reports.

Theoretical background

The third part of the dissertation project describes the theoretical background of this study. The household production model developed by BECKER (1965) is considered to be particularly applicable as health cannot be seen as a good available on the market, but rather as an output ("commodity") of a particular production process taking place in a household. Health state is believed to be determined by a unique production function, which is formed by a number of health inputs, personal characteristics and characteristics of the environment. It is assumed that individuals can choose their health inputs such as a particular diet pattern or regular visits to a doctor and that these choices are constrained by other variables, among which are prices and income. Further, the chapter outlines the potential difficulties related to empirical estimation of health production functions such as endogeneity of health inputs, unobservability of health endowments, omission of relevant variables, and error-in-variables problems. Finally, it is stressed that the estimation of a health production model is a complex tool that makes it possible to account for multiple decisions, i.e., a person's demand for health inputs as well as decisions related to combinations of these inputs in production of a particular health state.

Empirical methodology

Section 4 gives an overview of the estimation approaches relevant for the actual study. Due to the complexity of interrelations amongst variables in a health production model, a single-equation approach (e.g., OLS) presuming an exogenous nature of all regressors, cannot be employed. Such relations should be modelled by simultaneous-equations methods, which are divided into single-equation and system methods. Single-equation (limited-information) approaches foresee an estimation of several equations in the model, where each equation is estimated separately (one at a time) (e.g., 2SLS, IV). Conversely, the "systems" (full-information methods) allow estimation of all the equations simultaneously, while knowledge of all the restrictions in the model can be utilised (e.g., 3SLS, SEM). The IV method can be used for an estimation of the health production function with numerous empirical examples existing in health-economic literature. However, it is discussed that a SEM approach may offer a number of additional features considered to be particularly relevant for the actual study. Generally, SEM is the statistical method that can be described as a development of multivariate regression analysis with an incorporation of measurement models for latent variables. It allows flexibility when modelling complex interrelations as well as offers *additional features*, which are employed in this study:

- Specification and testing of complex model interrelations, including a) the demand relationships related to the individual's choice of health inputs and b) the relationship among the chosen inputs and health outcome in the form of a health production function.

- Estimation of all parameters of the system simultaneously (measurement and structural parts of the model) with a full-information approach.
- Testing of the hypothesised relations between endogenous variables in the model such as smoking and weight or dietary quality and weight.
- Testing of the direct and indirect effects among model variables. Especially relevant is a possibility of disentangling the direct health effects of the exogenous variables from their indirect impact on health via lifestyle choices.
- Possibility of modelling the central concept of the model, cardiovascular health, as a latent variable and to test its adequacy.
- Comparison of the alternative models: an alternative model of cardiovascular health is tested with a health concept presented as a multidimensional latent variable.

These features present the methodological advantages of this study. In addition, the reverse causality between model variables can be tested via SEM. The potential reciprocal relations among model variables have been discussed. Due to the fact that such analysis shall be performed based on longitudinal data, this could be a subject for further research. Moreover, the relations between unobserved latent variables can be analysed. This feature is not used in this study as health status is the single latent variable in the model. The examples of empirical analysis employing these two SEM features can be found in e.g., GIUFFRIDA *et al.* (2005) and ERBSLAND *et al.* (1996).

Empirical results

The empirical estimation is performed using the SEM approach the advantages of which are summarised above. Importantly, the dataset used in the empirical analysis is provided by the representative health and nutrition survey conducted in the USA on a regular basis, i.e., the NHANES 2005-2006. The empirical analysis employed the weighting procedure, which allows the generalisation of the obtained results[53].

Part I - Dietary quality of the adults in the USA

In the first stage, the *investigation of the dietary quality* as one of the main inputs into the health production function was performed. The advantage of this study is the usage of multiple methods when assessing dietary quality, and, thus, the possibility of cross-validation

[53] The descriptive analysis of the study sample (section 5.1), the dietary quality analysis (section 5.2), and analysis of all health behaviours of the sample relevant for the structural model (5.3.2) were performed with application of sample weights. However, the weighting was not performed during the SEM due to the inability of the software to handle weighting variables.

of the obtained results that contributes to their credibility. In this study not only the usual economic research methods are employed (e.g., energy supply and its structure, nutrient density, self-assessment), but also the indicators from the medical and epidemiological fields. Thus, besides the data from the 2-day dietary self-reports, the biological markers of nutritional quality are used. These are obtained in laboratory conditions (e.g., via blood tests) and, therefore, are considered to be more objective compared to the dietary self-reports.

The results indicate a low nutritional status of the sample. The majority of the adults do not comply with the existing recommendations about fats, sodium and cholesterol and intakes of the important minerals and vitamins. This is in line with the existing empirical evidence (SCHILLER *et al.*, 2012; ERVIN, 2011; BASIOTIS *et al.*, 2002).

Interestingly, a large discrepancy between dietary quality as perceived by individuals and their actual nutritional status is observed. Thus, while about 70% of the respondents consider their diet to be good, very good or excellent, the analysis conducted in this work suggests a rather low quality of the adults' diets, which is in line with the current knowledge (USDA and HHS, 2010). This discrepancy between own perception and actual dietary status might be an indication that American adults are lacking awareness about healthy dietary patterns, which calls for more attention of public health policy.

As a part of the dietary assessment, the analysis of the F&V intakes was performed. A contribution of this dissertation project is its focus given to F&V preparation forms, which has not received much attention previously in empirical studies. Not accounting for this aspect may have contributed to the inconsistencies in the empirical literature with regard to impact of F&V intake to the weight status of an individual (e.g., TOHILL *et al*., 2004). This study makes use of the advantage offered by the NHANES dataset, which is a unique and very detailed source of information about consumed F&V including their amounts, form (i.e., whole, juice), processing degree (i.e., cooked, canned) and additional ingredients accompanying an intake. The reported intakes were aggregated by the author into seven subgroups indicating the degree of processing. The insights obtained from the empirical analyses proved the importance of considering this aspect. It has been revealed that specific groups in the adult population have finite consumption patterns with regard to F&V, which contributes to the overall healthiness of their diet. While the majority of adults consume very low amounts of F&V (occasional intake as a compound of another dish, e.g., lettuce leaf in a sandwich), a specific part of the population intakes F&V predominantly (or exclusively) in the form of fruit juice. Although the diet of these *"Intensive fruit juice consumers"* showed a higher adequacy in terms of vitamin C intake, it was high in terms of sugar[54].

The study suggests that more attention of health policy is needed to the ways F&V are incorporated into the diet as well as to the delivery of clear recommendations on F&V intakes. It must be mentioned that the most recent version of the Dietary Guidelines for Americans has already highlighted the need to monitor the intake of 100% fruit juice amongst children and adolescents as it is suggested to have an impact on body weight (USDA and HHS, 2010).

Part II - The structural model of cardiovascular health

The next part of the empirical analysis is devoted to the structural model of cardiovascular health. After its theoretical and empirical specification, the empirical estimation followed. The main findings are summarised below.

The measurement model of the cardiovascular health

The three indicators initially selected to represent the latent variable of cardiovascular health (systolic and diastolic blood pressure and total cholesterol), showed to be meaningfully related to the cardiovascular health construct and, thus, proposed its adequate representation (Hyp1 is confirmed). However, the indicator of the blood cholesterol, although being an important indicator of cardiovascular health, has a weaker relation to the latent health compared to the blood pressure indicators. Therefore, it was further discussed that cardiovascular health may have a more complex (multidimensional) structure, where the blood pressure indicators represent its one dimension (hypertension) and the cholesterol level underlies another dimension (lipids risk). This hypothesis was tested at a later stage.

Insights from the full structural model with one-dimensional latent health variable

Relationships between health inputs and cardiovascular health:

- Positive impact of F&V consumption on health (in line with e.g., HUFFMAN *et al.,* 2006, VAN DUYN and PIVONKA, 2000).
- Negative impact of high energy, alcohol intake and sedentary leisure time activities. The latter result has been also shown in SHIROMA and LEE (2010) and GRØNTVED and HU (2011).
- Very strong direct influence of larger weight on higher risk of CVDs, when other health inputs are accounted for (Hyp2 is confirmed). MAZZOCCHI and TRAILL (2008) came to this conclusion in their study, too. In contrast, obesity was not significantly

[54] For a detailed discussion, see DEMYDAS (2011).

related to heart disease in their later study (MAZZOCCHI and TRAILL, 2011). The authors stress the limitations of the short-term data used for empirical estimations and discuss the need to include lagged variables in the model.

- No direct effect of medication and smoking on health could be revealed. No consistent relationship between these variables is found in the literature. The reported effects range from no effect, to negative and positive effects (e.g., OR, 2000; BLAYLOCK and BLISARD, 1992; CONTOYANNIS AND JONES, 2004).

Interrelations among endogenous health inputs:

- Negative influence of smoking on weight. This is in line with our expectations (Hyp3 is confirmed) and the affirmation of outcomes of the previous studies (e.g., CHOU *et al.*, 2004; LOUREIRO and NAYGA, 2005; HU *et al.*, 2002; FLEGAL *et al.*, 1995; RÖMLING and QAIM, 2011). However, the empirical literature on this relationship is not consistent with some opposite evidence existing (e.g., MOLARIUS *et al.*, 2001). Thus, the exact linkages between being a smoker and having lower weight remain unclear and are a subject for further exploration.
- Positive relation between sedentary leisure time activities and weight (in line with FOSTER *et al.*, 2006; JEFFERY and FRENCH, 1998).
- Positive contribution of nutritional knowledge to a better diet in terms of F&V intake.
- Positive impact of F&V consumption on weight was found. The review of the empirical studies done by TOHILL *et al*. (2004) indicates that very few studies have specifically addressed this issue. The existing investigations vary in methodology and report inconsistent findings that call for a need of further research.
- No impact of *caloric intake* on weight could be explained by the cross-sectional character of the data. Previously it has been shown that the increase in calories over time may lead to obesity (CUTLER *el al*., 2003).

Personal exogenous characteristics, health inputs and cardiovascular health (direct and indirect effects)

Education

- Higher education is negatively related to alcohol intake, smoking, and sedentary leisure time activities and positively impacts the obtaining of professional medical care. Positive relationship between education and health-related behaviour has been discussed in BEHRMAN and WOLFE (1987) and FUCHS (2004).

- A small in magnitude but significant negative direct effect of education on weight was revealed. The latter is in line with the existing studies (e.g., RASHAD *et al.*, 2006 and HUFFMAN and RIZOV, 2010).
- When looking at the indirect effects, a higher education contributed to lower weight via less sedentary activities rather than via better diet (although small in magnitude).
- No significant direct effect of education on diet quality was found. Thereby, nutrition knowledge showed to be an important intervening variable in this relation. i.e., higher education contributes to better awareness of nutrition-related aspects that in turn lead to a healthier diet (Hyp4 is confirmed). Importance of nutritional knowledge for dietary quality has been demonstrated elsewhere (e.g., NAYGA, 2000; VARIYAM *et al*., 1996; BLAYLOCK *et al*., 1999).
- Also, no direct effect of education on health was revealed. The strongest indirect positive effect of education on cardiovascular health was via weight. HÄKKINEN (1991) also showed in his structural model of health and health care determinant that the effects of income and education on health are much smaller compared to their effects on lifestyle variables such as smoking and overweight.

Income

- Higher income is associated with less smoking and less frequent sedentary activities during leisure time, but it is related to a greater alcohol intake.
- Similar to education, income contributes to better a diet indirectly via better nutritional knowledge, while its direct effect on diet showed to be insignificant.
- Higher income is directly associated with lower weight. This is in line with CHOU *et al*. (2004) and RASHAD (2006) and contrary to the findings of SUBRAMANIAN *et al.* (2011).
- The indirect effect of income on weight (although very small in magnitude) is somewhat higher due to engaging in more active leisure-time activities rather than choosing a healthier diet. MCINTOSH *et al*. (2001) in their review have also concluded that higher incomes are often related to larger intakes of less nutritious foods.
- No direct effect of income on health was observed. The largest indirect effect of income on health was via person's weight, i.e., higher income is associated with better health due to its (positive) impact on weight status. Thus, hypothesis Hyp5 ("*Being wealthy helps to be healthy")* is confirmed only partly as income contributed to healthier choices of particular health inputs, but not directly to health itself.

