The Impact of Diabetes on an Aging Developing Country: Costa Rica

By

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To my husband Martín,
my mate along this journey and beyond

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Abstract

Along with many other countries in Latin America and the Caribbean, Costa Rica is undergoing very high rates of growth of the elderly population. These populations are experiencing an increase in the prevalence of obesity-related conditions such as diabetes. Diabetes is a major cause of both morbidity and mortality among the elderly and represents a source of demands on already constrained healthcare systems. In this dissertation I estimate diabetes incidence and prevalence, identify its most important determinants, and assess the impact on years of life lost and the economic burden on the public health care system.

More than a fifth of Costa Rican elderly experience diabetes. Incidence is estimated at 5 per 1000 person-years in population 30+. The disease is strongly associated with increased premature mortality, especially at ages 60-69. Family history of diabetes is a non trivial risk factor. I find a clear gradient between diabetes and obesity. Individuals who are obese and have an increased waist circumference experience much higher risk of contracting diabetes. Similarly, I find that geographical barriers to health care translate into a lower probability of diagnosis.

Health care costs associated with diabetes are very high as this population requires much larger expenditures in hospitalizations, outpatient care and medications than the non-diabetic. Diabetes prevalence will continue to increase in the near future. At least 27% of the elderly is expected to be diabetic by 2025 and the elderly population with the disease will double between 2010 and 2025 implying a massive increase in the health care costs. The impact of diabetes on life

expectancy at age 60 around the year 2025 is estimated to lead to a loss of about 7 months. Public policy targeted on education about the behaviors that prevent the onset of diabetes will save lives and reduce costs to the public health care system. Prevention also requires a population health approach to create environments in which individuals are encouraged to alter behaviors. The ultimate influence of diabetes in Costa Rica will be brought under control only if policies aimed at reducing risk factors, especially obesity, are quickly put in place.

CHAPTER 1. Background

A balanced nutrition and regular physical activity throughout life are healthy habits that later on translate into autonomy and independence in the elderly. Although healthy aging is associated with genetics and quality of medical health care, environmental and lifestyle factors have been recognized as the most important determinants. As the aging process goes on, inevitable and irreversible changes occur. Chronic diseases, diabetes mellitus among them, become more prevalent, especially among the most susceptible population (Brown, 2008).

1.1. Diabetes mellitus

Diabetes mellitus is a chronic disorder of carbohydrate, fat, and protein metabolism, characterized by hyperglycemia resulting from defects in insulin secretion, insulin action, or both. There are two main forms of diabetes. Type 1 diabetes is due to an absolute insulin deficiency that makes patients take exogenous insulin for survival. Its frequency is low relative to type 2 diabetes, which accounts for over 90% of cases globally.

Type 2 diabetes (DM2) is characterized by insulin resistance and/or abnormal insulin secretion leading to relative rather than absolute insulin deficiency. Overweight and obesity may lead to insulin resistance, which, given genetic susceptibility, may in turn lead to type 2 diabetes (Prentice, 2001). Patients with type 2 diabetes are not dependent on exogenous insulin, although may require it to control their condition (Zimmet et al., 2001). About two thirds of elderly persons with type 2 diabetes mellitus are currently treated with an oral antihyperglycemic agent. Metformin is recommended by the American Diabetes Association as a first-line therapy in type 2 diabetes mellitus, and it is the most commonly prescribed oral antihyperglycemic agent (Suh et al., 2008).

Diagnostic criteria for diabetes are the same for the elderly and younger adult individuals. Criteria are mainly based on clinical laboratory tests, but also include the presence of clinical symptoms or hyperglycemic crisis. Clinical laboratory tests include fasting plasma glucose, hemoglobin A1C, 2-hour plasma glucose during an oral glucose tolerance test, and random plasma glucose.

The prevalence of diabetes mellitus is increasing to epidemic proportions all over the world (Dankner et al. 2007). The diabetes epidemic relates particularly to type 2 diabetes, and is taking place both in developed and developing nations. In virtually all populations, higher fat diets and decreased physical activity have accompanied the benefits of modernization. These changes, which have led to an increasing prevalence of obesity, combined with increasing longevity have formed the basis for dramatic increases in the prevalence of DM2 worldwide.

Urbanization processes in developing countries play a role on the increase of the prevalence of diabetes. To some extent urbanization is a proxy for lifestyle changes, with an effect of a more sedentary lifestyle, and increased obesity (Shaw, Sicree & Zimmet, 2010). Previous studies have shown that in nearly all developing countries, women in urban areas are more likely to be overweight than women in rural areas (Popkin, 2007). In Latin America, the increasing prevalence of diabetes is most likely explained by a rise in life expectancy, accompanied with sedentary lifestyle, and inappropriate dietary patterns (Albala, 2001), all of these processes embedded in urbanization dynamics.

Furthermore, population composition will play an important role in the impact this epidemic will have in the years to come. As stated by Shaw, Sicree & Zimmet (2010), from 2010 to 2030 the number of diabetic individuals in the developing world is expected to increase for each age-group, with a doubling for the over 60 year age-group. Whereas for developed countries slight decreases in the number of diabetic individuals are predicted for the younger age-groups, and an increase of 38% is only expected for the over 60 age group.

Diabetes is known to be associated with obesity. There is evidence that the principal, albeit not exclusive, driver of the type 2 diabetes epidemic is overweight and obesity, especially abdominal fat deposition (Hu et al., 2001). According to the World Health Organization (WHO), obesity is a disease and is defined as the condition of excess body fat to the extent that health is impaired.

Obesity can be measured using the Body Mass Index (BMI), which is a measure of general obesity, or it can be measured using waist circumference (WC) and waist to hip ratio (WTHR), both of which are measurements of central obesity. Central obesity measures visceral adipose tissue. Waist circumference has been shown to be the best simple anthropometric index of abdominal visceral adipose tissue (Ho et al. 2001, Woo et al. 2002).

Most patients with type 2 diabetes (DM2), or adult-onset diabetes, are obese or have an increased percentage of body fat distributed predominantly in the abdominal region. Obesity itself causes some degree of insulin resistance in most patients.

1.2. Costa Rica's profile in context

Costa Rica is a small Central American country that has achieved outstanding health standards. The population aging process is on its way in the country. With a current population of about 4.6 million, 10% are aged 60 or older. Total life expectancy is 79 years, higher than the US total life expectancy of 78 years. This is despite Costa Rica having a per capita gross national income (GNI) of less than one-fifth that of the US (Population Reference Bureau, 2011).

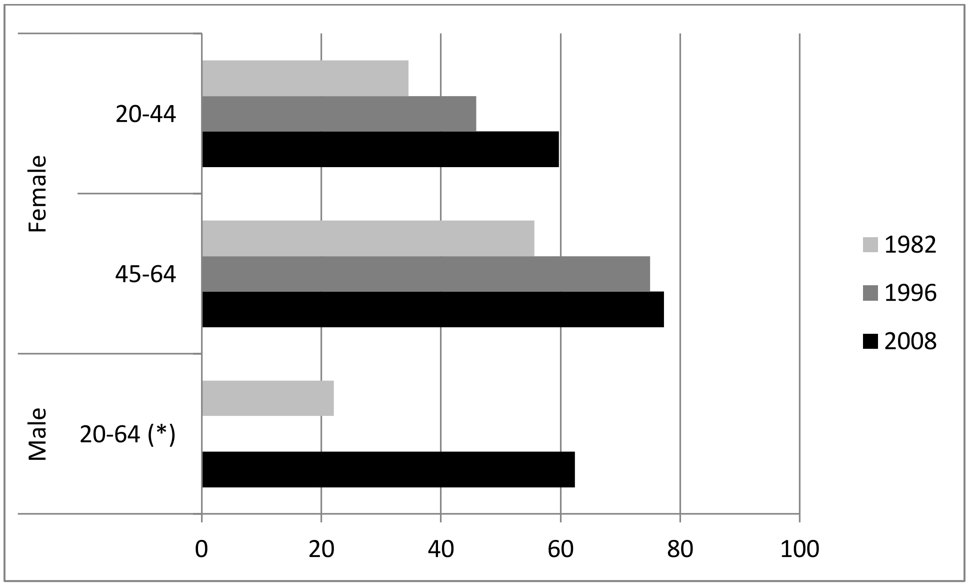
Costa Rican medicine is highly socialized. The country has a subsidized health care system, which was a government initiative established in 1941. There has been a high coverage of public medical services ever since (Rosero-Bixby, 1996). Nowadays, more than half a century later, its health policies have strengthened the access to care through public services and universal social health insurance (Unger, 2008). This has been a very important pathway to the country's high health standards. The high life expectancy in Costa Rica has been attributed to the directing of resources towards education, to a strong primary care focus in the health care system, and to the role of a national health insurance fund in reducing economic barriers to health care access (Caldwell, 1986).

According to Rosero-Bixby (2002), although high life expectancy of Costa Rican adults is thought to come mainly from a lower incidence of cardiovascular diseases, lung cancer and breast cancer, Costa Ricans are at considerable disadvantage regarding diabetes mellitus, stomach cancer and cervical cancer.

As a result of the demographic and epidemiological transitions in Costa Rica, the causes of morbidity and death have shifted from communicable to non-communicable diseases (Rosero-Bixby, 1991), and there has been an important upsurge in the prevalence of diabetes.

Overweight and obesity are common in Costa Rica. In general, 6 out of 10 adults are currently overweight or obese. As revealed by the last three national nutrition surveys, BMI has been steadily increasing in all age and sex groups during the last quarter of century. Women aged 45 to 64 are the most affected specific group. But it is especially worrisome that from 1982 to 2008 the prevalence of overweight and obesity tripled in adult men (graph 1). Male population is rapidly catching up with women in terms of malnutrition problems.

Graph 1. Prevalence of overweight and obesity in the adult population, by sex. Costa Rica 1982, 1996, 2008 (percentages).

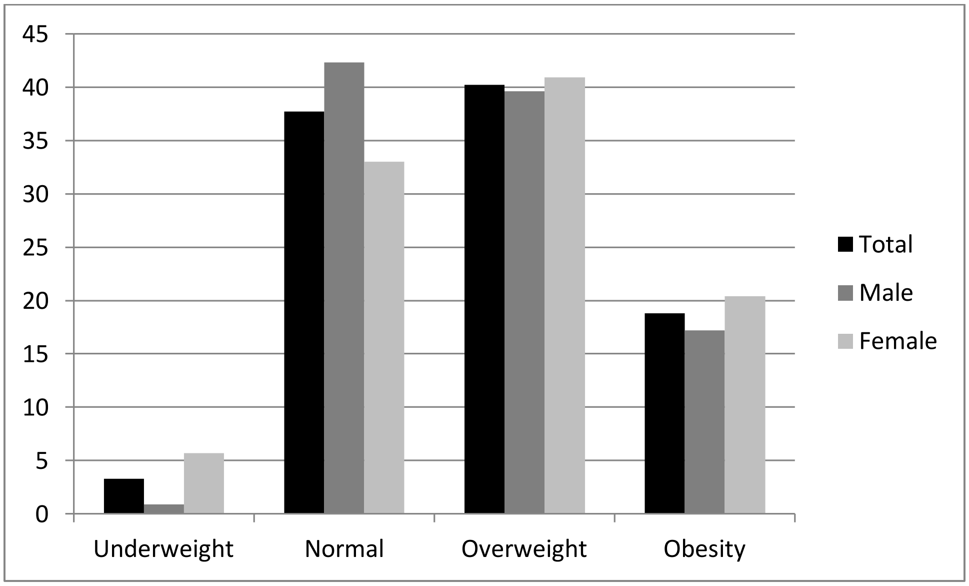


(*) Information collected in 1982 refers to males aged 20-59. No information on this age and sex group was collected in 1996. Prevalence in 2008 refers to males aged 20-64

Source: Own elaboration based on results from Ministerio de Salud et al., 2009

Among the elderly (65+), the prevalence of overweight and obesity is as high as in the adult population. Overweight and –most importantly- obesity prevalence is higher among women. Only 4 out of 10 elderly have normal weight, but males are the most advantaged group, they have the highest prevalence of normal weight: 42% vs. 33% (graph 2).

Graph 2. Nutritional status of the elderly population. Costa Rica, 2008 (percentages).



Source: Own elaboration based on results from Ministerio de Salud et al., 2009

Costa Rica, along with other Latin American countries, is in the middle of a diabetes and obesity epidemic which has in part resulted of sedentary habits and a westernized diet. Levels of self reported diabetes and obesity in Latin America and the Caribbean (LAC) have been found to be as high or even higher than in the US. The comparative prevalence of diabetes (WHO standard) in the year 2011 for the population aged 20-79 years is estimated at 8.5% worldwide, 8.8% in Costa Rica, and 9.5% in the United States (International Diabetes Federation, 2011).

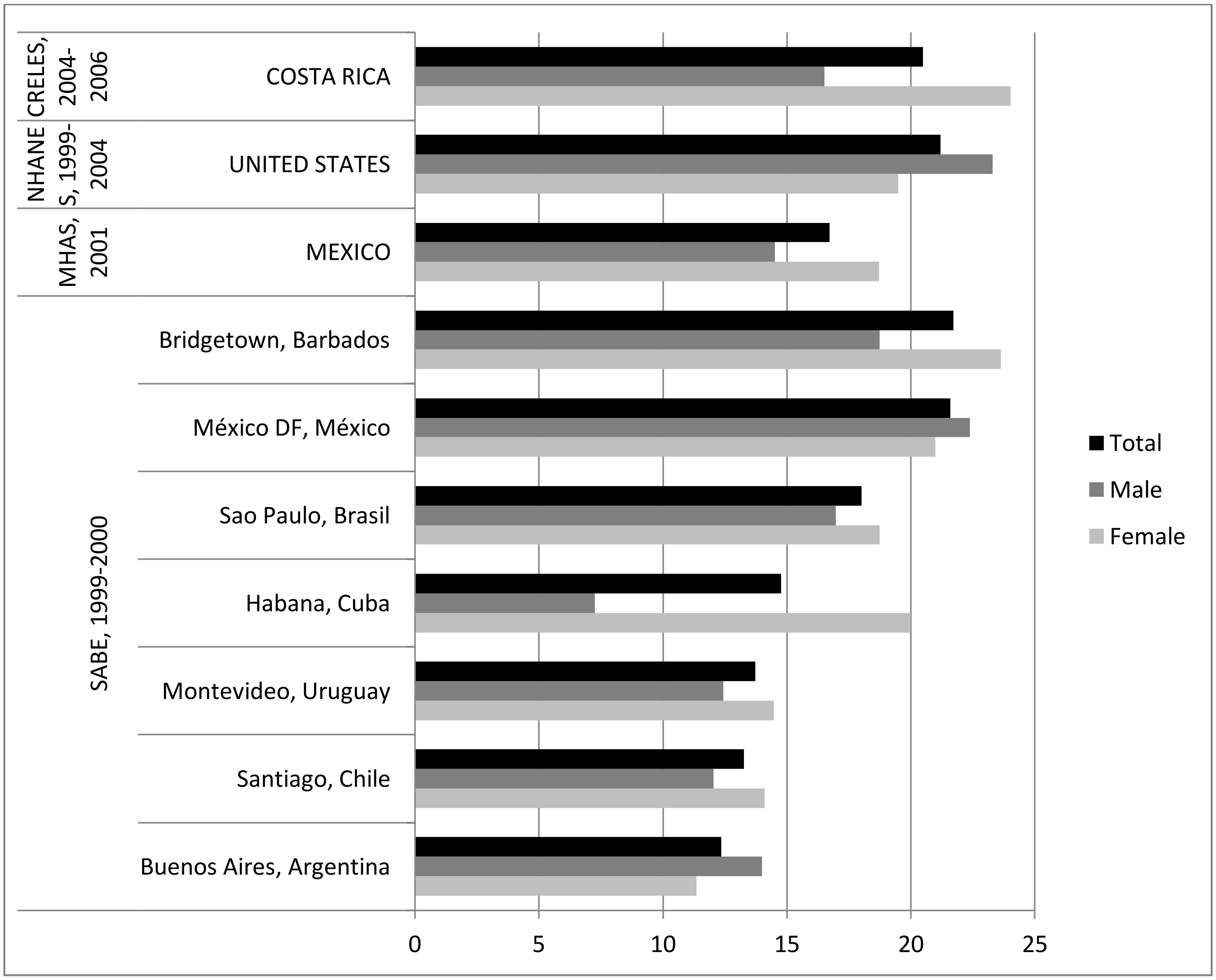
More specifically for the elderly, the prevalence of diabetes in the US population aged 65 or older has been estimated at 21.2% based on NHANES: National Health and Nutrition Examination Survey, 1999-2004 (McDonald et al., 2009). The prevalence of this condition in Costa Rican individuals aged 60 or older has been estimated to be very similar to that in the US:

21.0% (Brenes-Camacho and Rosero-Bixby, 2008a). This estimation for Costa Rica is based on CRELES: Costa Rican Longevity and Healthy Aging Study, same data source that is used in this dissertation. It refers to population aged 60+ during 2004-2006.

Diabetes prevalence for adults aged 50 or older has been estimated at 17% in Mexico based on MHAS: Mexican Health and Aging Study, 2001 (Andrade, 2006). The same author estimated that between 1999 and 2000 diabetes prevalence in the elderly (60+) of seven LAC cities ranged from 12.4% in Buenos Aires, Argentina to 21.7% in Bridgetown, Barbados.

A comparison of diabetes prevalence in Costa Rica, United States, Mexico, and seven LAC cities is presented in graph 3. Although these figures are not strictly comparable in terms of age of the reference population or the year the survey was conducted, they all refer to elder populations and were collected in a similar period of time.

Graph 3. Prevalence of diabetes in the elderly population, by sex. Selected countries and cities (percentages).



Source: Own elaboration based on results from Brenes-Camacho and Rosero-Bixby, 2008a; McDonald et al., 2009; Andrade, 2006.

Graph 3 shows that compared to the LAC region, prevalence of diabetes in Costa Rican elderly is among the highest ones. Prevalence is higher in female elderly in most of these countries or cities, Costa Rica included. Despite being a developing country, Costa Rica is facing the diabetes epidemic at a similar rate than developed countries such as the United States. High prevalence also occurs in other LAC countries and cities, and an increasing prevalence is expected in the rest of the region in the years to come because of the growing obesity epidemic and the population aging process that is already in place. Marked economic and structural differences between developed and developing countries allow the former to cope better with the pressure the epidemic exerts.