Thus, in this study, education and income have a positive impact on most behavioural patterns beneficial to health. It has been shown that a positive effect of income and education on dietary quality was due to the positive contribution of these factors to a person's awareness of nutrition-related aspects. Thereby, no direct impact of education and income on health was revealed. Although a number of indirect relations via health inputs could be shown, they were very small in magnitude. It must be also noted that there has been no consistency in the literature with regard to the above-discussed relations, i.e., between education, income, health state and lifestyles. The results tend to vary across genders, different age groups and countries. As discussed before, a number of various mechanisms through which these variables affect the state of health may exist, e.g., via third (unobservable) variables or due to reverse causality. As these are usually hard to account for empirically, this may contribute to the existing disagreement in empirical studies.

Gender

Further insights in the structural model are related to *gender*. An especially strong association was revealed between cardiovascular health and being male, which is in line with the official statistics in the USA (ROGER *et al.*, 2012). Furthermore, the indirect effects of male gender on health contribute greatly to this outcome. Thus, being male is related to all health-related choices considered negative in the model, e.g., higher energy intake, greater weight, more frequent smoking, alcohol consumption and sedentary leisure-time activities and lower level of nutritional knowledge. These indirect effects summed up with a direct impact of male gender on CVDs produce a strong negative total effect of this variable on health. This indicates a need in greater attention to this population group.

Insights from the alternative full structural model with a two-dimensional latent health variable

Further, the alternative full structural model, with cardiovascular health presented as a multidimensional concept was specified and tested. The alternative model incorporated the hypertension dimension and the lipid risk dimension of cardiovascular health. The estimation results indicated that the model had a better fit compared to the initial model. Furthermore, the alternative model provided further important insights into the hypothesised relationships. This confirmed the usefulness of treating cardiovascular health as a multidimensional construct. Moreover, these two dimensions of the same disease are (partly) explained by the other model variables.

Higher weight negatively and significantly impacts both health dimensions. However, dietary quality (diets rich in FV) is strongly related to the blood pressure factor, thus lowering the risk of hypertension. The latter is in line with existing scientific evidence. On the other hand, the negative health inputs such as alcohol consumption and sedentary leisure-time activities have a stronger relation to the lipid dimension of cardiovascular health. Moreover, while the effect of smoking on health in the initial model was non-significant, in the alternative model smoking had a significant negative impact on the lipid dimension of cardiovascular health. These findings need further exploration and insights from the medical field.

Another interesting outcome is regarding the role of education in the model. Higher education contributes to lower blood fat measurements and, thus, to the lower health risk. However, no significant relationship was found between education and the risk of hypertension. This finding may be an indication for health policy that more educated individuals possess higher awareness of the risks related to an elevated cholesterol level than about the risks related to high blood pressure.

To summarise, the consideration of the complexity of the health status measure contributes to obtaining deeper insights in the existing interrelations and suggest a need for deeper analysis and collaboration of different disciplines.

Reciprocal relations among model variables

This study acknowledges that a number of reciprocal relations may exist between health outcome and health inputs. However, the estimation of alternative models aimed to test such relations was not successful due to the arising underidentification problem, which could not be solved due a lack of adequate instruments. Moreover, it is discussed that such relations should be rather investigated using a longitudinal study design. Therefore, Hyp6 could not be tested and remains for further research.

Finally, the health production process presents a complex interaction of a number of variables that can hardly be fully presented and estimated using single-period cross-section data. Due to numerous factors playing a role in determining a particular health state (e.g., behavioural, epidemiological, economic), we believe that an interdisciplinary approach including a collaboration of social, medical and economic disciplines can contribute to a better understanding of these relations. In spite of the discussed limitations, we consider that the results provide interesting insights and present a step towards an interdisciplinary research approach.

Literature list

ADELAJA, A., NAYGA, R.M. and T. LAUDERBACH (1997): Income and Racial Differentials in Selected Nutrient Intakes. In: *American Journal of Agricultural Economics* 79(5), 1452-1460.

ADLER, N.E. and J.M. OSTROVE (1999): Socioeconomic Status and Health: What We Know and What We Don't. In: *Annals of the New York Academy of Sciences* 896, 3-15.

AINSWORTH, B.E., HASKELL, W.L., LEON, A.S., JACOBS, D.R. JR, MONTOYE, H.J., SALLIS, J.F. and R.S. PAFFENBARGER (1993): Compendium of Physical Activities: Classification of Energy Costs of Human Physical Activities. In: *Medicine and Science in Sports and Exercise* 25(1), 71-80.

AINSWORTH, B.E., HASKELL, W.L., WHITT, M.C., IRWIN, M.L., SWARTZ, A.M., STRATH, S.J., O'BRIEN, W.L., BASSETT, D.R. JR, SCHMITZ, K.H., EMPLAINCOURT, P.O., JACOBS, D.R. JR and A.S. LEON (2000): Compendium of Physical Activities: An Update of Activity Codes and MET Intensities. In: *Medicine and Science in Sports and Exercise* 32 (Suppl. 9), S498-504.

AGRAS, W.S., HAMMER, L.D., MCNICHOLAS, F. and H.C. KRAEMER (2004): Risk Factors for Childhood Overweight: A Prospective Study from Birth to 9.5 Years. In: *Journal of Pediatrics* 145(1), 20-25.

AKBARTABARTOORI, M., LEAN, M.I. and C.R. HANKEY (2005): Relationships Between Cigarette Smoking, Body Size and Body Shape. In: *International Journal of Obesity* 29, 236-243.

AKIN, J., D.K. GUILKEY, P. HUTCHINSON, and M. MCINTOSH (1998): Price Elasticities of the Demand for Curative Health Care with Control for Sample Selectivity and Endogenous Illness: An Analysis for Sri Lanka. In: *Health Economics* 7(6), 509-531.

AMERICAN LUNG ASSOCIATION (2011): Trends in Tobacco Use. In: http://www.lung.org/finding-cures/our-research/trend-reports/Tobacco-Trend-Report.pdf (10.06.2012).

ARBUCKLE, J.L. (2010): IBM SPSS Amos (Version 19.0) [Computer Program]. IBM Corporation, New York.

ARBUCKLE, J.L. (2007): Amos16.0 User's Guide. SPSS Inc., Chicago.

ASHER, H.B. (1986): Casual Modeling, 2nd ed., Sage, Beverly Hills.

AUSTER, R., LEVESON, I. and D. SARACHEK (1969): The Production of Health, an Exploratory Study. In: *The Journal of Human Resources* 4(4), 411-436.

BACKHAUS, K. (2006): Multivariate Analysemethoden: Eine Anwendungsorientierte Einführung, 11th ed., Springer, Berlin.

BAILEY, R.L., GUTSCHALL, M.D., MITCHELL, D.C. *et al.* (2006): Comparative Strategies for Using Cluster Analysis to Assess Dietary Patters. In: *Journal of American Dietetic Association* 106(8), 1194-1200.

BARALDI, A.N. and C.K. ENDERS (2010): An Introduction to Modern Missing Data Analyses. In: *Journal of School Psychology* 48(1), 5–37.

BARRETT, P. (2007): Structural Equation Modelling: Adjudging Model Fit. In: *Personality and Individual Differences* 42(5), 815–824.

BASIOTIS, P.P., CARLSON, A., GERRIOR, S.A., JUAN, W.Y. and M. LINO (2002): The Healthy Eating Index: 1999-2000. CNPP-12. U.S. Department of Agriculture, Center for Nutrition Policy and Promotion, Washington, D.C.

BECKER, G.S. (1965): A Theory of the Allocation of Time. In: *Economic Journal* 75(299), 493-517.

BECKER, G. S. (1976): The Economic Approach to Human Behaviour. The University of Chicago Press, London.

BEHRMAN, J.R. and B.L. WOLFE (1987): How Does Mother's Schooling Affect Family Health, Nutrition, Medical Care Usage, and Household Sanitation? In: *Journal of Econometrics* 36(1-2), 185-204.

BEHRMAN, J.R. and A.B. DEOLALIKAR (1988): Health and Nutrition. In: CHENERY, H. and T.N. SRINIVASAN (Eds.), *Handbook of Development Economics*, Volume I. Elsevier Science Publishers, Amsterdam, 631-711.

BEHRMAN, J.R., A.B. DEOLALIKAR, and B.L. WOLFE (1988): Nutrients: Impacts and Determinants. In: *World Bank Economic Review* 2(3), 299-320.

BENTLER, P.M. and D.C. BONNET (1980): Significance Tests and Goodness of Fit in the Analysis of Covariance Structures. In: *Psychological Bulletin* 88(3), 588-606.

BERGER, M.C. and J.P. LEIGH (1989): Schooling, Self-selection, and Health. In: *Journal of Human Resources* 24(3), 433-455.

BERLIN, J.A. and G.A. COLDITZ (1990): A Meta-Analysis of Physical Activity in the Prevention of Coronary Heart Disease. In: *American Journal of Epidemiology* 132(4), 612-628.

BERMAN, P., KENDALL, C. and K. BHATTACHARYYA (1994): The Household Production of Heath: Integration of Social Science Perspectives on Micro-Level Health Determinants. In: *Social Science and Medicine* 38(2), 205-215.

BERRY, W.D. (1984): Nonrecursive Causal Models. Sage, Beverly Hills.

BISHAI, D.M. (1996): Quality Time: How Parents' Schooling Affects Child Health Through its Interaction With Childcare Time in Bangladesh. In: *Health Economics* 5(5), 383-407.

BLACK, A.E. (2000): Critical Evaluation of Energy Intake Using the Goldberg Cut-off for Energy Intake: Basal Metabolic Rate. A Practical Guide to its Calculation, Use and Limitations. In: *International Journal of Obesity* 24(9), 1119-1130.

BLAIR, S.N. and J.R. MORROW (1998): Introduction: Cooper Institute/American College of Sports Medicine 1997 Physical Activity Intervention Conference. In: *American Journal of Preventative Medicine* 15, 255-256.

BLAYLOCK, J.R. and W.N. BLISARD (1992): Self-evaluated Health Status and Smoking Behaviour. In: *Applied Economics* 24(4), 429-435.

BLAYLOCK, J.R., VARIYAM, J.N. and B.-H. LIN (1999): Maternal Nutrition Knowledge and Children's Diet Quality and Nutrient Intakes. Food Assistance and Nutrition Research Report No. 1. U.S. Department of Agriculture, Economic Research Service, Food and Rural Economics Division, Washington, D.C.

BOLLEN, K.A. (1989): Structural Equations with Latent Variables. John Wiley, New York.

BOLLEN, K.A. (2002): Latent Variables in Psychology and the Social Sciences. In: *Annual Review of Psychology* 53(1), 605-634.

BOOMSMA, A. (2000): Reporting Analyses of Covariance Structures. In: *Structural Equation Modeling* 7(3), 461–483.

BOUND, J., JAEGER, D.A. and R.M. BAKER (1995): Problems with Instrumental Variables Estimation When the Correlation between the Instruments and the Endogenous Explanatory Variable Is Weak. In: *Journal of the American Statistical Association* 90(430), 443-450.

BOWLING, A. (1991): Measuring Health: A Review of Quality of Life Measurement Scales. Open University Press, Buckingham.

BRESLOW, R.A. and B.A. SMOTHERS (2005): Drinking Patterns and Body Mass Index in Never Smokers. National Health Interview Survey, 1997–2001. In: *American Journal of Epidemiology* 161(4), 368-376.

BRESLOW, L. (2006): Health Measurement in the Third Era of Health. In: *American Journal of Public Health* 96(1), 17-19.

BRIEFEL, R.R. and C.L. JOHNSON (2000): Secular Trends in Dietary Intake in the United States. In: *Annual Review of Nutrition* 24, 401-431.

BROWN, T.A. (2006): Confirmatory Factor Analysis for Applied Research. The Guilford Press, New York.

BROWNE, M.W. and R. CUDECK (1992): Alternative Way of Assessing Model Fit. In: *Sociological Methods of Research* 21(2), 230-258.

BROWNELL, K.D. and K. BATTLE HORGEN (2004): Food Fight. The Inside Story of the Food Industry, America's Obesity Crisis and What We can Do About It. The McGraw Hill, New York.

BROWNING, M., BOURGUIGNON, F., CHIAPPORI, P. A., and V. LECHENE (1994): Income and Outcomes: A Structural Model of Intrahousehold Allocation. In: *Journal of Political Economy* 102(6), 1067-1096.

BUCHHOLZ, A.C. and J.M. BUGARESTI (2005): A Review of Body Mass Index and Waist Circumference as Markers of Obesity and Coronary Heart Disease Risk in Persons with Chronic Spinal Cord Injury. In: *Spinal Cordiology* 43, 513-518.

BULLOCK, H.E., HARLOW, L.L. and S.A. MULAIK (1994): Causation Issues in Structural Equation Modeling Research. In: *Structural Equation Modeling* 1(3), 253-267.

BUSH, J.W., FANSHEL, S. and M.M. CHEN (1972): Analysis of a Tuberculin Testing Program Using a Health Status Index. In: *Socio-Economic Planning Sciences* 6(1), 49-68.

BYRNE, B.M. (2001): Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming, 2nd ed., Taylor and Francis, New York.

CAMERON, C.A. and P.K. TRIVEDI (2005): Microeconometrics. Methods and Applications. Cambridge University Press, New York.

CASAGRANDE, S.S., WANG, Y., ANDERSON, C. and T.L. Gary (2007): Have Americans Increased Their Fruit and Vegetable Intake? The Trends Between 1988 and 2002. In: *American Journal of Preventive Medicine* 32(4), 257-263.

CATANZARO, J.A. and R. SUEN (1996): Clinical Laboratory Indicators of Cardiovascular Disease Risk. In: *Alternative Medical Review* 1(3), 185-194.

CDC (2000): Measuring Healthy Days: Population Assessment of Health-related Quality of Life. Centers for Disease Control and Prevention*,* Atlanta, Georgia.

CDC (2007): NHANES 2005-2006: Questionnaires, Datasets, and Related Documentation. In: http://wwwn.cdc.gov/nchs/nhanes/search/nhanes05_06.aspx (05.07.2009).

CDC (2007a): Laboratory Procedure Manual. Glucose in Refrigerated Serum NHANES 2005–2006. In: http://www.cdc.gov/nchs/data/nhanes/nhanes_05_06/glu_d_met_fasting_glucose.pdf (22.10.2010)

CDC (2007b): Laboratory Procedure Manual. Sodium in Refrigerated Serum NHANES 2005–2006. In: http://www.cdc.gov/nchs/data/nhanes/nhanes_05_6/biopro_d_met_sodium.pdf (22.10.2010)

CDC (2007c): Laboratory Procedure Manual. Serum Folate and Vitamin B12 in Serum and RBC Folate in Whole Blood NHANES 2005–2006. In: http://www.cdc.gov/nchs/data/nhanes/nhanes_05_06/folate_b12_d_met.pdf (22.10.2010)

CDC (2007d): Laboratory Procedure Manual. 25-Hydroxyvitamin D in Serum NHANES 2005-2006. In: http://www.cdc.gov/nchs/data/nhanes/nhanes_05_06/vid_d_met_ vitamin_d.pdf (22.10.2010)

CDC (2007e): Laboratory Procedure Manual. Vitamin C in Serum NHANES 2005-2006. In: http://www.cdc.gov/nchs/data/nhanes/nhanes_05_06/vic_d_met.pdf (22.10.2010)

CDC (2008): About the National Health and Nutrition Examination Survey. In: http://www.cdc.gov/nchs/nhanes/about_nhanes.htm (02.05.2009).

CDC (2008a): NHANES Sample Design. In: http://www.cdc.gov/nchs/tutorials/NHANES/SurveyDesign/SampleDesign/intro.htm (02.05.2009).

CDC (2013): Genomics and Health. Heart Disease and Family History. In: http://www.cdc.gov/genomics/resources/diseases/heart.htm (10.05.2013).

CDC and NIH (2010): Healthy People 2010: Objectives for Improving Health. In: http://www.cdc.gov/dhdsp/docs/hp2010.pdf (05.07.2010).

CHANG, V. and W.D. LAUDERDAL (2005): Income Disparities in Body Mass Index and Obesity in the United States, 1971-2002. In: *Archive of Internal Medicine* 165(18), 2122-2128.

CHEN, S.-N., SHOGREN, J.F., ORAZEM, P.F. and T.D. CROKER (2002): Prices and Health: Identifying the Effects of Nutrition, Exercise and Medication Choices on Blood Pressure. In: *American Journal of Agricultural Economics* 84(4), 990-1002.

CHOU, S.-Y., GROSSMAN, M. and H. SAFFER (2004): An Economic Analysis of Adult Obesity: Results From the Behavioral Risk Factor Surveillance System. In: *Journal of Health Economics* 23(3), 565-587.

CLARK, A. and F. ETILÉ (2002): Do Health Changes Affect Smoking? Evidence from British Panel Data. In: *Journal of Health Economics* 21(4), 533-562.

CLIFF, N. (1983): Some Cautions Concerning the Application of Causal Modeling Methods. In: *Multivariate Behavioral Research* 18(1), 115-126.

COBAS, J.A., BALCAZAR, H., BENIN, M.B., KEITH, V.M. and Y. CHONG (1996): Acculturation and Low-Birthweight Infants among Latino Women: A Reanalysis of HHANES Data with Structural Equation Models. In: *American Journal of Public Health* 86(3), 394-396.

CONNELL, C.L., YADRICK, K., JOHNSON, J.T. and L.J. SU (2001): Structural Analysis of the Relationship of Food Insufficiency to Cardiovascular Disease Risk and Outcomes among Adults from the Southern Region of NHANES III. Food Assistance and Nutrition Programs: RIDGE Project Summary, USDA. In: http://srdc.msstate.edu/ridge/files/recipients/00_connell_final.pdf. (09.11.2011)

CONTOYANNIS, P. and A.M. JONES (2004): Socio-economic Status, Health and Lifestyle. In: *Journal of Health Economics* 23(5), 965-995.

COWEN, T. (1989): Are All Tastes Constant and Identical? A Critique of Stigler and Becker. In: *Journal of Economic Behavior and Organization* 11(1), 127-135.

CROWLEY, S.L. and X. FAN (1997): Structural Equation Modeling: Basic Concepts and Applications in Personality Assessment Research. In: *Journal of Personality Assessment* 68(3), 508-531.

CUTLER, D.M and A. LLERAS-MUNEY (2010): Understanding Differences in Health Behaviors by Education. In: *Journal of Health Economics* 29(1), 1-28.

CUTLER, D.M., GLAESER, E.L. and J.M. SHAPIRO (2003): Why Have Americans Become More Obese? In: *Journal of Economic Perspectives* 17(3), 93-118.

DALLONGEVILLE, J., MARECAUX, N., FRUCHART, J.C. and P. AMOUYEL (1998): Cigarette Smoking is Associated with Unhealthy Patterns of Nutrient Intake: A Meta-Analysis. In: *Journal of Nutrition* 128(9), 1450-1457.

DAVANZO, J. and P. GERTLER (1990): Household Production of Health: A Microeconomic Perspective on Health Transitions. The Rand Publication Series. The Rand Corporation, Santa Monica.

DAVIS, C.G. (1982): Linkages Between Socioeconomic Characteristics, Food Expenditure Patterns, and Nutritional Status of Low Income Households: A Critical Review. In: *American Journal of Agricultural Economics* 64(5), 1017-1025.

DEMYDAS, T. (2011): Consumer Segmentation Based on the Level and Structure of Fruit and Vegetable Intake: An Empirical Evidence for US Adults from the National Health and Nutrition Examination Survey (NHANES) 2005–2006. In: *Public Health Nutrition* 14(6), 1088-1095.

DEMYDAS, T. (2013): Lifestyle Factors, Dietary Quality and Health: Econometric Evidence from US Micro Data. In: *Review of Agricultural and Environmental Studies* 94(2), 135-163.

DENTON, M. and V. WALTERS (1999): Gender Differences in Structural and Behavioural Determinants of Health: An Analysis of the Social Production of Health. In: *Social Science and Medicine* 48(9), 1221-1235.

DESALVO K.B., BLOSER N., REYNOLDS K., HE J. and P.J. MUNTNER (2006): Mortality Prediction with a Single General Self-Rated Health Question. A Meta-Analysis. In: *Journal of General Internal Medicine* 21(3), 267-275.

DOBBELSTEYN, C.J., JOFFRES, M.R., MACLEAN, D.R. and G. FLOWERDEW (2001): A Comparative Evaluation of Waist Circumference, Waist-to-Hip Ratio and Body Mass Index as Indicators of Cardiovascular Risk Factors. The Canadian Heart Health Surveys. In: *International Journal of Obesity* 25(5), 652-661.

DOMINICK, K.L., AHERN F.M., GOLD C.H. and D.A. HELLER (2002): Relationship of Health-Related Quality of Life to Health Care Utilization and Mortality Among Older Adults. In: *Aging Clinical and Experimental Research* 14(6), 499-508.

DONG, D. and B.H. LIN (2009): Fruit and Vegetable Consumption by Low-Income Americans: Would a Price Reduction Make a Difference? Economic Research Report No. 70, U.S. Department of Agriculture, Economic Research Service, Washington, D.C.

DRESCHER, L., THIELE, S. and G.B. MENSINK (2007): A New Index to Measure Healthy Food Diversity Better Reflects a Healthy Diet Than Traditional Measures. In: *The Journal of Nutrition* 137(3), 647-651.

DRESCHER, L. (2007): Healthy Food Diversity as a Concept of Dietary Quality: Measurement, Determinants of Consumer Demand, and Willingness to Pay. Cuvillier, Göttingen.

DREWNOWSKI, A. (2005): Concept of Nutritious Food: Toward a Nutrient Density Score. In: *American Journal of Clinical Nutrition* 82(4), 721-732.

DREWNOWSKI, A., HENDERSON, A.S., DRISCOLL, A. and B.J. ROLLS (1997): The Dietary Variety Score: Assessing Diet Quality in Healthy Young and Older Adults. In: *Journal of American Dietetic Association* 97(3), 266-271.

DUFFY, P., ZIZZA, C. and H. KINNUCAN (2009): Obesity, BMI, and Diet Quality: How Does the South Measure Up? Selected Paper Prepared for Presentation at the Southern Agricultural Economics Association Annual Meeting, January 31-February 3, Atlanta, Georgia.

DWYER, D.S. and O.S. MITCHELL (1999): Health Problems as Determinants of Retirement: Are Self-Rated Measures Endogenous? In: *Journal of Health Economics* 18(2), 173–193.

EDWARDS, L.N. and M. GROSSMAN (1979): Adolescent Health, Family Background, and Preventive Medical Care. Working Paper No. 398, National Bureau of Economic Research, Cambridge, MA.

EISENMAN, C.J., Bartee, R.T. and M.Q. Wang (2002): Physical Activity, TV Viewing, and Weight in U.S. Youth: 1999 Youth Risk Behavior Survey. In: *Obesity Research* 10(5), 379-385.

EGERTER, S., BRAVEMAN, P., SADEGH-NOBARI, T., GROSSMAN-KAHN, R. and M. DEKKER (2009): Education Matters for Health. Education and Health. Issue Brief 6, Robert Wood Johnson Foundation, Commission to Build Healthier America, Princeton.

ERBSLAND, M., RIED, W. and V. ULRICH (1994): Health, Health Care, and the Environment. Econometric Evidence from German Micro Data. Discussion Paper No. 94-16, Centre for European Economic Research (ZEW), University of Mannheim.

ERBSLAND, M., W. RIED and V. ULRICH (1995): Health, Health Care, and the Environment. Econometric Evidence from German Micro Data. In: *Health Economics* 4(3), 169-182.

ERVIN, R.B. (2011): Healthy Eating Index–2005 Total and Component Scores for Adults Aged 20 and Over: National Health and Nutrition Examination Survey, 2003–2004. National Health Statistics Reports No. 44, U.S. Department for Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics, Washington, D.C.

ETILÉ, F. (2007): Social Norms, Ideal Body Weight and Food Attitudes. In: *Health Economics* 16(9), 945-966.

EVENSON, R.E. (1981): Food Policy and the New Home Economics. In: *Food Policy* 6(3), 180-193.

FINNEY, S.J. and C. DISTEFANO (2006): Non-Normal and Categorical Data in Structural Equation Modeling. In: Hancock, G.R. and R.O. Mueller (Eds.), *Structural Equation Modeling: A Second Course*. Information Age Publishing Inc., Greenwich.