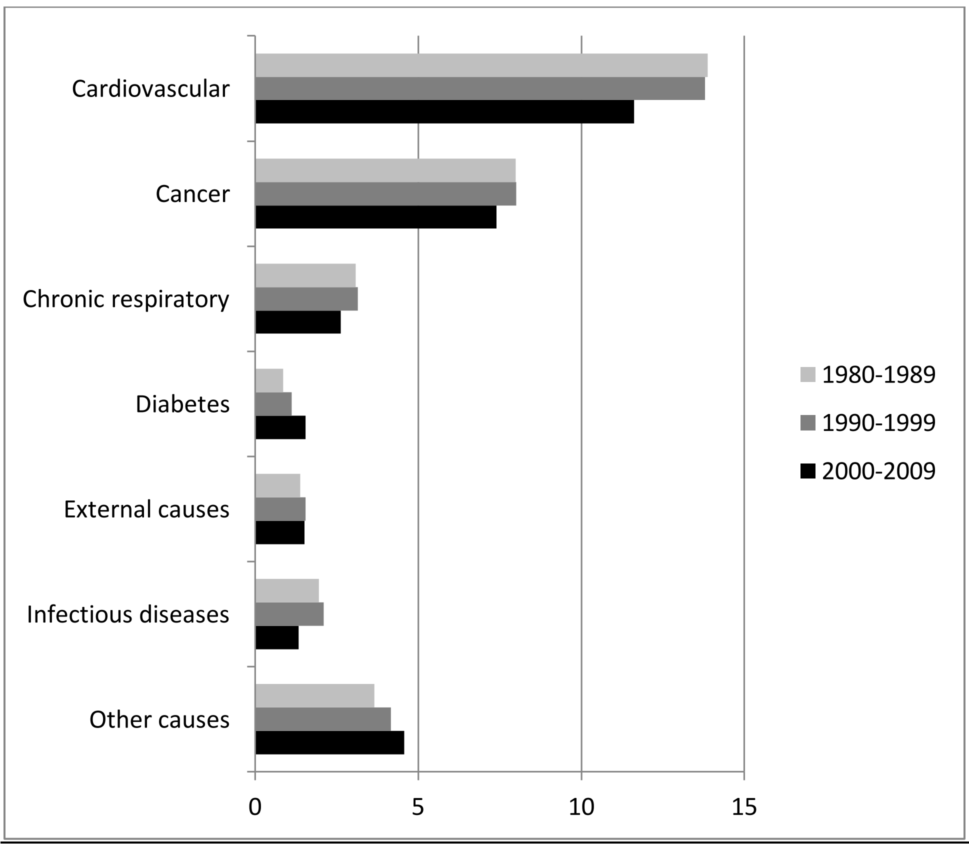
1.3. The burden of diabetes

There are enormous human and economic costs associated to this epidemic. Some of diabetes costs come from premature mortality and from the burden on the health system which is exacerbated by morbidity associated to diabetes complications. This dissertation focuses on the burden on diabetes in terms of both mortality and economic cost to the health care system.

It must certainly be acknowledged that the burden of diabetes on health systems reflects only a fraction of the financial disruptions they cause to diseased individuals, their families and communities. Diabetes imposes costs on society in terms of lower returns on education, decreased income, lost production from job absenteeism and premature mortality, premature retirement and unemployment, and higher dependence on welfare (Yach et al., 2006; Solli et al., 2010).

According to official statistics from the Death Index, diabetes is currently the fourth cause of death in the elderly, and has been increasing for the last three decades in Costa Rica (graph 4).

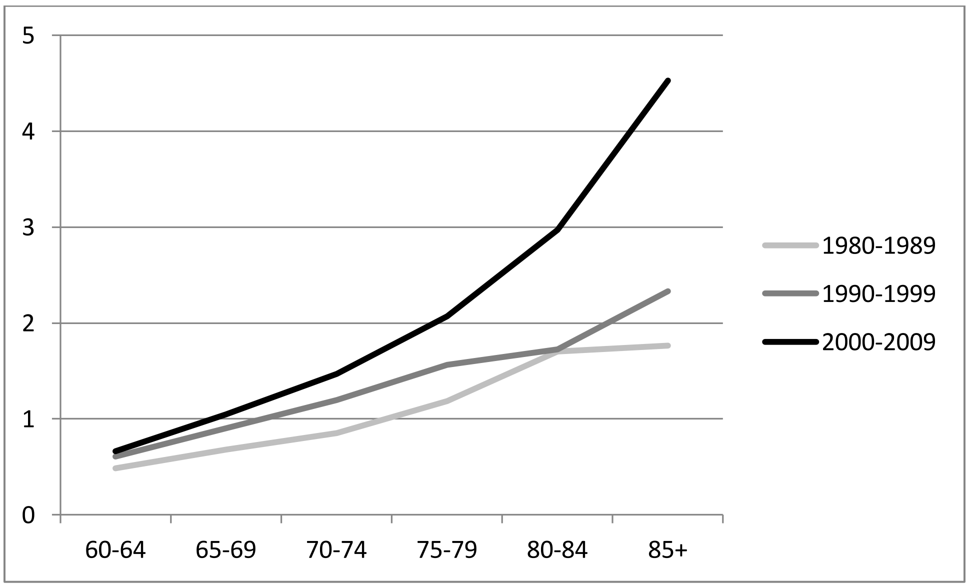
Graph 4. Cause-specific mortality rates in the elderly population (60+). Costa Rica: 1980-2009 (annualized rates per 1 000 people).



Source: Own estimation based on official data available at http://ccp.ucr.ac.cr/censos/

Diabetes mortality rates shown in graphics 4, 5 and 6 should be taken as floor estimates. Mortality due to this condition as registered in the Death Index is known to underestimate the real burden of the disease because of underreporting issues. In most cases diabetes-caused mortality is recorded as mortality due to cardiovascular disease (Laclé-Murray, 2012), which is the most important group of causes of death in the country (graph 4).

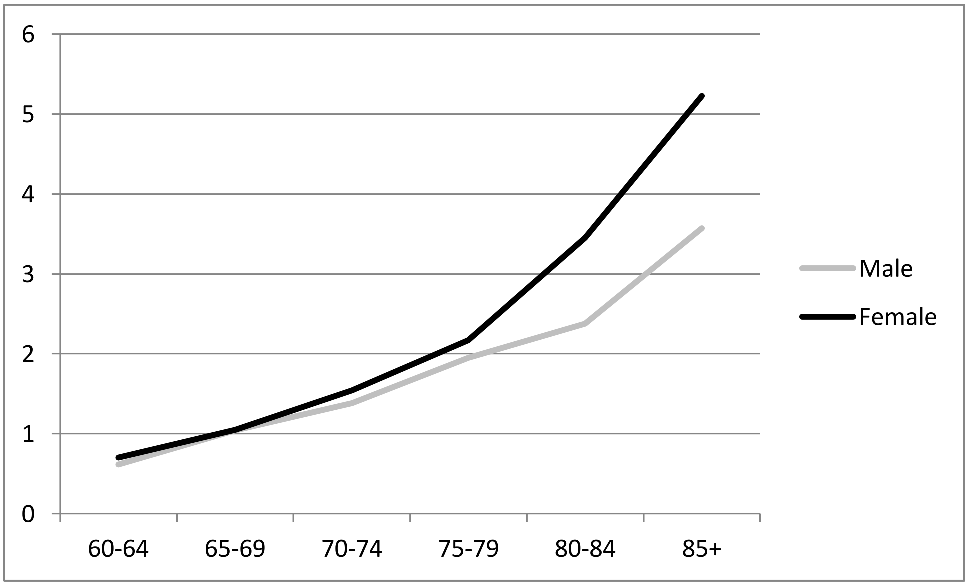
Graph 5. Age-specific diabetes mortality rates in the elderly population (60+). Costa Rica: 1980-2009 (annualized rates per 1 000 people).



Source: Own estimation based on official data available at http://ccp.ucr.ac.cr/censos/

Having in mind that these are low estimates of mortality due to diabetes in the elderly, an increase has been observed in diabetes mortality during the last three decades, especially in the oldest old (graph 5). Mortality in the elderly is also higher in Costa Rican female after the age of 70 (graph 6).

Graph 6. Age-specific diabetes mortality rates in the elderly population (60+), by sex. Costa Rica: 2000-2009 (annualized rates per 1000 people).



Source: Own estimation based on official data available at http://ccp.ucr.ac.cr/censos/

Diabetes is a major cause of both morbidity and mortality in the elderly. Type 2 diabetes mellitus is a well-established risk factor for coronary heart disease (CHD) (Grundy et al., 1999). Furthermore, hypertension –the silent killer- is more prevalent in the diabetic population than in their non-diabetics peers. Diabetes is a risk factor for cardiovascular and cerebrovascular diseases (Barceló, 2000).

Microvascular and macrovascular diseases are some of the diabetes- related complications that add to the burden of diabetes. Complications may result in disability in the elderly population. In the US for example, as reported by Jamison et al. (2006), disabilities are more pronounced among older people, and a much higher proportion of people with diabetes than of people without diabetes have physical limitations: 66 percent compared with 29 percent.