FLEGAL, K.M., CARROLL, M.D., OGDEN, C.L. and L.R. CURTIN (2010): Prevalence and Trends in Obesity Among US Adults, 1999-2008. In: *The Journal of the American Medical Association* 303(3), 235-241.

FLETCHER, J.M., FRISVOLD, D.E. and N. TEFFT (2010): The Effects of Soft Drink Taxes on Child and Adolescent Consumption and Weight Outcomes. In: *Journal of Public Economics* 94(11-12), 967-974.

FOGELHOLM, M. and K. KUKKONEN-HARJULA (2000): Does Physical Activity Prevent Weight Gain - A Systematic Review. In: *Obesity Review* 1(2), 95-111.

FORD, E.S., LI, C., ZHAO, G., PEARSON, W.S., TSAI, J. and J.R. CHURILLA (2010): Sedentary Behaviour, Physical Activity, and Concentrations of Insulin Among US Adults. In: *Metabolism Clinical and Experimental* 59(9), 1268-1275.

FOSTER, E.M. and S. MCLANAHAN (1996): An Illustration of the Use of Instrumental Variables: Do Neighbourhood Conditions Affect a Young Person's Chance of Finishing High School? In: *Psychological Methods* 1(3), 249-260.

FOSTER, J.A., GORE, S.A. and D. WEST (2006): Altering TV Viewing Habits: An Unexplored Strategy for Adult Obesity Intervention? In: *American Journal of Health Behavior* 30(1), 3-14.

FOX, J. (2006): An Introduction to Structural Equation Modelling. ESRC Oxford Spring School. In: http://socserv.mcmaster.ca/jfox/Courses/Oxford-2006/index.html (14.08.2009)

FRONE, M.R., RUSSELL, M. and M.L. COOPER (1994): Relationship Between Job and Family Satisfaction: Causal or Noncausal Covariation? In: *Journal of Management* 20(3), 565-579.

FU, A.Z., LIU, G.G. and D.B. CHRISTENSEN (2004): Inappropriate Medication Use and Health Outcomes in the Elderly. In: *Journal of American Geriatric Society* 52(11), 1934-1939.

FUCHS, V. (1967): The Basic Forces Influencing Costs of Medical Care. The Address Given at the National Conference on Medical Care Costs, June 27, 1967, Washington, D.C.

FUCHS, V. (1982): Time Preference and Health: An Exploratory Study. In: Fuchs, V.R. (Ed.), *Economic Aspects of Health*. University Chicago Press, Chicago.

FUCHS, V. (1986): The Health Economy, 1st ed., Harvard University Press, Cambridge, MA.

FUCHS, V. (2004): Reflections on the Socio-Economic Correlates of Health. In: *Journal of Health Economics* 23(4), 653-661.

FULKERSON, J.A. and S.A. FRENCH (2003): Cigarette Smoking for Weight Loss or Control Among Adolescents: Gender and Racial/ethnic Differences. In: *Journal of Adolescent Health* 32(4), 306-313.

GAO, S., MOKHTARIAN, P.L. and R.A. JOHNSTON (2008): Non-normality of Data in Structural Equation Models. Presentation at the Transportation Research Board's 87th Annual Meeting, Washington, D.C.

GARSON, G.D. (2011): Structural Equation Modeling, from Statnotes: Topics in Multivariate Analysis. In: http://faculty.chass.ncsu.edu/garson/PA765/structur.htm (04.11.2011).

GERDTHAM, U.G., JOHANNESSON, M., LUNDBERG, M. and D. ISACSON (1999): The Demand for Health: Results From New Measures of Health Capital. In: *European Journal of Political Economy* 15(3), 501-521.

GERDTHAM, U.G. and M. JOHANNESSON (1999): New Estimates of the Demand for Health: Results based on a Categorical Health Measure and Swedish Micro Data. In: *Social Science & Medicine* 49(10), 1325-1332.

GIUFFRIDA, A., IUNES, R.F. and W.D. SAVEDOFF (2005): Health and Poverty in Brazil: Estimation by Structural Equation Model with Latent Variables. Technical Note on Health No. 1, Inter-American Development Bank, New York, Washington, D.C.

GOLDMAN, D., LAKDAWALLA, D. and Y. ZHENG (2009): Food Prices and the Dynamics of Body Weight. NBER Working Paper No. 15096, National Bureau of Economic Research, Cambridge, MA.

GRACE, J.B., ANDERSON, T.M., OLFF, H. and S.M. SCHEINER (2010): On the Specification of Structural Equation Models for Ecological Systems. In: *Ecological Monographs* 80(1), 67-87.

GREENE, W.H. (2003): Econometric Analysis, 5th ed., Pearson Education, Inc., New Jersey.

GREENWOOD, D.C., CADE, J.E., DRAPER, A., BARRETT, J.H., CALVERT, C. and A. GREENHALGH (2000): Seven Unique Food Consumption Patterns Identified Among Women in the UK Women's Cohort Study. In: *European Journal of Clinial Nutrition* 54(4), 314-320.

GREINER, W., WEIJNEN, T., NIEUWENHUIZEN, M., OPPE, M., BADIA, X., BUSSCHBACH, J., BUXTON, M., DOLAN, P., KIND, P., KRABBE, P., OHINMAA, A., PARKIN, D., ROSET, M., SINTONEN, H., TSUCHIYA, A. and F. DE CHARRO (2003): A Single European Currency for EQ-5D Health States. Results From a Six-country Study. In: *European Journal of Health Economics* 4(3), 222-231.

GRONAU, R. (1977): Leisure, Home Production and Work: The Theory of the Allocation of Time Revisited. In: *The Journal of Political Economy* 85(6), 1099-1123.

GROSSMAN, M. (1972): On the Concept of Health Capital and the Demand for Health. In: *Journal of Political Economy* 80, 223-255.

GROSSMAN M. (2004): The Demand for Health, 30 Years Later: A Very Personal Retrospective and Prospective Reflection. In: *Journal of Health Economics* 23(4), 629-636.

GRØNTVED, A. and F. HU (2011): Television Viewing and Risk of Type 2 Diabetes, Cardiovascular Disease, and All-Cause Mortality. A Meta-analysis FREE. In: *The Journal of the American Medical Association* 305(23), 2448-2455.

GUENTNER, P., REEDY, J. and S.M. KREBS-SMITH (2008): Development of the Healthy Eating Index-2005. In: *Journal of American Dietary Association* 108(11), 1896-1901.

GUENTHER, P.M., CASAVALE, K.O., REEDY, J., KIRKPATRICK, S.I., HIZA, H.A.B., KUCZYNSKI, K.J., KAHLE, L.L. and S.M. KREBS-SMITH (2013): Update of the Healthy Eating Index: HEI-2010. In: *Journal of the Academy of Nutrition and Dietetics* 113(4), 569-580.

GUIFFRIDA, A., IUNES, R.F. and W.D. SAVEDOFF (2005): Health and Poverty in Brazil: Estimation by Structural Equation Model with Latent Variables. Technical Note on Health No. 1, Inter-American Development Bank, Washington, D.C.

HAINES, P.S., SIEGA-RIZ, A.M. and B.M. POPKIN (1999): The Diet Quality Index Revised: a Measurement Instrument for Populations. In: *Journal of American Dietetic Association* 99(6), 697-704.

HAIR, J.F., ANDERSON, R.E., TATHAM, R.L. and W.C. BLACK (1995): *Multivariate Data Analysis with Readings*, 4th ed., Prentice Hall, New York.

HANCOCK, G.R. and R.O. MUELLER (2001): Rethinking Construct Reliability Within Latent Variable System. In: CUDECK, R, DU Toit, S. and D. SORBOM (Eds.), *Structural Equation Modeling: Present and Future*. Scientific Software International Inc. Chicago, IL, 195-216.

HAVEMAN-NIES, A., TUCKER, K.L., DE GROOT, L.C., WILSON, P.W. and W.A. van STAVEREN (2001): Evaluation of Dietary Quality in Relationship to Nutritional and Lifestyle Factors in Elderly People of the US Framingham Heart Study and the European SENECA Study. In: *European Journal of Clinical Nutrition* 55(10), 870-880.

HAYDUK, L., CUMMINGS, G.G., BOADU, K., PAZDERKA-ROBINSON, H., and S. BOULIANNE (2007): Testing! Testing! One, Two Three – Testing the Theory in Structural Equation Models! In: *Personality and Individual Differences* 42(2), 841-850.

HAYES, D.K., DENNY, C.H., KEENAN, N.L., CROFT, J.B. and K.J. GREENLUND (2008): Health Related Quality of Life and Hypertension Status. Awareness, Treatment, and Control: National Health and Nutrition Examination Survey, 2001-2004. In: *Journal of Hypertension* 26, 641-647.

HAYS, R.D., REVICKI, D. and K.S. COYNE (2005): Application of Structural Equation Modeling to Health Outcomes Research. In: *Evaluation and Health Professions* 28(3), 295-309.

HÄKKINEN, U. (1991): The Production of Health and the Demand for Health Care in Finland. In: *Social Science and Medicine* 33(3), 225-237.

HEIDENREICH, P.A., TROGDON, J.G., KHAVJOU, O.A. *et al.* (2011): Forecasting the Future of Cardiovascular Disease in the United States: A Policy Statement from the American Heart Association. In: *Circulation* 123, 933-944.

HEIMAN, A., JUST, D.R., MCWILLIAMS, B. and D. ZILBERMAN (2001): Incorporating Family Interactions and Socioeconomic Variables into Family Production Functions: The Case of Demand for Meats. In: *Agribusiness* 17(4), 455-468.

HENDLER, R. (1975): Lancaster's New Approach to Consumer Demand and its Limitations. In: *The American Economic Review* 65(1), 194-199.

HHS (2001): The Surgeon General's Call to Action to Prevent and Decrease Overweight and Obesity 2001. US Public Health Service, Office of the Surgeon General. In: http://www.surgeongeneral.gov/topics/obesity/calltoaction/CalltoAction.pdf (20.07.2010).

HHS (2004): The Report of the Dietary Guidelines Advisory Committee on Dietary Guidelines for Americans, 2005, Part D. Science Base, Section 1. Aiming to Meet Nutrient Intake Recommendations. In: http://www.health.gov/dietaryguidelines/dga2005/report/default.htm (12.06.2012)

HHS and USDA (2005): Dietary Guidelines for Americans, 2005, 6th ed., U.S. Government Printing Office, Washington, D.C.

HHS (2008): *Physical Activity Guidelines for Americans, Be Active, Healthy, and Happy!,* U.S. Government Printing Office, Washington, D.C.

HILL, J.O. and J.C. PETERS (1998): Environmental Contributions to the Obesity Epidemic. In: *Science* 280(5368), 1371-1374.

HOOPER, D., COUGHLAN, J. and M.R. MULLEN (2008): Structural Equation Modelling: Guidelines for Determining Model Fit. In: *The Electronic Journal of Business Research Methods* 6(1), 53-60.

HOPWOOD, C.J. and M.B. DONNELLAN (2010): How Should the Internal Structure of Personality Inventories be Evaluated? In: *Personality and Social Psychology Review* 14(3), 332-346.

HOX, J.J. and T.M. BECHGER (1998): An Introduction to Structural Equation Modelling. In: *Family Science Review* 11, 354-373.

HOYLE, R.H. and G.T. SMITH (1994): Formulating Clinical Research Hypotheses as Structural Equation Models: A Conceptual Overview. In: *Journal of Consulting and Clinical Psychology* 62(3), 429-440.

HÖFER, S., BENZER, W., ALBER, H., RUTTMANN, E., KOPP, M., SCHÜSSLER, G. and S. DOERING (2005): Determinants of Health-Related Quality of Life in Coronary Artery Disease Patients: A Prospective Study Generating a Structural Equation Model. In: *Psychosomatics* 46(3), 212-223.

HU, L.T. and P.M. BENTLER (1999): Cut off Criteria for Fit Indices in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives. In: *Structural Equation Modeling* 6(1), 1-55.

HUANG, C.H. and S.K. MISRA (1991): Assessing Nutritional Adequacy of Americans Based on Individual Food Intake Patterns. In: *Journal of Consumer Studies and Home Economics* 15(2), 147-159.

HUANG, C.L. and B.H. LIN (2007): A Hedonic Analysis of Fresh Tomato Pricing among Regional Markets. In: *Review of Agricultural Economics* 29(4), 783-800.

HUANG, T., HOWARTH, N.C. LIN, B.-H., ROBERTS, S.B. and M.A. MCCRORY (2004): Energy Intake and Meal Portions: Associations with BMI Percentile in U.S. Children. In: *Obesity Research* 12(11), 1875-1885.

HUFFMAN, W., HUFFMAN, S.K., TEGENE, A. and K. RICKERTSEN (2006): The Economics of Obesity-Related Mortality Among High Income Countries. Working Paper No. 06021, Department of Economics, Iowa State University.

HUFFMAN, S.K. and M. RIZOV (2010): The Rise of Obesity in Transition: Theory and Empirical Evidence from Russia. In: *Journal of Development Studies* 46(3), 574-594.

HUGHES, M.A., PRICE, R.L. and D.W. MARRS (1986): Linking Theory Construction and Theory Testing: Models with Multiple Indicators of Latent Variables. In: *The Academy of Management Review* 11(1), 128-144.

HUIJBREGTS, P., FESKENS, E., RÄSÄNEN, L., FIDANZA, F., NISSINEN, A., MENOTTI, A. and D. KROMHOUT (1997): Dietary Pattern and 20 Year Mortality in Elderly Men in Finland, Italy, and The Netherlands: Longitudinal Cohort Study. In: *British Medical Journal* 315(7099), 13-17.

HUNTER, J.E., and D.W. GERBING (1982): Unidimensional Measurement, Second Order Factor Analysis, and Causal Models. In: *Research in Organizational Behavior* 4, 267-320.

INSTITUTE OF MEDICINE (2002): Dietary Reference Intakes for Energy, Carbohydrates, Fiber, Fat, Fatty Acids, Cholesterol, Protein, and Amino Acids. The National Academies Press, Washington, D.C.

INSTITUTE OF MEDICINE (2011): Leading Health Indicators for Healthy People 2020: Letter Report. The National Academies Press, Washington, D.C. In: http://books.nap.edu/openbook.php?record_id=13088&page=R1 (12.03.2010)

JACOBSON, M.F. and K.D. BROWNELL (2000): Small Taxes on Soft Drinks and Snack Foods to Promote Health. In: *American Journal of Public Health* 90(6), 854–857.

JAMES, L.R. and B.K. SINGH (1978): An Introduction to the Logic, Assumptions, and Basic Analytic Procedures of Two-Stage Least Squares. In: *Psychological Bulletin* 85(5), 1104-1122.

JEFFERY, R.W. and S.A. FRENCH (1998): Epidemic Obesity in the United States: Are Fast Foods and Television Viewing Contributing? In: *American Journal of Public Health* 88(2), 277-280.

JOHNSON J.A., ERGO A. and S.J. COONS (1998): Valuation of the EuroQol (EQ-5D) in Adult US Sample. In: *Pharmaco Economics* 13(4), 421-433.

JONES, A.M. (2000): Health Econometrics. In: NEWHOUSE, J.P. and A.J. CULYER (Eds.), *Handbook of Health Economic,* Volume 1A, Part 1, Chapter 6. Elsevier, The Netherlands, 265-344.

JOYCE, T. (1987): The Demand for Health Inputs and Their Impact on the Black Neonatal Mortality Rate in the U.S. In: *Social Science and Medicine* 24(11), 911-918.

KANT, A.K. and B.I. GRAUBARD (2008): Ethnic and Socioeconomic Differences in Variability in Nutritional Biomarkers. In: *American Journal of Clinical Nutrition* 87(5), 1464-1471.

KANT, A.K., SCHATZKIN, A., HARRIS, T.B., ZIEGLER, R.G. and G. BLOCK (1993): Dietary Diversity and Subsequent Mortality in the First National Health and Nutrition Examination Survey Epidemiologic Follow-up Study. In: *American Journal of Clinical Nutrition* 57(3), 434-440.

KAPLAN, G.A. and J.E. KEIL (1993): Socioeconomic Factors and Cardiovascular Disease: a Review of the Literature. In: *Circulation* 88, 1973-1998.

KAZIS, L.E., J.J. ANDERSON and R.F. MEENAN (1989): Effect Sizes for Interpreting Changes in Health Status. In: *Medical Care* 27(3), Advances in Health Status Assessment (Suppl.), S178-S189.

KAWACHI, I. ADLER, N.E. and W.H. DOW (2010): Money, Schooling, and Health: Mechanisms and Causal Evidence. In: *Annals of the New York Academy of Sciences*. *Issue: The Biology of Disadvantage* 1186, 56–68.

KEMNA, H.J. (1987): Working Conditions and the Relationship Between Schooling and Health. In: *Journal of Health Economics* 6(3), 189-210.

KENKEL, D.S. (1991): Health Behavior, Health Knowledge, and Schooling. In: *The Journal of Political Economy* 99(2), 287-305.

KENKEL, D.S. (1995): Should You Eat Breakfast? Estimates from Health Production Functions. In: *Health Economics* 4(1), 15-29.

KENNEDY, E., OHLS, J., CARLSON, S. and K. FLEMING (1995): The Health Eating Index: Design and Application. In: *Journal of American Diet Association* 95(10), 1103–1108.

KENNEDY, P. (2003): A Guide to Econometrics, 5th ed., Blackwell Publishing, Oxford.

KIISKINEN, U. (2003): A Health Production Approach to the Economic Analysis of Health Promotion. Academic Dissertation for the Degree of Doctor of Philosophy. National Public Health Institute. Julkaisija – Utgivare – Publisher, Helsinki.

KLINE, P. (1994): An Easy Guide to Factor Analysis. TJ International Ltd, London.

KLINE, R.B. (1998): Principles and Practice of Structural Equation Modeling. The Guilford Press, London.

KÖNIG, H.H., BERNERT, S. and A.C. ANGRMEYER (2005): Gesundheitszustand der Deutschen Bevölkerung: Ergebnisse einer Repräsentativen Befragung mit dem EUROQOL-Instrument. In: *Gesundheitswesen* 67(3), 173-182.

KREBS-SMITH, S.M., COOK D.A., SUBAR, A.F., CLEVELAND, L. and J. FRIDAY (1995): US Adults' Fruit and Vegetable Intakes, 1989 to 1991: A Revised Baseline for the Healthy People 2000 Objective. In: *American Journal of Public Health* 85(12), 1623-1629.

KRÖMKER, D. and J. VOGLER (2011): Übergewicht und Adipositas – Eine Diätgeschichte. Ergebnisse einer bundesweiten Befragungsstudie mit Kindern und Jugendlichen aus psycho-sozialer Sicht. In: Zwick, M., Deuschle, J. and O. Renn (Eds.), *Übergewicht und Adipositas bei Kindern und Jugendlichen.* VS Verlag, Wiesbaden, 115-136.

LAKDAWALLA, D.N., GOLDMAN, D. and B. SHANG (2005): The Health and Cost Consequences Of Obesity Among the Future Elderly. In: *Health Affairs* 10, 29-41.

LANCASTER K.J. (1966): A New Approach to Consumer Theory. In: *The Journal of Political Economy* 74(2), 132-157.

LARSON, J.S. (1997): The MOS 36-Item Short Form Health Survey: A Conceptual Analysis. In: *Evaluation and the Health Professions* 20(1), 14-27.

LEE, J. (1987): The Demand for Varied Diet with Econometric Models for Count Data. In: *American Journal of Agricultural Economics* 69(3), 687-692.

LEI, P.-W., and W. WU (2007): Introduction to Structural Equation Modeling: Issues and Practical Considerations. In: *Educational Measurement: Issues and Practice* 26(3), 33-43.

LEIGH, J.P. (1983): Direct and Indirect Effects of Education on Health. In: *Social Science and Medicine* 17(4), 227-234.

LIN, B.H. and R. MENTZER MORRISON (2002): Higher Fruit Consumption Linked with Lower Body Mass Index. In: *Food Review* 25(3), 28-32.

LLOYD-JONES, D., ADAMS, R.J., BROWN, T.M., CARNETHON, M., DAI, S., DE SIMONE, G. *et al.* (2010): Heart Disease and Stroke Statistics-2010 Update. A Report from the American Heart Association. In: *Circulation* 121, e46-e215.

LOUREIRO, M.L. and R.M. NAYGA (2005): International Dimensions of Obesity and Overweight Related Problems: An Economic Perspective. In: *American Journal of Agricultural Economics* 87(5), 1147-1153.

MA, Y., BERTONE, E.R., STANEK, E.J., REED, G.W., HEBERT, J.R., COHEN, N.L., MERRIAM, P.A. and I.S. OCKENE (2003): Association between Eating Patterns and Obesity in a Free-living US Adult Population. In: *American Journal of Epidemiology* 158(1), 85-92.

MACKINNON, D.P., KRULL, J.L. and C.M. LOCKWOOD (2000): Equivalence of the Mediation, Confounding and Suppression Effect. In: *Prevention Scienc*e 1(4), 173-181.

MANNING, W.G., NEWHOUSE J.P. and J.E. WARE (1982): The Status of Health in Demand Estimation: Beyond Excellent, Good, Fair and Poor. In: FUCHS, V. (Ed.), *Economic Aspects of Health*. University of Chicago Press, Chicago, 141-184.

MARSH, H.W., HAU, K.T. and Z. WEN (2004): In Search of Golden Rules: Comment on Hypothesis-Testing Approaches to Setting Cutoff Values for Fit Indices and Dangers in Overgeneralizing Hu and Bentler's Findings. In: *Structural Equation Modeling* 11(3), 320-341.

MARUYAMA, G.M. (1998): Basics of Structural Equation Modelling. SAGE Publications Inc., London.

MAZZOCCHI, M. and W.B. TRAILL (2008): A Structural Model of Wealth, Obesity and Healt in the UK. Selected Paper Presented at the 12th Congress of European Association of Agricultural Economists (EAAE), August 26-29, Ghent, Belgium.

MAZZOCCHI, M. and W.B. TRAILL (2011): Calories, Obesity and Health in OECD Countries. In: *Applied Economics* 43(26), 3919-3929.

MAZZOCCHI, M., TRAILL, W.B. and J.F. SHOGREN (2009): Fat Economics: Nutrition, Health, and Economic Policy. Oxford University Press, New York.

MCALISTER, A.L., KROSNICK, J.A. and M.A. MILBURN (1984): Causes of Adolescent Cigarette Smoking: Tests of a Structural Equation Model. In: *Social Psychology Quarterly* 47(1), 24-36.

MCCANN, S.E, RANDALL, E., MARSHALL, J.R., GRAHAM, S., ZIELEZNY, M. and J.L. FREUDENHEIM (1994): Diet Diversity and Risk of Colon Cancer in Western New York. In: *Nutrition and Cancer* 21(2), 133-141.

MCINTOSH, A., DAVIS, G., NAYGA, R., ANDING, J., TORRES, C., KUBENA, K., PERUSQUIA, E., YELEY, G. and W. YOU (2006): Parental Time, Role Strain, and Children's Fat Intake and Obesity-Related Outcomes. Report No. 19, Texas A&M University under a Cooperative Research Contract with USDA's Economic Research Service. In: http://naldc.nal.usda.gov/download/32790/PDF (12.10.2011)

MCDOWELL, I. and C. NEWELL (1987): Measuring Health: A Guide to Rating Scales and Questionnaires. Oxford University Press, New York.

MCHORNEY, C.A. (1999): Health Status Assessment Methods For Adults: Past Accomplishments and Future Challenges. In: *Annual Review of Public Health* 20, 309-335.

MEDICAL NEWS TODAY (2009): What Is Health? What Does Good Health Mean? Famous Health Quotes. In: http://www.medicalnewstoday.com/articles/150999.php (08.06.2013).

MELTON, B.E., HUFFMAN, W.E. and J.F. SHOGREN (1996): Economic Values of Pork Attributes: Hedonic Price Analysis of Experimental Auction Data. In: *Review of Agricultural Economics* 18(4), 613-627.

MICHAEL, R.T. and G.S. BECKER (1973): On the New Theory of Consumer Behavior. In: *The Swedish Journal of Economics* 75(4), 378-396.

MILLEN, B.E., QUATROMONI, P.A., GAGNON, D.R., ADRIENNE CUPPLES, L., FRANZ, M. and R.B. D'AGOSTINO (1996): Dietary Patterns of Men and Women Suggest Targets for Health Promotion: The Framingham Nutrition Studies. In: *American Journal of Health Promotion* 11(1), 42-53.