The chronic hyperglycemia of diabetes is associated with long-term damage, dysfunction, and failure of organs, especially the eyes, kidneys, nerves, heart, and blood vessels. Diabetes also significantly increases the risk of stroke, chronic kidney disease, cancer and their associated mortality as well as all-cause mortality (So et al., 2008). For a Costa Rican urban population of adult diabetic patients, Laclé-Murray and Valero (2009) have reported a 33.6% prevalence of nephropathy, 30.6% prevalence of neuropathy, and 24.8% prevalence of microproteinuria. These are high prevalences of complications that add to the burden to the health care system.

The large prevalence of diabetes could have its origin in the adoption of a westernized life style, and could also be related to the exposure to poor nutritional conditions in the early childhood. In any case, the increase in diabetes prevalence is increasingly constraining the health care systems and imposing a high economic burden (Barceló, 2003; Palloni et al., 2006). Higher proportions of older people combined with an increasing number of diabetics -who have higher risk of premature mortality- have made of diabetes a challenge for the medical care systems in Latin America (Barceló, 2000; Barceló et al., 2006) and in developed regions (Sloan et al., 2008; Solli et al., 2010).

Developing countries in Latin America are experiencing the process of demographic aging at an unprecedented speed. The time it will take a Latin American country to attain around 15% people 60 or older is less than two fifths the length of time it took the US. These older populations are experiencing both an increase in the prevalence of obesity-related conditions such as diabetes, and an increase in the proportion of people with chronic diseases who are elderly.

The proportion of Costa Rican elderly is projected to increase in the coming decades. As a consequence of this demographic aging and of the prevalence of diabetes risk factors, the elderly population with type 2 diabetes is expected to continue growing.

1.4. Importance of this research

Little is known about the prevalence of diabetes and the determinants for this condition among elderly populations in Latin America, because most epidemiologic studies have focused on the general population or on younger population segments (Barceló et al. 2007). An estimation of the burden of diabetes in the years to come will be an important input for the establishment of public policy that is relevant not only to Costa Rica but to other developing countries that will be facing similar scenarios in the Latin American region.

With the global rising of overweight and obesity, concern about the harmful effects of the diabetes epidemic on life expectancy and health care costs has risen in different contexts (Danaei et al., 2011). This increasing burden of diabetes has already been perceived by Costa Rican authorities. A research conducted in a Costa Rican population more than a decade ago showed that diabetic individuals made 1.55 more medical visits and had 1.98 times more hospitalizations than their non-diabetic peers (Morice et al., 1999). Currently, the most frequent causes of consultation in the elderly (22%) are those related to the circulatory system, which include hypertension. The second most important causes (16%) are endocrine, nutritional and metabolism pathologies, which include diabetes and hypercholesterolemia (Chaves & León, 2010). These causes of morbidity, diabetes being one of the most relevant, represent high costs to the health care system. Diabetes-caused mortality has also been increasing as shown before. Nevertheless, diabetes economic burden to the health care system or the impact it has in terms of lives lost has not been quantified thus far.

Costa Rican Social Security Fund, in charge of universal health care provision and the pension system in Costa Rica, is currently facing a deep financial crisis. This situation has received a lot of public attention because of the implications it is expected to have in the near future (PAHO, 2011). This panorama adds more importance to the specific estimation of diabetes burden in Costa Rica. Furthermore, results from this research will prove to be useful for future resource planning in other aging developing countries in the Latin American and Caribbean region which may not have first hand information available.

1.5. Objective and research questions

The objective of this dissertation is to quantify the diabetes burden in Costa Rica, both in terms of life years lost, and in terms of cost of public healthcare services.

This research will provide estimates of current diabetes prevalence and diabetes mortality in the elderly, as well as estimates of the incidence of diabetes in the adult population, and how these three processes are associated with their determinants.

Furthermore, this study will provide estimates of the prevalence of diabetes in the elderly and the economic burden on the health care system it will imply for the years to come up to 2025. Finally, some recommendations will be given regarding the need of strategies to diminish the impact of the diabetes epidemic in Costa Rica.

Research question

What impact has the diabetes epidemic in Costa Rican elderly on life expectancy and public healthcare services cost?

Subsidiary research questions

1. What are the prevalence, incidence, and mortality rates of diabetes among the elderly and what are their determinants?
2. What is the current economic burden that the diabetic elderly represents to the public health care system as compared to the non-diabetic elderly?
3. What is the projected share the diabetic population will have in the elderly in the future?
4. What is the projected economic burden the diabetes epidemic will put on the health care system?
5. What is the projected impact of diabetes on life expectancy in the future?

CHAPTER 2. Data source

2.1. The CRELES study

The CRELES study (Costa Rican Longevity and Healthy Aging Study), a three- wave longitudinal study, is the main source of data for this research. This is a project conducted by the Central American Population Center in collaboration with the Institute for Health Research at the University of Costa Rica. Other public organizations that have collaborated at different stages of the project are the Costa Rican Social Security Fund (CCSS, for its Spanish acronym) and the National Council for the Elderly.

Sample size was 2,827 individuals in wave 1. Follow-up interviews were attained for 2,364 individuals in wave 2 and 1,863 in wave 3. It is a nationally representative sample of the elderly in Costa Rica, with an oversampling of the oldest adults. Only Costa Rican residents were part of the study, regardless of their nationality. These individuals were born in 1945 o earlier. They were aged 60 or older when interviewed in the first wave, between 2004 and 2006. The second wave was conducted between 2006 and 2007, and the third wave between 2008 and 2009. Only the person who was selected to be part of the study was interviewed in each household, regardless of the number of elderly individuals living in the same dwelling.

2.1.1. Sampling frame

The sample was obtained from a two-step procedure. First, a master sample of 9,600 individuals who were interviewed in the 2000 Census was randomly selected. The mother sample was stratified by 5-year age groups. Within each stratum, individuals were randomly selected using a systematic procedure. Sampling fractions ranged from 1.1% among those born in 1941–45 to 100% for those born before 1905.

In a second step, the individuals in the master sample were grouped into 102 geographical clusters according to the 102 existing “health areas". Health areas are administrative population units defined by the government for the purpose of providing health care services nationwide. A sub sample of 60 health areas was selected at random from a total of 102 health areas from the entire country. This sub sample was taken in a probabilistic way such that all individuals in the master sample had the same probability of being part of the sub sample.

The sub sample of 60 areas, which covered 59% of Costa Rican territory, included nearly 5,300 individuals from the master sample, yielding the following non-response rates: 19% deceased by the contact date, 18% not found in the field, 2% moved to other addresses, 2% rejected the interview, 2% pending interviews after several visits (likely rejections).

Those who either were not found in the field or had moved, concentrate at younger ages, they live mainly in urban areas and have a higher socioeconomic status. To correct this differential non response, normalized sampling weights were used. Sampling weights corrected for age (5-year groups), sex, urban/rural residence and education (less than complete primary, and complete primary school or more). These sampling weights allow reproducing the Costa Rican population structure at the index date (mid 2005) by age, sex, urban residence, and education.

The resulting sample size in wave 1 was 2 827 individuals. Final sampling weights were computed as the inverse of selection probabilities, which take into account the sampling design (selection of the master sample and of the second sub-sample), as well as differential non-response rates. These weights range from 0.07 (males 95+, poor education) to 3.85 (rural males, 60–64, and high education). Statistical analyses conducted in this dissertation take sampling weights into account, unless otherwise stated.

2.1.2. Data collection

Blood and urine samples were collected. They were used to obtain a number of biomarkers. Anthropometric measurements were also taken. All the data, measurements, and samples were collected at the participants' homes, usually in two visits. During the field work the data was gathered by Computer Assisted Interviews (CAIs), using Personal Digital Assistants (PDAs) or handheld computers, with software applications developed by *Centro Centroamericano de Población* (CCP) for this study. This technology permits to control for data inconsistencies in the field and to generate information continuously (Hidalgo et al., 2007).

In the first visit, participants provided a written informed consent that had been previously approved by the University of Costa Rica's Institutional Review Board (Reference: VI-763-CEC-23-04). The individuals answered a 90-minute long questionnaire that addressed topics such as: self-reported health status, functional limitations, household characteristics, utilization of health care services, insurance and working status, inter-generational transfers, and demographic characteristics. It also included some mobility tests and two blood-pressure measures. Dietary data was collected using a modified version of a food-frequency questionnaire (FFQ) of about 30 food-tracer items that was developed and validated for Costa Rican adult population (Kabagambe et al., 2001; El-Sohemy et al., 2001). Finally, during the first visit, the interviewer made a list of all medications the interviewee was taking, that had been prescribed by a health care professional.

In a shorter second visit, fasting blood samples were collected by venipuncture: 1 EDTA purple top tube (for 3–4 ml. of whole blood) and 2 serum separating tubes (SST) with a clot activator (for 10–12 ml. of blood, to obtain 4–6 ml. of serum). During this visit the fieldwork team also picked up an ice chest containing a 12-hour overnight urine sample and took the anthropometric measurements.

Blood specimens were analyzed in several laboratories according to the methods described elsewhere (Méndez-Chacón et al. 2007). Linear adjustments were performed to have comparable measurements across laboratories; technical support for the adequacy of these linear adjustments was provided by microbiologists (Brenes-Camacho, Rosero-Bixby, 2008b).

Respondent's vital status was traced in a longitudinal fashion using the Death Index. Retrospective information -like the age at which certain events occurred in the past- was also collected by this survey.