MOCAN, N. and E. TEKIN (2011): Obesity, Self-esteem, and Wages. In: GROSSMAN, M. and N. MOCAN (Eds.), *Economic Aspects of Obesity*. University of Chicago Press, Chicago.

MOLARIUS, A., PARSONS, R.W., DOBSON, A.J., EVANS, A.,PORTMANN, S.P., JAMROZIK, K., KUULASMAA, K., MOLTCHANOV, V., SANS, S., TUOMILEHTO, J., PUSKA, P. and WHO MONICA Project (2001): Trends in Cigarette Smoking in 36 Populations from the Early 1980s to the Mid-1990s: Findings from the WHO MONICA Project. In: *American Journal of Public Health* 91(2), 206-212.

MORITZ, K.H. (1993): Mikroökonomische Theorie des Haushalts. R. Oldenbourg Verlag, München.

MUSIL, C.M., JONES, S.L. and C.D. WARNER (1998): Structural Equation Modeling and Its Relationship to Multiple Regression and Factor Analysis. In: *Research in Nursing & Health* 21(3), 271-281.

MUTHEN, B.O. and A. SATORRA (1995): Complex Sample Data. In: *Sociological Methodology* 25, 267-316.

MWABU, G. (2007): Health Economics for Low-Income Countries. In: SCHULTZ, P. and J. STRAUSS (Eds.), *Handbook of Development Economics,* Volume 4. Elsevier, North-Holland, 3305-3374.

NAYGA, Jr., R. (1994): Consumer Characteristics Associated with Healthful Diets: The Case of Low-Calorie and Low-Fat, Low-Cholesterol Foods. In: *Journal of Agribusiness* 12(2), 111-124.

NAYGA, R.M. (2000): Schooling, Health Knowledge and Obesity. In: *Applied Economics* 32(7), 815-822.

NAYGA, R.M. (2008): Nutrition, Obesity and Health: Policies and Economic Research Challenges. In: *European Review of Agricultural Economics* 35(3), 281-302.

NETEMEYER, R. and P. BENTLER (2001): Structural Equations Modeling and Statements Regarding Causality. In: *Journal of Consumer Psychology* 10(1/2), 83-85.

NEUHOUSER, M.L., PATTERSON, R.E. KING, I.B., HORNER, N.K. and J.W. LAMPE (2003): Selected Nutritional Biomarkers Predict Diet Quality. In: *Public Health Nutrition* 6(7), 703-709.

NEVITT, J. and G.R. HANCOCK (2001): Performance of Bootstrapping Approaches to Model Test Statistics and Parameter Standard Error Estimation in Structural Equation Modeling. In: *Structural Equation Modeling* 8(3), 353-377.

NEWHOUSE, J.P. and M.J. FRIEDLANDER (1977): The Relationship Between Medical Resources and Measures of Health: Some Additional Evidence. Rand Corporation Document R-2066-HEW. The Rand Corporation, Santa Monica, CL.

NIELSEN, S.J. and L. ADAIR (2007): An Alternative to Dietary Data Exclusions. In: *American Dietetic Association* 107(5), 792-799.

NIH (2002): Third Report of the National Cholesterol Education Program (NCEP) Expert Panel on Detection, Evaluation, and Treatment of High Blood Cholesterol in Adults (Adult Treatment Panel III) Final Report. Publication No. 02-5215. In: http://www.nhlbi.nih.gov/guidelines/cholesterol/atp3full.pdf (09.02.2011)

OH, H. and W. SEO (2001): Development of a Structural Equation Model for Causal Relationships Among Arteriosclerosis Risk Factors. In: *Public Health Nursing* 18(6), 409–417.

O'KEEFE, J.H., BYBEE, K.A. and C.J. LAVIE (2007): Alcohol and Cardiovascular Health: The Razor-Sharp Double-Edged Sword. In: *Journal of the American College of Cardiology* 50(11), 1009–14.

OLINSKY, A., CHEN, S. and L. HARLOW (2003): The Comparative Efficacy of Imputation Methods for Missing Data in Structural Equation Modeling. In: *European Journal of Operational Research* 151(1), 53-79.

OR, Z. (2000): Determinants of Health Outcomes in Industrialized Countries: A Pooled, Cross-Country, Time-Series Analysis. In: *OECD Economic Studies* 30, 53-77.

OVESEN, L. and H. BOEING (2002): The Use of Biomarkers in Multicentric Studies with Particular Consideration of Iodine, Sodium, Iron, Folate and Vitamin D. In: *European Journal of Clinical Nutrition* 56 (Suppl. 2), S12-S17.

PARSONS, T.J., POWER, C., LOGAN, S. and C.D. SUMMERBELL (1999): Childhood Predictors of Adult Obesity: A Systematic Review. In: *International Journal of Obesity and Related Metabolic Disorders* 23 (Suppl. 8), S1-S107.

PEARL, J. (2012): The Causal Foundations of Structural Equation Modeling. In: HOYLE, R.H. (Ed.), *Handbook of Structural Equation Modeling*. Guilford Press, New York, 68-91.

PERKINS, K.A. (1992): Metabolic Effects of Cigarette Smoking. In: *Journal of Applied Physiology* 72(2), 401-409.

POPKIN, B.M., BARCLAY, D.V. and S.J. NIELSEN (2005): Water and Food Consumption Patterns of U.S. Adults From 1999 to 2001. In: *Obesity Research* 13(12), 2146-2152.

POTISCHMAN, N. (2003): Biologic and Methodologic Issues for Nutritional Biomarkers. In: *The Journal of Nutrition* 133(3), 875-880.

POWELL, L.M., AULD, M.C., CHALOUPKA, F.J., O'MALLEY, P.M. and L.D. JOHNSTON (2007): Access to Fast Food and Food Prices: Relationship with Fruit and Vegetable Consumption and Overweight Among Adolescents. In: *Advances in Health Economics and Health Services Research* 17, 23-48.

POWELL, L.M. and F.J. CHALOUPKA (2009): Food Prices and Obesity: Evidence and Policy Implications for Taxes and Subsidies. In: *The Milbank Quarterly* 87(1), 229-257.

PRYER, J.A., NICHOLS, R., ELLIOTT, P., THAKRARC, B., BRUNNERD, E. and M. MARMOTD (2001): Dietary Patterns Among a National Random Sample of British Adults. In: *Journal of Epidemiology and Community Health* 55, 29-37.

RANDALL, E., MARSHALL, J.R., GRAHAM, S. and J. BRASURE (1990): Patterns in Food Use and Their Associations with Nutrient Intakes. In: *American Journal of Clinical Nutrition* 52(4), 739-745.

RASHAD, I. (2006): Structural Estimation of Caloric Intake, Exercise, Smoking, and Obesity. In: *The Quarterly Review of Economics and Finance* 46(2), 286-283.

RASHAD, I., GROSSMAN, M. and S.-Y. CHOU (2006): The Super Size of America: An Economic Estimation of Body Mass Index and Obesity in Adults. In: *Eastern Economic Journal* 32(1), 133-148.

RIGDON, E.E. (1995): A Necessary and Sufficient Identification Rule for Structural Models Estimated in Practice. In: *Multivariate Behavioral Research* 30(3), 359-383.

ROGER, V.L., GO, A.S., LLOYD-JONES, D.M. *et al.* (2012): Heart Disease and Stroke Statistics-2012 Update: A Report From the American Heart Association. In: *Circulation* 125, e2-e220.

ROSENZWEIG, M.R. and P.T. SCHULTZ (1983): Estimating a Household Production Function: Heterogeneity, the Demand for Health Inputs, and Their Effects on Birth Weight. In: *The Journal of Political Economy* 91(5), 723-746.

RÖDER, C. (1998): Determinanten der Nachfrage nach Nahrungsmitteln und Ernährungsqualität in Deutschland. Eine ökonometrische Analyse auf der Grundlage der Nationalen Verzehrsstudie. In: *Agrarwirtschaft Sonderheft* 161. AgriMedia, Bergen/Dumme.

RÖMLING, C. and M. QAIM (2011): Direct and Indirect Determinants of Obesity: The Case of Indonesia. Global Food Discussion Papers, Georg-August-University of Göttingen.

SATORRA, A., and P.M. BENTLER (1988): Scaling Corrections for Chi-square Statistics in Covariance Structure Analysis. In: *1988 Proceedings of Business and Economics Sections*. American Statistical Association, Alexandria.

SAVY, M., MARTIN-PREVE, Y., SAWADOGO, P., KAMELI, Y. and F. DELPEUCH (2005): Use of Variety/Diversity Scores for Diet Quality Measurement: Relation with Nutritional Status of Women in a Rural Area in Burkina Faso. In: *European Journal of Clinical Nutrition* 59, 703-716.

SCHAFER, J.L. and J.W. GRAHAM (2002): Missing Data: Our View of the State of the Art. In: *Psychological Methods* 7(2), 147-177.

SCHILLER, J.S., LUCAS, J.W., WARD, B.W. and J.A. PEREGOY (2012): Summary Health Statistics for U.S. Adults: National Health Interview Survey, 2010. National Center for Health Statistics. In: *Vital Health Statistics* 10(252), 1-208.

SCHROETER C. and J. LUSK (2008): Economic Factors and Body Weight: An Empirical Analysis. In: *Journal of Agricultural and Applied Economics* 40(2), 523-538.

SCHROETER, C., LUSK, J. and W. TYNER (2005): Determining the Impact of Food Price and Income Changes on Obesity. Selected Paper Prepared for Presentation at the American Agricultural Economics Association Annual Meeting Providence, July 24-27, Rhode Island.

SCHULTZ, T.P. (1984): Studying the Impact of Household Economic and Community Variables on Child Mortality. In: *Population and Development Review* 10 (Suppl.), S215-S235.

SCHULTZ, T.P. (1997): Assessing the Productive Benefits of Nutrition and Health: An Integrated Human Capital Approach. In: *Journal of Econometrics* 77, 141-158.

SERDULA, M.K., GILLESPIE, C., KETTEL-KHAN, L., FARRIS, R., SEYMOUR, J. and C. DENNY (2004): Trends in Fruit and Vegetable Consumption Among Adults in the United States: Behavioral Risk Factor Surveillance System, 1994–2000. In: *American Journal of Public Health* 94(6), 1014-1018.

SHEN, B.-J. and D.T. TAKEUCHI (2001): A Structural Model of Acculturation and Mental Health Status Among Chinese Americans. In: *American Journal of Community Psychology* 29(3), 387-418.

SHIROMA, E.J. and I.M. LEE (2010): Exercise in Cardiovascular Disease. Physical Activity and Cardiovascular Health. Lessons Learned From Epidemiological Studies Across Age, Gender, and Race/Ethnicity. In: *Circulation* 122, 743-752.

SIEGA-RIZ, A.M., POPKIN, B.M. and T. CARSON (2000): Differences in Food Patterns at Breakfast by Sociodemographic Characteristics among a Nationally Representative Sample of Adults in the United States. In: *Preventive Medicine* 30(5), 415-424.

SMITH, J.P. (1999): Healthy Bodies and Thick Wallets: The Dual Relation Between Health and Economic Status. In: *Journal of Economic Perspectives* 13(2), 145-166.

STAUDIGEL, M. (2012): On the Application of Household Production Theory to Health and Nutrition. Selected Paper Prepared for the Presentation at the 52nd Annual Conference of GEWISOLA, September 26-28, University of Hohenheim.

STEIGER, J.H. (2007): Understanding the Limitations of Global Fit Assessment in Structural Equation Modeling. In: *Personality and Individual Differences* 42(5), 893-898.

STEINER, B.E. (2004) Australian Wines in the British Wine Market: A Hedonic Price Analysis. In: *Agribusiness* 20(3), 287-307.

STEINMETZ, K.A. and J.D. POTTER (1996): Vegetables, Fruit and Cancer Prevention: A Review. In: *Journal of American Dietetic Association* 96(10), 1027-1039.

STEWART, H. and J.M. HARRIS (2005): Obstacle to Overcome in Promoting Dietary Variety: The Case of Vegetables. In: *Review of Agricultural Economics* 27(1), 21-36.

STIGLER, G.J. and G.S. BECKER (1977): De Gustibus non est Disputandum. In: *The American Economic Review* 67(2), 76-90.

STRAUSS, J. and D. THOMAS (1995): Human Resources: Empirical Modeling of Household and Family Decision. In: SRINIVASAN, T.N. and J.R. BEHRMAN (Eds.), *Handbook of Development Economics,* Volume III. North-Holland, Amsterdam, 1883-2023.

STRAUSS, R.S. (1999): Comparison of Measured and Self-reported Weight and Height in a Cross-sectional Sample of Young Adolescents. In: *International Journal of Obesity* 23(8), 904-908.

SUBRAMANIAN, S.V., PERKINS, J.M. ÖZALTIN, E. and G.D. SMITH (2011): Weight of Nations: a Socioeconomic Analysis of Women in Low- to Middle-income Countries. In: *American Journal of Clinical Nutrition* 93(2), 413-421.

TABACHNICK, B.G. and L.S. FIDELL (2007): Using Multivariate Statistics, 5th ed., Allyn and Bacon, New York.

TERZA, J.V., BASU, A. and P.J. RATHOUZ (2008): Two-Stage Residual Inclusion Estimation: Addressing Endogeneity in Health Econometric Modeling. In: *Journal of Health Economics* 27(3), 531-543.

TEUBER, R. (2010): Estimating the Demand for Sensory Quality – Theoretical Considerations and an Empirical Application to Specialty Coffee. In: *German Journal of Agricultural Economics* 59(3), Special Issue, 173-186.

THE WHOQOL GROUP (1995): The World Health Organization Quality of Life Assessment (WHOQOL): Position Paper From the World Health Organization. In: *Social Science and Medicine* 41(10), 1403-1409.

THIELE, S, and C. WEISS (2003): Consumer Demand for Food Diversity: Evidence for Germany. In: *Food Policy* 28(2), 99-115.

THIELE, S., MENSINK, G. and R. BEITZ (2004): Determinants of Diet Quality. In: *Public Health Nutrition* 7(1), 29-37.

TOHILL, B.C., SEYMOUR, J., SERDULA, M., KETTEL-KHAN, L. and B.J. ROLLS (2004): What Epidemiologic Studies Tell Us about the Relationship Between Fruit and Vegetable Consumption and Body Weight. In: *Nutrition Reviews* 62(10), 365-374.

TOMARKEN, A.J. and N.G. WALLER (2005): Structural Equation Modelling: Strengths, Limitations, and Misconceptions. In: *Annual Review of Clinical Psychology* 1, 31–65.

USDA (2005): The Food Guide Pyramid. Home and Garden Bulletin No. 252. In: http://www.cnpp.usda.gov/Publications/MyPyramid/OriginalFoodGuidePyramids/FGP/FGPPamphlet.pdf (05.05.2010)

USDA and CNPP (2013): Diet Quality of Americans in 2001-02 and 2007-08 as Measured by the Healthy Eating Index-2010. Nutrition Insight 51. In: http://www.cnpp.usda.gov/Publications/NutritionInsights/Insight51.pdf (10.05.2013).

USDA and HHS (2010): Dietary Guidelines for Americans 2010, 7th ed., U.S. Government Printing Office, Washington, D.C.

VAN DE VEN, WPMM and J. VAN DER GAAG (1982): Health as an Unobservable: a MIMIC Model for Health Care Demand. In: *Journal of Health Economics* 1(2), 157-183.

VAN DER GAAG, J. and B. WOLFE (1991): Estimating Demand for Medical Care: Health as a Critical Factor for Adults and Children. In: DURU, G. and J.H.P. PAELINCK (Eds.), *Econometrics of Health Care*. Kluwer, Amsterdam, 31-58.

VAN DUYN, M.A. and E. PIVONKA (2000): Overview of the Health Benefits of Fruit and Vegetable Consumption for the Dietetics Professional: Selected Literature. In: *Journal of American Dietetic Association* 100(12), 1511-1521.

VAN VLIET, R.C. and B.M. VAN PRAAG (1987): Health Status Estimation on the Basis of MIMIC-health Care Models. In: *Journal of Health Economics* 6(1), 27-42.

VARIYAM, J.N., BLAYLOCK, J. and D. SMALLWOOD (1996): A Probit Latent Variable Model of Nutrition Information and Dietary Fiber Intake. In: *American Journal of Agricultural Economics* 78(3), 628-639.

VARIYAM, J.N., BLAYLOCK, J. and D. SMALLWOOD (1998): *USDA's Healthy Eating Index and Nutrition Information*. Bulletin No. 1866, Center for Nutrition Policy and Promotion, USDA, Washington, D.C.

VARIYAM, J.N., BLAYLOCK, J., LIN, B.H., RALSTON, K. and D. SMALLWOOD (1999): Mother's Nutrition Knowledge and Children's Dietary Intakes. In: *American Journal of Agricultural Economics* 81(2), 373-384.

VARIYAM, J.N., SHIM, Y. and J. BLAYLOCK (2001): Consumer Misperceptions of Diet Quality. *Journal of Nutrition Education* 33(6), 314-321.

VARIYAM, J.N. (2003): Factors Affecting the Macronutrient Intake of U.S. Adults. Electronic Economic Research Service. Bulletin No. 1901, USDA, Washington, D.C.

WAGSTAFF, A. (1986): The Demand for Health: Some New Empirical Evidence. In: *Journal of Health Economics* 5(3), 195–233.

WAGSTAFF, A. (1993): The Demand for Health: An Empirical Reformulation of the Grossman Model. In: *Health Economics* 2(2), 189-198.

WAIJERS, P.M. and E.J. FESKENS (2005): Indices of Overall Diet Quality. In: A Review of the Literature. RIVM report 350010003/2005, Center for Nutrition and Health, Bilthoven. In: hhttp://www.rivm.nl/bibliotheek/rapporten/350010003.pdf (20.05.2010).

WALTER, C., FRIEDRICH, L. and I.-U. LEONHÄUSER (2008): Ernährungsweise und -zustand von Nürnberger Grundschulkindern. Eine regionale Studie zur Untersuchung sozioökonomisch bedingter Unterschiede. In: *Ernährung* 2, 58-67.

WANG, C.-Y., HASKELL, W.L., FARRELL, S.W, LAMONTE, M.J., BLAIR, S.N., CURTIN, L.R., HUGHES, J.P. and V.L. BURT (2010): Cardiorespiratory Fitness Levels Among US Adults 20–49 Years of Age: Findings From the 1999–2004 National Health and Nutrition Examination Survey. In: *American Journal of Epidemiology* 171(4), 426-435.

WARD, C.E., LUSK, J.L. and J.M. DUTTON (2008): Implicit Value of Retail Beef Product Attributes. In: *Journal of Agricultural and Resource Economics* 33(3), 364-381.

WAYMAN, J.C. (2003): Multiple Imputation For Missing Data: What Is It And How Can I Use It? Paper presented at the 2003 Annual Meeting of the American Educational Research Association, Chicago, IL.

WHO (1986): Ottawa Charter for Health Promotion. WHO Press, Copenhagen.

WHO (1990): Diet, Nutrition, and the Prevention of Chronic Diseases. Report of a WHO Study Group, WHO Technical Report Series No. 797, WHO Press, Geneva.

WHO (2005): Fruit and Vegetables for Health. Report of a Joint FAO/WHO Workshop, 1–3 September 2004, Kobe, Japan, WHO Press, Geneva.

WHO (2006): Constitution of the World Health Organization. Basic Documents, 45th ed. (Suppl). In: www.who.int/governance/eb/who_constitution_en.pdf (12.06.2010).

WHO (2011): Global Status Report on Noncommunicable Diseases 2010. WHO Press, Geneva.

WHO (2011a): Noncommunicable Diseases Country Profiles 2011. United States of America. WHO Press, Geneva.

WILLET, W.C., HOWE, G.R. and L.H. KUSHI (1997): Adjustment for Total Energy Intake in Epidemiologic Studies. In: *American Journal of Clinical Nutrition* 65 (Suppl.), S1220-S1228.

WILSON, P.W., D'AGOSTINO, R.B., SULLIVAN, L., PARISE, H. and W.B. KANNEL (2002): Overweight and Obesity as Determinants of Cardiovascular Risk. The Framingham Experience. In: *Archives of Internal Medicine* 162(16), 1867-1872.

WIRFÄLT, A.K. and R.W. JEFFERY (1997): Using Cluster Analysis to Examine Dietary Patterns: Nutrient Intakes, Gender, and Weight Status Differ Across Food Pattern Clusters. In: *Jornal of American Dietetic Association* 97(3), 272-279.

WIRFÄLT, E., MATTISSON, I. and B. GULLBERG (1999): Food Patterns Defined by Cluster Analysis and Their Utility as Dietary Exposure Variables: A Report from the Malmö Diet and Cancer Study. In: *Public Health Nutrition* 3(2), 159-173.

WOLFE, B.L. and J.R. BEHRMAN (1984): Determinants of Women's Health Status and Health-Care Utilization in a Developing Country: A Latent Variable Approach. In: *Review of Economics and Statistics* 56(4), 696-703.

WONG, C. and K.S. LAW (1999): Testing Reciprocal Relations by Nonrecursive Structural Equation Models Using Cross-Sectional Data. In: *Organizational Research Methods* 2(1), 69-87.

WOOLDRIDGE, J.M. (2002): Econometric Analysis of Cross Section and Panel Data. The MIT Press, Cambridge.

WRIGHT, S. (1934): The Method of Path Coefficients. In: *Annals of Mathematical Statistics* 5(3), 161-215.

YOU, W. and M. NAYGA (2005): Household Fast Food Expenditures and Children's Television Viewing: Can They Really Significantly Influence Children's Dietary Quality? In: *Journal of Agricultural and Resource Economics* 30(2), 302-314.

YOUNG, D. (1996): Changing Tastes and Endogenous Preferences: Some Issues in Modelling the Demand for Agricultural Products. In: *European Review of Agricultural Economics* 23(3), 281-300.

YUAN, K.-H. and H. HAYASHI (2003): Bootstrap Approach to Inference and Power Analysis Based on Three Statistics for Covariance Structure Models. In: *British Journal of Mathematical and Statistical Psychology* 56(1), 93-110.

YUAN, K.-H. and P.M. BENTLER (2001): Effect of Outliers on Estimators and Tests in Covariance Structure Analysis. In: *British Journal of Mathematical and Statistical Psychology* 54(1), 161-175.

ZELLNER, A. (1962): An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. In: *Journal of American Statistical Association* 57(298), 348-368.

Appendix

Appendix A

Table A1 Estimated calorie requirements (in kilocalories) per day by age, gender, and physical activity level [a)]

Gender		**Activity Level**		
	Age (years)	Sedentary[b)]	Moderately Active[c)]	Active[d)]
Child	2-3	1,000-1200	1,000-1,400	1,000-1,400
Female	4-8	1,200-1400	1,400-1,600	1,400-1,800
	9-13	1400-1,600	1,600-2,000	1,800-2,200
	14-18	1600-1,800	2,000	2,400
	19-30	1800	2,000-2,200	2,400
	31-50	1,800-2000	2,000	2,200
	51+	1,800	1,800	2,000-2,200
Male	4-8	1200-1,400	1,400-1,600	1,600-2,000
	9-13	1600-2000	1,800-2,200	2,000-2,600
	14-18	2000-2,400	2,400-2,800	2,800-3,200
	19-30	2,400-2600	2,600-2,800	3,000
	31-50	2,200-2400	2,400-2,600	2,800-3,000
	51+	2,000-2200	2,200-2,400	2,400-2,800

[a)] These levels are based on Estimated Energy Requirements (EER) from the Institute of Medicine Dietary Reference Intakes macronutrients report, 2002, calculated by gender, age, and activity level for reference-sized individuals. "Reference size," as determined by IOM, is based on median height and weight for ages up to age 18 years of age and median height and weight for that height to give a BMI of 21.5 for adult females and 22.5 for adult males. [b)] Sedentary means a lifestyle that includes only the light physical activity associated with typical day-to-day life. [c)] Moderately active means a lifestyle that includes physical activity equivalent to walking about 1.5 to 3 miles per day at 3 to 4 miles per hour, in addition to the light physical activity associated with typical day-to-day life. [d)] Active means a lifestyle that includes physical activity equivalent to walking more than 3 miles per day at 3 to 4 miles per hour, in addition to the light physical activity associated with typical day-to-day life.
Source: USDA and HHS (2010).