From those interviewed at baseline, 94% provided blood sample and 95% had anthropometric measurements taken. Before being interviewed all participants were asked to complete a short cognitive questionnaire to establish their ability to respond the interview themselves. If it was detected that the individual was unable to respond by himself, the information was obtained from a proxy informant. From the entire sample 25% required a proxy to answer the questionnaire at baseline.

Sample size was 2 827 individuals in the first wave, 2 364 in the second, and 1 863 in the third wave. Attrition rate between first and second wave was 16%: 10% deceased by the contact date and 6% refused or could not be located. Between second and third wave attrition rate was 21%:

11% deceased by the contact date and 10% refused or could not be located. Taking the first wave as reference point, attrition rate at the end of third wave (2009) was 34%: 20% deceased and 14% refused or were not located.

Respondent's vital status was followed up by two means: linking the CRELES dataset with the Costa Rican Death Index (National Vital Registration System), and through a descendant questionnaire that was applied by CRELES fieldworkers whenever the respondent was deceased by second or third wave. Regarding the linkage with the Death Index, observations were censored on December 31, 2010. Taking the first wave as reference point, 27% of individuals had deceased by the end of 2010. This figure is 7 percent points higher than the deceased percentage found at the end of third wave because of two reasons. First, it includes deaths occurred after third wave in 2009 and by the end of 2010. Secondly, it captures the deaths occurred by the third wave that had not been recorded because neither the participant nor a descendant was located during fieldwork.

2.2. Cost of health care services

The costs of health care services used in this research are the institutional costs reported by the Costa Rican Social Security Fund (CCSS, for its Spanish acronym) for the following services: hospitalizations, outpatient consultations, and drug prescriptions. Monthly current costs are available at http://www.ccss.sa.cr. These monthly costs for each health care service are estimated by the CCSS as the total expenses incurred in one specific service divided by the total production in the same service over one month. Mean costs used in this study are the average monthly costs over a one year period, starting at July 2010, ending at June 2011. The objective of using information over an entire year is avoiding any bias that could eventually be introduced because of stationality in the pattern of expenses and production on these services.

2.3. Official population projections

Official population projections were used to estimate the future prevalence of diabetes, as described in the next chapter. Costa Rican population figures from official National Population Projections are available at http://www.ccp.ucr.ac.cr. Diabetic elderly population sizes and their corresponding prevalence rates based on these official population figures were estimated up to year 2025.

2.4. Mortality historical data

Historical mortality series were used to forecast all-cause mortality using the Lee-Carter method described in the next chapter. Costa Rican population figures from official National Population Projections as well as death counts from the official National Vital Statistics are available at http://www.ccp.ucr.ac.cr. Although death counts are available from 1970 up to 2010, and mortality series could therefore be estimated for that entire 41 years period; only data for the 31 years period from 1980 to 2010 were used for mortality forecasting, as explained in next chapter. General, as well as cause-specific mortality (diabetes-caused, and non-diabetes-caused mortality rates), was estimated for the same 31 years time-period.

CHAPTER 3. Methods

Data analyses and estimations were conducted with the STATA computer software (StataCorp, 2011). The analyses include descriptive statistics, multiple regression models, and survival analysis models depending on the nature of the phenomena to be described. Lee-Carter mortality forecasts were estimated with the LCFIT software, a software application for performing Lee-Carter mortality modeling, forecasting, and projection (Sprague, 2009).

3.1. Clinical diagnosis and control of diabetes

There are four criteria for the diagnosis of diabetes that are recommended by the American Diabetes Association (ADA, 2012). They include either (1) hemoglobin A1C >=6.5%; or (2) fasting plasma glucose >=126 mg/dl; or (3) 2-hour plasma glucose >=200 mg/dl during an oral glucose tolerance test (OGTT); or (4) the presence of symptoms or hyperglycemic crisis and a random plasma glucose >=200 mg/dl.

Glycated hemoglobin (HbA1C) is a widely used marker of chronic glycemia that reflects average glycemia over a 2- to-3 month period of time (ADA, 2012) and it is used to monitor the results of treatment on diabetes patients (Davidson et al. 1999). Although an expert committee had in the past recommended not using this biomarker for clinical diagnosis because of the lack of unified standards among laboratories (ECDCDM, 2003); in the United States, as well as in Costa Rica, unified standards among laboratories have been established during the last years (Brenes, 2008; Saudek et al., 2008). Now that HBA1C assays are highly standardized, an International Expert Committee recommended its use to diagnose diabetes (International Expert Committee, 2009) and the American Diabetes Association has affirmed this decision (ADA, 2011).

Although the current ADA criteria for the diagnosis of diabetes refer to three tests: HBA1C, fasting plasma glucose, and OGTT, I will not refer to the latter since that biomarker was not collected in the CRELES study. I will rather turn to HBA1C and fasting plasma glucose (FPG) which are available for this elderly sample. Glycated hemoglobin measures the glucose metabolism in the last three months, whereas fasting glucose is a measure that is more susceptible to variation due to temporary conditions, and to the possibility that some individuals may have reported to be fasting when the blood sample was taken even though they were not. Fasting glucose is the usual criteria for the initial diagnosis of diabetes in Costa Rica, and glycated hemoglobin is used as a control test in the public health care system (Brenes et al., 2006).

HBA1C has several advantages to the FPG for individual diagnosis of diabetes. It is a more chronic marker of dysglycemia as compared to FPG, which is an acute marker. It is also of greater convenience since fasting is not required and it is subject to less day-to-day perturbation during periods of stress and illness (ADA, 2012; Bennett et al., 2007; Droumaguet et al., 2006).

3.2. Identification of individuals with diabetes in population studies

The requirements for individual diagnosis of diabetes differ from those of population studies (WHO, 1999; WHO, 2006). A difference needs to be stressed regarding the clinical diagnosis of patients with diabetes and the classification of individuals by their blood glucose concentration for population studies of diabetes.

In population studies two different biomarkers (glycated hemoglobin and fasting glucose) can be used to know whether or not the person is likely to have the condition. These clinical tests yield additional information to the self-report made by the respondents regarding their diabetes status. Self-reported diabetes is prone to substantial underestimations of the true prevalence of diabetes (Bonora et al., 2004). In this particular study, self reports are complemented with the glycated hemoglobin test, as well as with medications use.

3.3. Classification of individuals' diabetes status in this study

Since this is a population study, I do not intend to make any clinical diagnosis, but to classify individuals as diabetic or non diabetic for data analysis purposes. Three different sources of information will be used: self-reports, biomarkers (glycated hemoglobin), and current use of medications. The approach of using the presence of diabetes medications to identify individuals who are likely to be diabetic has also been used by other researchers (Rockwood et al., 2000; Suh et al., 2008).

For the purpose of this dissertation diabetes has been identified primarily by self-reporting. The corresponding item in the questionnaire was: *"Has a medical doctor ever told you that you have diabetes or high blood sugar levels?"*

The method used to identify diabetic subjects is very important since it has been estimated that a high percentage of late-onset cases go undiagnosed. Self-reports of diabetes are known to underestimate true prevalence. They have high specificity (ability to identify correctly those who *do not have* the disease), but lower sensitivity (ability to identify correctly those who *have* the disease). Discrepancies in classifications may certainly affect the estimates of prevalence and incidence of this condition.

In order to test the sensitivity of the results to the classification of individuals' diabetes status, the analyses are run for both classifications: (1) based on self-reports only, and (2) self-reports complemented with biomarkers (glycated hemoglobin) and medications the individual was currently taking when interviewed.

To avoid potential confounding by type 1 diabetes, I included only individuals reporting a diagnosis of diabetes at 30 years or older. This criterion has been used in other studies (Suh et al., 2008; Hu et al., 2001; Hu et al., 2007).

Under the second definition, elderly individuals in this sample have been classified as diabetic if they meet any of the following criteria:

1. Diagnosed as diabetic by a medical doctor at age 30 or older.
2. Currently under drug treatment for diabetes. Participants were classified as diabetic if during a medication inventory they were identified as users of insulin, or oral hypoglycemic agents.
3. Glycated hemoglobin (HbA1c) is equal or greater than 7%. This cut-off point is higher than the 6.5% used for clinical diagnosis. It has been chosen because the probability of correctly classifying individuals as diabetic (sensitivity) based on this biomarker is higher if the cut-off point is moved forward from the established threshold for diagnosis. It therefore implies a trade-off between sensitivity and specificity.

3.4. Definition of variables

Diabetes definition, as self-report or self-report complemented with biomarkers has just been presented in section 3.3. This section contains definitions for other relevant variables that were used in descriptive information at baseline, or in the prevalence, incidence, mortality, and economic burden multivariate regression models. These variables are classified as sociodemographic characteristics, diabetes risk factors, access to health care, and comorbidities.

3.4.1. Sociodemographic characteristics

Age was used as a continuous variable in the prevalence, incidence, mortality, and economic burden models. Only for descriptive information at baseline, age is categorized in three groups: 60-69, 70-79 and 80+ years.

Sex was a dichotomous variable, with female as the reference category in the prevalence, incidence, mortality, and economic burden models. Education was also treated as a dichotomous variable that refers to incomplete or complete primary school. Elementary school in Costa Rica comprises a total of six grades. Individuals with complete primary had therefore at least six years of education. Incomplete primary school was the reference category.