Table A2 Selected nutrients in the USDA Food Guide [a)] and the DASH Eating Plan [b)]

Nutrient	USDA Food Guide (2000 kcals)	DASH Eating Plan (2000 kcals)
Protein, g	91	105
Protein, % kcal	18	20
Carbohydrate, g	271	281
Carbohydrate, % kcal	55	54
Total fat, g	65	60
Total fat, % kcal	29	26
Saturated fat, g	17	12
Saturated fat, % kcal	7.8	6
Monounsaturated fat, g	24	25
Monounsaturated fat, % kcal	11	12
Polyunsaturated fat, g	20	16
Polyunsaturated fat, % kcal	9.0	7
Linoleic acid, g	18	14
Alpha-linolenic acid, g	1.7	2.2
Cholesterol, mg	230	136
Total dietary fiber, g	31	34
Potassium, mg	4,044	4,721
Sodium, mg	1,779	2,096[f]
Calcium, mg	1,316	1,406
Magnesium, mg	380	554
Copper, mg	1.5	1.9
Iron, mg	18	22
Phosphorus, mg	1,740	1,955
Zinc, mg	14	14
Thiamin, mg	2.0	1.7
Riboflavin, mg	2.8	2.7
Niacin equivalents, mg	22	50
Vitamin B_6, mg	2.4	2.9
Vitamin B_{12}, µg	8.3	5.6
Vitamin C, mg	155	162
Vitamin E (AT)[c)]	9.5	19
Vitamin A, µg (RAE)[d)]	1,052	925

[a)] USDA nutrient values are based on population-weighted averages of typical food choices within each food group or subgroup. [b)] DASH nutrient values are based on a 1-week menu of the DASH Eating Plan. [c)] AT is mg d-α-tocopherol. [d)] RAE is Retinol Activity Equivalents.
Source: HHS and USDA (2005).

Table A3 Sample USDA Food Guide and the DASH Eating Plan at the 2000-Calorie Level [a)]

Food Groups and Subgroups	USDA Food Guide Amount[b)]	DASH Eating Plan Amount[c)]	Equivalent Amounts
Fruit Group	2 cups (4 servings)	2 to 2.5 cups (4 to 5 servings)	½ cup-equivalent is: □ ½ cup fresh, frozen, or canned fruit □ 1 med fruit □ ¼ cup dried fruit □ ½ cup fruit juice
Vegetable Group Dark green Orange vegetables Legumes (dry beans) Starchy vegetables Other vegetables	2.5 cups (5 servings) 3 cups/week 2 cups/week 3 cups/week 3 cups/week 6.5 cups/week	2 to 2.5 cups (4 to 5 servings)	½ cup equivalent is: □ ½ cup of cut-up raw or cooked vegetable □ 1 cup raw leafy vegetable □ ½ cup vegetable juice
Grain Group Whole grains Other grains	6 ounce-equivalents 3 ounce-equivalents 3 ounce-equivalents	6 to 8 ounce-equivalents (6 to 8 servings)	1 ounce-equivalent is: □ 1 slice bread □ 1 cup dry cereal □ ½ cup cooked rice, pasta, cereal □ DASH: 1 oz dry cereal (½-1¼ cup depending on cereal type—check label)
Meat and Beans Group	5.5 ounce-equivalents	6 ounces or less meats, poultry, fish	1 ounce-equivalent is: □ 1 ounce of cooked lean meats, poultry, fish □ 1 egg □ USDA: ¼ cup cooked dry beans or tofu, 1 Tbsp peanut butter, ½ oz nuts or seeds □ DASH: 1½ oz nuts, 2 Tbsp peanut butter, ½ oz seeds, ½ cup cooked dry beans
		4 to 5 servings per week nuts, seeds, and legumes[d)]	
Milk Group	3 cups	2 to 3 cups	1 cup-equivalent is: □ 1 cup low-fat/fat-free milk, yogurt □ 1½ oz of low-fat, fat-free, or reduced fat natural cheese □ 2 oz of low-fat or fat-free processed cheese
Oils	27 grams (6 tsp)	8 to 12 grams (2 to 3 tsp)	DASH: 1 tsp equivalent is: □ 1 tsp soft margarine □ 1 Tbsp low-fat mayo □ 2 Tbsp light salad dressing □ 1 tsp vegetable oil
Discretionary Calorie Allowance Example of distribution: Solid fat[e)] Added sugars	267 calories 18 grams 8 tsp	~2 tsp of added sugar (5 Tbsp per week)	DASH: 1 Tbsp added sugar equivalent is: □ 1 Tbsp jelly or jam □ ½ cup sorbet and ices □ 1 cup lemonade

[a)] All servings are daily unless otherwise specified. USDA vegetable subgroup and DASH nuts, seeds, and dry beans subgroup amounts are weekly. [b)] See the USDA Food Guide for information about recommendations for other calorie levels (in total 12 levels). [c)] Recommendations are updated to reflect the 2006 DASH Eating Plan. [d)] Nuts, seeds and legumes are a separate food group from meats, poultry, and fish in the DASH Eating Plan. [e)] The oils listed in this table are not considered to be part of discretionary calories because they are a major source of vitamin E and polyunsaturated fatty acids, including essential fatty acids, in the food pattern. In contrast, solid fats (i.e., saturated and *trans* fats) are listed separately as a source of discretionary calories.
Source: HHS and USDA (2005).

Table A4 Nutrient contributions of fruit and vegetable food groups averaged over food patterns at all energy levels

Food Group	Major contribution(s) [a)]	Substantial contribution(s) [b)]
Fruit group	Vitamin C	Thiamin Vitamin B_6 Folate Magnesium Copper Potassium Carbohydrate Fiber
Vegetable group	Vitamin A Potassium	Vitamin E Vitamin C Thiamin Niacin Vitamin B_6Folate Calcium Phosphorus Magnesium Iron Zinc Copper Carbohydrate Fiber Alpha-linolenic acid
Vegetable subgroups:		
Dark green vegetables		Vitamin A Vitamin C
Orange vegetables	Vitamin A	
Legumes		Folate Copper Fiber
Starchy vegetables		Vitamin B_6 Copper
Other vegetables		Vitamin C

[a)] Major contribution means that the food group or subgroup delivers more of the nutrient than any other single food group, averaged over all calorie levels. [b)] Substantial contribution indicates that the food group or subgroup provides ≥10% of the total amount of the nutrient in the food patterns, averaged over all calorie levels.
Source: HHS (2004).

Appendix B

Table B1 Classification of total cholesterol, LDL cholesterol, HDL cholesterol and triglyceride

Total Cholesterol		LDL Cholesterol		HDL Cholesterol		Triglyceride	
mg/dL							
<200	Desirable	<100	Optimal	<40	Low	<150	Normal
200-239	Borderline high	100-129	Near optimal/ above optimal	≥60	High [a)]	150-199	Borderline high
≥240	High	130-159	Borderline high			200-499	High
		160-189	High			≥ 500	Very high
		≥ 190	Very high				

[a)] High HDL cholesterol is associated with reduced risk for CHD.
Source: NIN (2002).

Table B2 Fit indices and their acceptable thresholds [a)]

Fit Index	Acceptable threshold levels	Description
Absolute Fit Indices		
Chi-Square $\chi 2$	low $\chi 2$ relative to degrees of freedom; insignificant *p* value ($p > 0.05$)	Fit statistics; sensitive to sample size, i.e., the Chi-Square statistic nearly always rejects the model when large samples are used (Bentler and Bonnet, 1980)
Relative $\chi 2$ ($\chi 2$/df)	2:1 (Tabachnik and Fidell, 2007) 3:1 (Kline, 1998)	Adjusts for sample size.
RMSEA	≤ 0.07 (Steiger, 2007) ≤ 0.05 (Backhaus, 2006; Byrne, 2001). ≤ 0.05 good fit, 0.05 to 0.08 acceptable fit, and ≥ 0.08 unacceptable fit (Browne and Cudeck, 1992)	Most informative criteria (Byrne, 2001).
GFI	≥ 0.95 (Hu and Bentler, 1999) ≥0.90 (Backhaus, 2006; Hooper *et al.*, 2008)	Sensitive to sample size.
AGFI	≥0.90 (Backhaus, 2006; Hooper *et al.*, 2008)	Adjusts the GFI on the number of degrees of freedom.
RMR	small values in a good model (Tabachnik and Fidell, 2007)	Residuals based.
SRMR	≤ 0.08 (Hu and Bentler, 1999) ≤ 0.10 (Kline, 1998)	Standardised version of the RMR; it is easier to interpret.
Incremental Fit Indices		
NFI	≥ 0.95 (Hu and Bentler, 1999) ≥0.90 (Backhaus, 2006)	Shows the improvement of the hypothesised and independence model (where all relationships assumed to be 0). Tends to underestimate fit in small samples.
CFI	≥ 0.95 (Hu and Bentler, 1999) ≥0.90 (Backhaus, 2006)	Modified version of NFI. May be less affected by sample size (Byrne, 2001).

[a)] The values of all indices except $\chi 2$ and relative $\chi 2$ range between 0 and 1.
Source: Own presentation based on Hooper *et al.* (2008), Kline (1998); Byrne (2001) and Backhaus (2006).

Appendix C

Table C1 Correlation matrix of model variables [a)]

	Age	Age^2	Male	White	HH size	HH inc	Educ	Know	Alc	TV	Weight	Smok	SBP	DBP	TC	Calorie	Diet	TR	Med
Age	1																		
Age^2	**.991**	1																	
Male	-.011	-013	1																
White	**.110**	**.114**	.036	1															
HH size	**-.181**	**-.198**	.005	**-.223**	1														
HH inc	**.111**	**.098**	.034	**.217**	**.065**	1													
Educ	**.066**	**.062**	**-.064**	**.295**	**-.308**	**.366**	1												
Know	**114**	**.112**	**-.300**	**.220**	**-.186**	**.196**	**.432**	1											
Alc	**-.207**	**-.209**	**.242**	**.083**	.002	.024	**-.053**	**-.126**	1										
TV	.029	**.043**	**.042**	**-.093**	**-.074**	**-.120**	**-.096**	**-.093**	.035	1									
Weight	**.223**	**.213**	**.157**	.018	-.009	-.037	**-.058**	-.023	**-.061**	**.133**	1								
Smok	-.022	-.023	**.093**	**.107**	**-.043**	**-.133**	**-.148**	**-.127**	**.211**	**.144**	-.029	1							
SBP	**.292**	**.297**	**.182**	**-.046**	**-.098**	-.024	-.036	-.027	.008	**.072**	**.257**	-.007	1						
DBP	**.290**	**.271**	**.101**	**.055**	**-.075**	**.076**	**.053**	.012	-.020	**.050**	**.219**	-.029	**.517**	1					
TC	**.249**	**.237**	.015	**.080**	-.015	**.048**	-.027	-.018	.007	**.045**	**.126**	.023	**.134**	**.167**	1				
Calorie	**-.098**	**-.103**	**.473**	**.083**	.009	**.044**	.026	**-.166**	**.217**	.023	**048**	**.067**	**.086**	**.075**	.020	1			
Diet	**.168**	**.162**	**.042**	**.082**	**-045**	**.082**	**.099**	**.128**	-.013	**-.075**	-.017	**-.125**	.000	.025	**.057**	**.203**	1		
TR	**.077**	**.072**	**.112**	.019	.014	.002	**-.048**	**-.047**	**.039**	**.091**	**.151**	**.073**	**.087**	**.090**	**.249**	.038	.004	1	
Med	**.184**	**.181**	**-.164**	**.113**	**-.081**	**.133**	**.202**	**.268**	**-.120**	-.002	**.085**	**-.062**	026	**.059**	.011	**-.090**	.018	-.026	1

[a)] In bold are correlations significant at least at the 0.05 level (2-tailed).
Source: Own calculation with the NHANES 2005-2006 data (CDC, 2007).

Declaration

I declare that the dissertation here submitted is entirely my own work, written without any illegitimate help by any third party and solely with materials as indicated in the dissertation. I have indicated in the text where I have used texts from already published sources, either word for word or in substance, and where I have made statements based on oral information given to me. At all times during the investigations carried out by me and described in the dissertation, I have followed the principles of good scientific practice as defined in the "Statutes of the Justus Liebig University Giessen for the Safeguarding of Good Scientific Practice".

Giessen, 25th of March 2015