Income was defined as dichotomous variable with low and high income as its two categories. Cut-off point is about 100 USD 2011 (50 000 colones, Costa Rican currency) in average per elderly individual per month. That is the elder's own income if not married, or the average of the couple's monthly income if married. USD100 was considered the minimum income for an elderly to cover his expenses over a month during the time period of wave 1 (2004-2006). A greater than USD100 income was the reference category. This cut-off has been used in similar studies with CRELES (Méndez-Chacón et al., 2008; Brenes-Camacho & Rosero-Bixby, 2008b)

The aforementioned sociodemographic characteristics: age, sex, education and income, are presented in the descriptive data (table 1) and were used in the prevalence, incidence, and mortality analyses.

3.4.2. Diabetes risk factors

Regular physical activity

Regular physical activity was a dichotomous variable included in descriptive information at baseline. In CRELES, regular physical activity was defined as individuals responding “yes” to the question “In the last 12 months, did you exercise regularly or do other physical rigorous activities like sports, jogging, dancing, or heavy work, three times a week?” Regular therefore refers to a minimum of three days during a week. No regular exercise was the reference category.

Family history of diabetes

Family history of diabetes was a dichotomous variable. It refers to whether or not any of the individual’s parents, siblings or grandparents has ever had the condition. No family history of diabetes was the reference category.

Obesity

Obesity is known to be the main risk factor for diabetes. There are different indicators of obesity. Waist circumference (WC) and body mass index (BMI) are two of such indicators. The former is a measure of central or abdominal obesity; the latter is a measure of general obesity. Waist circumference is measured placing a measuring tape around the abdomen at a level midway the lowest rib and the upper hip bone. It can be measured in inches or centimeters. Body mass index is a ratio of weight and height. It is estimated as the individual's weight divided by the square of his height. Its unit of measure is kg/m^2.

Anthropometric measurements of weight, height, and waist circumference were collected during the interviews. People have different body compositions. Therefore no specific WC category is uniquely linked to a specific BMI category. When both WC and BMI measures were available, a variable that combines these indicators of central obesity and general obesity characteristics of each elderly was used for the analyses. Otherwise, only BMI measure was used to conduct the analyses.

BMI

Individuals were classified as (1) underweight if their BMI <18.5 kg/m2, (2) normal if 18.5-24.9 kg/m2, (3) overweight if 25-29.9 kg/m2, and (4) obese if ≥30 kg/m2 (WHO, 2000).

Waist circumference

Participants were also classified in the following waist circumference categories. For men: (1) normal if < 94 cm, (2) increased if 94-101 cm, and (3) substantially increased if ≥102 cm. For women: (1) normal if it < 80 cm (2) increased if 80-87 cm, and (3) substantially increased if ≥88 cm (WHO, 2000).

Combined measure of waist circumference and BMI

Waist circumference and BMI combined categories were used as follows: (1) normal WC, normal BMI; (2) normal WC, overweight or obese; (3) increased or substantially increased WC, normal BMI; (4) increased WC, overweight or obese; (5) substantially increased WC, overweight; and (6) substantially increased WC, obese. The first one (normal WC and normal BMI) was the reference category.

Descriptive information at baseline contains the distribution of participants according to the aforementioned three measures: waist circumference, BMI, and the combined measure of waist circumference and BMI.

Prevalence models were estimated with the combined measure only since this variable, through its six categories can better capture the association between diabetes and a range of different body compositions.

Incidence models rely solely on body mass index as a time dependent covariate. BMI estimates are available for participants at age 25 and at waves 1, 2, and 3. Waist circumference information is not available for individuals at age 25, but only during the three waves of the CRLES study. For each of the three waves the objective information on anthropometric measurements, rather than self-reports was used to estimate BMI.

Estimation of BMI at age 25

Baseline BMI at the age of 25 used in the incidence models was estimated as follows. CRELES questionnaire included self-reported information on weight at the age of 25, as well as each individual's classification of their body at the age of 25 using the Figure Rating Scale (FRS) developed by Stunkard et al. in 1983.

The FRS is a scale that consists of nine schematic silhouettes ranging from very thin to very obese. It was developed and validated to index the weight status of research subjects' relatives when measured or self-reported values were unavailable (Sorensen et al., 1983; Stunkard et al., 1983).

There is evidence that FRS is a valid scale that has been tested in populations of different age groups and geographical contexts. For example, Scagliusi et al. (2006) concluded that FRS was a valid measure of body image in a Brazilian context. Cardinal et al. (2006) studied a community female population in the United States and found that BMI and figure ratings were highly correlated; they concluded that FRS could be used as an index of women's weight status. Also, after examining the validity and reliability of FRS in Chinese adolescents, Lo et al. (2011) supported the use of the FRS scale in that population.

For individuals who reported their weight at age 25, FRS information was not used. Body mass index in these cases was estimated using participants' weight self-report at age 25 and their height measurement in wave 1. Self-reported weight was used for 46.2% of the weighted sample.

For those who did not report weight at the age of 25, a BMI category was imputed based on their choice of silhouette in the FRS scale. Imputation procedure is described below. Imputed BMI category was used for 41.3% of participants of the weighted sample in wave 1.

No estimation of BMI at age 25 was feasible for 12.5% of individuals who had none information on weight at age 25. Most of them (12.3%) were not asked this retrospective information because they needed a proxy respondent for the interview. Only 0.2% of participants who were direct respondents could not have an estimation of their BMI category at age 25 because they had missing weight self-report and FRS.

Criteria for imputation of BMI categories at age 25 was developed based on the comparison of actual BMI in wave 1 and reported current silhouette of participants. Mean BMI and standard deviation was estimated by silhouette category and sex (Annex 1, table 1). Mean actual BMI increased as silhouette categories increased. Sex differences were observed within the nine silhouette categories. Given they had reported the same silhouette category; female respondents had greater mean BMI values than men.

Normal BMI range is [18.5-24.9], with an interval midpoint of 21.7 kg/m^2. Overweight BMI range is [25.0-29.9], with an interval midpoint of 27.5; and obesity is defined as BMI equals or greater than 30 kg/m^2. Categories of silhouettes were grouped in such a way that they could better reflect real BMI intervals' midpoints. Proposed grouping took into account sex differentials, as shown in Annex 1, table 2.

Categorization of BMI at age 25 according to the Figure Rating Scale was as follows. For men, FRS silhouettes 1-4 were classified as normal BMI, 5-6 as overweight, and 7-9 as obese. For women, FRS silhouettes 1-3 were classified as normal BMI, 4-5 as overweight, and 6-9 as obese.

The aforementioned diabetes risk factors: regular physical activity, family history of diabetes, waist circumference, BMI, and combined waist circumference and BMI, are presented in the descriptive data (table 1) and were used in the prevalence and incidence analyses.

3.4.3. Behavioral health risks

Smoking and alcohol drinking used in prevalence and incidence analyses

Both behaviors smoking (Kowall et al., 2010; Willi et al., 2007; Zhang et al., 2011) and alcohol drinking (Baliunas et al., 2009; Beulens et al., 2005; Nayanishi et al., 2003; Pietraszek et al., 2010) have been described to have an association with diabetes.

Information on active and passive smoking was used for the analyses. Those who were not current active smokers but lived with a smoking partner were classified as passive smokers. Questions regarding active smoking behavior in this study were asked only to those who had smoked 100 or more cigarettes or cigars along their lives. The corresponding items in the questionnaire were: *"Have you smoked more than 100 cigarettes or cigars in your life?"* and *"Do you currently smoke?"* A categorical variable regarding smoking was created. It has four categories: (1) never smoked, (2) former active or passive smoker, (3) current passive smoker, and (4) current active smoker.

Information on alcohol refers to alcoholic drinks ever consumed along individuals' lives. The corresponding question was "*Have you regularly drunk alcoholic drinks in your life?"* Answers were classified into three categories: (1) never, (2) former and (3) current alcohol drinker.

Reverse causality could result from the fact that people stop drinking or smoking precisely because they have been diagnosed with diabetes. In order to mitigate this bias, timing information has been used to adjust the individuals' classification into their corresponding smoking and alcohol categories. Self- report of dates on diagnosis and the time individuals quitted smoking or drinking were used to disentangle whether they quitted after the diagnosis. Still, this approach has limitations since recall bias could be introduced. Differential inaccurate recall of quitting dates reported between diabetic and non-diabetic individuals would introduce recall bias (Szklo & Nieto, 2004). Nevertheless, this source of recall bias cannot be mitigated since there are no external sources of data to verify the exact dates events occurred.

An adjustment was made to the 'current active smoker' and 'former' categories for smoking and to the 'current' and 'former alcohol drinker' categories for the alcohol consumption variable. Those who declared to have smoked or drunk in the past were moved from the 'former' to the 'current' category if they quitted after their diabetes diagnosis. They represent a 2% of the total weighted sample. Individuals who used to smoke or drink by the time they were diagnosed as diabetic had the highest exposure to the risk factor at that time, and this is reflected in their classification as current rather than past tobacco or alcohol consumers.

Therefore, for both smoking and alcohol variables, the current category includes those who were current active smokers or drinkers plus those who quitted only after the diabetes diagnosis had occurred. The ‘former’ category includes those who smoked or drank in the past but did not anymore when interviewed, including the ones who quitted before being diagnosed. The never category includes all the individuals who reported to have never smoked or drunk alcohol.

Smoking and alcohol variables are presented in the descriptive data (table 1) as behavioral health risks and were used in the prevalence and incidence analyses.

Daily calorie intake used in prevalence models

Hyper caloric diets are considered risk factors for metabolic diseases such as DM2. The estimation of calorie daily consumption was made from the 10-minute frequency of tracer food consumption questionnaire that was part of the interview. A dichotomous variable was used to identify whether individuals had a daily consumption of more than 3 000 kcal/day. Reference category was <=3 000 kcal/day. This value is a standard cut point associated with differential risk of cardiovascular disease (Brown, 2008) and has been used in similar population studies (Méndez-Chacón et al., 2008; Rehkopf et al., 2010; Rosero-Bixby and Dow, 2009).

Calorie daily consumption in this population is presented in the descriptive data (table 1) as a behavioral health risk and was used in the prevalence analysis.

3.4.4. Access to health care

Access to health care is a complex concept. A population may have access if an adequate supply of services is available, but the extent to which a population actually gains access to health care depends on financial, organizational and social or cultural barriers. Access measured in terms of utilization of available services is therefore dependent on affordability, physical accessibility and acceptability of services (Gulliford et al., 2002). Still more elaborated theoretical models to measure access to health care have been proposed in the literature. One example is Andersen's theoretical model of access to medical care (Andersen, 1995), which was in fact used in the analysis of health care services utilization in this dissertation.

Nonetheless, because diabetes prevalence analyses were not centered in access to health care, access was measured following Gulliford and colleagues' argument of affordability, physical accessibility and acceptability of services as determinants of access.

Acceptability refers to the social and cultural influences that mediate the access to health care services. No measurements regarding this component of access were available in the CRELES project. Therefore access to health care was measured in this dissertation in terms of affordability and physical accessibility.

Affordability was measured with the variable “having a health insurance”. Physical accessibility was measured with two variables: “living in the Great Metropolitan Area (GMA)” and “mean time to the nearest health facility”. The former was included as a dichotomous variable, with not living in the GMA as the reference category; and the latter as a continuous variable measured in minutes. Living in the GMA was used as a measure of physical accessibility because that is the geographical area where the most important health care facilities are clustered in Costa Rica.

The three aforementioned measures of access -having health insurance, living in the GMA, and mean time to the nearest healthcare facility- are presented in the descriptive data (table 1) and were used in the prevalence analysis.

3.4.5. Health condition

Chronic morbidity

Six chronic conditions were included in mortality analyses: diabetes, cancer, lung disease, myocardial infarction, ischemic heart disease (not infarction), and stroke. All these chronic morbidities were defined as dichotomous variables. Not having the condition was the reference category. These variables refer to whether or not the individual has ever been told by a medical doctor to have the condition. Since diabetes was the main independent variable, one model was run using self-report of medical diagnosis, and another one using self-report complemented with biomarkers. See both definitions of diabetes in section 3.3.

Other than diabetes, questions in the CRELES questionnaire used to determine chronic morbidity conditions were the following:

"Has a medical doctor ever told you…

… that you have cancer or malign tumor, excluding small skin tumors?"

… that you have had a chronic respiratory or lung disease, such as emphysema, tuberculosis, asthma or chronic bronchitis?"

… that you have had an infarction or heart attack?"

… that you have had a heart disease without having had infarction?

… that you have had a stroke?"

The aforementioned five chronic morbidities, as well as diabetes prevalence are presented in the descriptive data (table 1) and were used in the mortality analysis.

Other measures of health condition

Other measures of health condition were also included in the models of economic burden on the health care system. They are described as follows.

Self perceived health

CRELES questionnaire used the following question to determine self-perceived health: *How would you rate your health currently? Excellent, very good, good, fair or poor?* Based on a recodification of categories for this question, a variable was created to assess poor self-perceived health.

Having a poor self-perceived health was a dichotomous variable. Individuals who reported either a fair or poor health belong to one category; and those who reported good, very good or excellent health belong to the reference category.

Limitations in activities of daily living

Participants of the CRELES study were asked about the following limitations in activities of daily living (ADL): crossing the bedroom from side to side, bathing, self feeding, going to bed, toileting, nail trimming, walking, climbing stairs, pushing objects, and raising arms. A dichotomous variable was created to assess whether or not individuals reported at least one ADL limitation. None ADL limitation was the reference category.

Limitations in instrumental activities of daily living

CRELES questionnaire asked individuals about limitations in the following instrumental activities of daily living (IADL): cooking, handling money, shopping, and taking medications. A dichotomous variable was created to assess whether or not individuals reported at least one IADL limitation. None IADL limitation was the reference category.

Hypertension

In CRELES blood pressure was measured twice during the interview. There are therefore two measures for diastolic and two measures for systolic pressure. Following Méndez-Chacón et al. (2008) hypertensive individuals were defined as those who had any of these characteristics: (1) had been told by a medical doctor that they were hypertensive; or (2) had blood pressure of 140/90 or higher in three out of the four measures; or (3) were taking antihypertensive medications.

Dyslipidemia

Dyslipidemia was assessed as having at least one of hypercholesterolemia or hypertriglyceridemia. Hypercholesterolemia was defined as elevated total/HDL cholesterol, and the variable was operationalized as follows.

The Total/HDL cholesterol ratio was estimated for this elderly sample based on blood biomarkers. Participants were classified as having elevated Total/HDL ratio if they had values of 5.92 or greater. Those who were not fastening when the blood sample was taken have missing information on HDL and total cholesterol and therefore in the corresponding ratio.

The hypertriglyceridemia or elevated triglycerides variable was operationalized as follows. Based on blood biomarkers CRELES participants were classified as having elevated triglycerides if their laboratory results showed a concentration of 150 mg/dl or greater when fastening. Those who were not fastening when the blood sample was taken have missing information on triglycerides level.

Cardiovascular disease

Cardiovascular disease was defined as having ever had at least one the following: myocardial infarction, ischemic heart disease without infarction, or stroke. The items in the CRELES questionnaire that originated the information on these three chronic morbidity conditions have been mentioned in the previous section. Having had none of them was used as the reference category.

Descriptive data (table 1) includes the prevalence of these conditions: hypertension, dyslipidemia and cardiovascular disease. These variables were included in the models of economic burden on the health care system. A further explanation on the framework used for those models follows.

3.4.6. Determinants of health care services utilization.

Variables used in the models of economic burden on the health care system are based on Andersen's theoretical model of health care use (Andersen, 1995). This theoretical model is widely used in the scientific literature and has already proven to adjust to the Costa Rican context (Brenes-Camacho and Rosero-Bixby, 2009; Llanos et al., 2009). This model proposes that the use of health care services is mediated by the interaction of three factors: (1) predisposing characteristics, (2) enabling resources, and (3) need (Andersen, 1995).

Predisposing characteristics include sociodemographic characteristics that use to have an association with certain levels of utilization. For this study, predisposing characteristics included in the model are: age, sex, living in the Great Metropolitan Area, married or in union, and retired. Age has been included as continuous variable, the rest of predisposing characteristics are dichotomous variables.

Enabling factors refer to such conditions that allow a greater availability and access to the services. They include individual as well as contextual characteristics. Among the individual characteristics, models estimated in this study include education and income. Among the contextual characteristics, models include health insurance and having been home visited by a health care professional during the last year. All of these are treated as dichotomous variables.

Need is the most proximate determinant of utilization, and it varies as a function of the predisposing and enabling factors. Cultural factors can also influence need, but no measurement of such variables was available in the CRELES questionnaire. Models estimated in this dissertation include the following variables: having a poor self-perceived health, having at least one limitation in activities of daily living (ADL), having at least one limitation in instrumental activities of daily living (IADL), and having been diagnosed with diabetes, cancer, lung disease, cardiovascular disease (myocardial infarction, ischemic heart disease, or stroke), hypertension, dyslipidemia (hypercholesterolemia or hypertriglyceridemia), arthritis, or osteoporosis. All of these variables have been defined in the previous section. They were all treated as dichotomous variables.

The aforementioned determinants of health care services utilization under the classification of predisposing characteristics, enabling resources and need, are described in section 4.1 (table 1) and were used in the analyses of the economic burden on health care services.

3.5. Prevalence

Point prevalence rates of diabetes and their 95% confidence intervals have been estimated by age and sex. Logistic regressions have been used to analyze the relation between individuals' diabetes status and sociodemographic characteristics, diabetes risk factors, behavioral health risks, and access to health care.

Two models have been estimated. Diabetes as a dichotomous variable was the dependent variable for the two of them. They are only different in terms of the diabetes definition used: (1) based on self-reports only, and (2) self-reports adjusted with biomarkers and medications the individual was currently taking when interviewed.

Sociodemographic characteristics included age, sex, education, and income. Diabetes risk factors included family history of diabetes, and body size and composition. Behavioral health risks included smoking, alcohol consumption, and daily calorie intake. Access to health care included having health insurance, living in the Great Metropolitan Area, and mean time to the nearest health care facility.

3.6. Incidence

Incidence rates and their 95% confidence intervals have been estimated by age and sex starting at the age of 30. Because of the longitudinal nature of the data, parametric regression models were used to estimate the association between the probability of becoming diabetic and sociodemographic characteristics, risk factors and behavioral health risks. The data was set as survival time, with entry date at the age of 30 and exit or right censoring at the date of third wave interview. Incidence rates were computed as the ratio of new diabetes diagnoses to the exact count of person-years.

Parametric survival models with a log-logistic distribution for the baseline hazard were used to model diabetes incidence. The log-logistic distribution has a fairly flexible functional form, it is one of the parametric survival time models in which the hazard may be decreasing, increasing, as well as initially increasing and then decreasing (Hosmer & Lemeshow, 1999). Reason to select this distribution is that the incidence process does not grow monotonically. Type 2 diabetes incidence increases from the age of 30 up to a certain point around the age of 60, and then starts going down at older ages. The log-logistic function can effectively represent a pattern of increasing incidence, followed by a decrease and was therefore selected for this analysis. Log-

logistic is a two-parameter function that allows for non-monotonic unimodal hazards. Hazard rates are characterized as:

$$h(t,X) = \frac{\lambda^{1/\gamma} t^{[(1/\gamma)-1]}}{\gamma\left[1 + \left(\lambda t^{1/\gamma}\right)\right]}$$

where $\lambda_i = e^{-(X_i\beta)}$

The log-logistic has two parameters, λ is the location parameter and γ is the shape parameter.

Follow-up time starts at the date each individual from the CRELES study was aged 30. Individuals are followed up during the three waves of the CRELES interviews. All three waves of the study were used to put together a dataset out of which hazard models were estimated. The event of interest is diabetes incidence. Censoring occurs when individuals are lost to follow-up - either because of death or because of other reasons-, or at the time of interview in the third wave.

Two incidence models have been estimated. Diabetes as a dichotomous variable is the dependent variable for the two of them. They are only different in terms of the diabetes definition used: (1) based on self-reports, and (2) self-reports adjusted with biomarkers and medications the individual was currently taking when interviewed. The specific criteria used for the latter definition has already been described in section 3.3.

The estimation of diabetes incidence in this study relies on both retrospective and prospective data on diagnosis timing for the elderly population in the CRELES study. Prospective information from the three waves of CRELES was used, as well as retrospective information that goes back to the age of 30 referring to self-report of age at diagnosis.

The date of the event (diagnosis of diabetes) was defined using information from the three waves. During the first wave questions asked regarding diabetes diagnosis and its timing were the following: *"Has a medical doctor ever told you that you have diabetes or high blood sugar levels?"* and *"How old were you when you were told to have diabetes"*. The interviewee was allowed to respond the latter question reporting either his age at time of diagnosis or the calendar year when he was given the diagnosis.

Using data from first wave, date of diagnosis was assigned as the individual's birthday of the year of diagnosis based on either age or year of diagnosis they reported. A few cases (2.1%) had missing information on date of diagnosis and corresponding dates were inputted using the predicted age that resulted from a linear regression of age at diagnosis on age and sex. For analysis purposes only, those individuals who were classified as diabetic based on medications or Hba1c -rather than medical doctor diagnosis-, were assigned the date of interview in wave 1 as date of diagnosis.

Only those who reported not to have been diagnosed with diabetes in wave 1 were asked in wave 2 whether they had received a diagnosis between the last and the current interview. Similarly, only those who had not received a diabetes diagnosis by the time of wave 2, were asked about a recent diagnosis in wave 3. The questions asked in the second and third wave questionnaires were the following: *"During the last two years has a medical doctor told you that you have* *diabetes or high blood sugar levels?"* and *"How long ago were you told to have diabetes?* "The interviewee was allowed three options to respond the latter question: (1) less than one year ago, (2) more than one year ago, and (3) with the results of this study.

Based on data from waves 2 and 3, date of diagnosis was assigned as follows. (1) If the person declared to have been diagnosed less than one year ago, date of diagnosis was the date of interview in wave 3 minus 6 months. This is under the assumption that diagnosis occurred at the mid-point (6 months) between the current date of interview and the date one year ago. (2) If the individual declared to have been diagnosed more than one year ago, the date of diagnosis was assigned as the date of current interview minus 1.5 years (18 months). Again, this is under the assumption that diagnosis occurred at the mid-point between the date one year ago and the date at previous interview, which took place about 2 years before. (3) If the interviewee reported to have been diagnosed with the results of the study, the date of diagnosis was assigned as the date of previous interview. Finally, if the individual declared to have been diagnosed at some point between previous and current interview, but could not remember the timing, the date of diagnosis was assigned as the date of current interview minus 1 year, which would be the mid-point between waves.

In the case an individual was identified as diabetic using biomarkers and medications information, the date of the corresponding interview was used as diagnosis date. But if that same individual declared to have been diagnosed by a medical doctor in a subsequent wave, date of diagnosis was replaced by applying the aforementioned rules to assign a date according to his self-report.

This estimation of incidence of diabetes will result in a conservative estimation of the real incidence phenomenon that takes place in Costa Rica. Although these incidence rates refer to the adult population, they are based on what the elderly population reported during the CRELES study. The estimates are therefore biased downwards by selection bias since they refer solely to the population that survived to the age of 60 and was therefore eligible for the study.

Self report of diabetes diagnosis and the date it occurred may also introduce recall bias, which might affect the estimations either upwards or downwards. Errors in the recall of timing of diagnosis result in misclassification of individuals as diabetic along observational time, thus biasing the results of the study. When reporting a previous medical diagnosis, people will likely offer approximate rather than exact dates of the diagnosis of their condition. There is no way to attenuate this bias since no external sources of data, such as medical records, are used in this study.

Errors in the recall of diagnosis itself result in misclassification of individuals as diabetic, which introduces bias, especially when only self reports are used to define diabetes status. When diabetes status is corrected by using biomarkers and medications, recall bias coming from this source is somehow attenuated. Nevertheless, it is important to keep in mind that this attenuation of the bias is limited to the finding of unreported cases only after the already elder individuals were first interviewed; not before then, when these individuals were younger adults. There is no information available on biomarkers and medications when participants were younger.

3.7. Mortality

3.7.1. Total mortality

Total mortality rates and their 95% confidence intervals have been estimated by age and sex, starting at the age of 60. Because of the longitudinal nature of the data, parametric regression models were used to estimate the association between mortality and sociodemographic characteristics and chronic morbidity. The data was set as survival time, with entry date at the age of 60 and exit or right censoring at December 31, 2010. Mortality rates were computed as the ratio of deaths to the exact count of person-years.

Parametric survival models with a Gompertz distribution for the baseline hazard were used to model mortality (Hosmer & Lemeshow, 1999). Costa Rican mortality rates have been shown to follow a Gompertz function, especially after the age of 45 (Rosero-Bixby and Antich, 2010). Gompertz is a two-parameter simple function, used to describe human mortality at adult ages, in which hazard increases exponentially with age. Hazard rates are characterized as:

$$h(t) = \lambda e^{\gamma t}$$

where $\lambda = e^{X\beta}$

The Gompertz has two parameters, λ is a constant term indicating in this particular case the level of mortality, and γ is a shape parameter that in this case indicates the instantaneous increase of mortality with every year increase of age.

Follow-up time starts at the date each individual was 60. Individuals are followed up during the three waves of the CRELES interviews. Respondent's vital status was traced in a longitudinal fashion by linking the CRELES dataset with the National Vital Registration System (the Death Index) using individuals' id number.

Costa Rican Death Index has a very high coverage although late registration of events occurs in some cases. About 3% to 4% of deaths are entered into the Death Index within 2 years of its occurrence. Because of the probability of late registration, mortality information from the Death Index was complemented with data from the descendent questionnaire interview. If a respondent was deceased by wave 2 or wave 3, CRELES fieldworkers interviewed a relative or close acquaintance of the former respondent about the circumstances of the death, which included date and cause of the event.

For individuals that could not be linked to the Death Index because of matching problems with their identification numbers, censoring occurs when individuals are lost to follow-up. For the rest of individuals, censoring occurs at the end of follow-up in December 31, 2010.

Two models were estimated with all-cause mortality as the dependent variable. They were only different in terms of the definition used for diabetes, which was now one of the independent variables. Diabetes was a dichotomous variable that used one of these two definitions for each model: (1) based on self-reports, and (2) self-reports adjusted with biomarkers and medications the individual was currently taking when interviewed. The specific criteria used for the latter definition has already been described in section 3.3.

3.7.2. Diabetes cause-specific mortality

Diabetes cause-specific mortality rates were estimated by age. Because of the longitudinal nature of data and the attrition process that leads to cause-specific mortality, competing risks regression models were used to estimate the probability of dying due to diabetes in the elder. All-cause or total mortality described in the previous section is a single decrement process in which individuals have only one recognized mode of exit from the "alive" state, which is death, no matter its cause. Different from total mortality, specific-cause mortality is a so called multiple decrement process (Preston et al., 2002). Specific-cause mortality implies competing risks of death. In this case, death due to all the rest of causes "competes" with diabetes to lead an individual to death.

Competing events are those that occur instead of the event of interest. They cannot be treated as censored because they might be dependent, and because it is not wise to assume a counter-factual scenario where the competing event does not exist (Cleves et al., 2010). In this particular case, dying of diabetes depends on not dying of any other cause; and one should not assume that those who died of diabetes had no probability of dying of any other cause. Therefore, a competing-risks model is the most appropriate approach.

In the presence of competing events, the analysis focuses on cause-specific rather than standard hazards and on the cumulative incidence function rather than the survival function. A cause-specific hazard is the instantaneous risk of failure from a specific cause given that failure from any cause has yet to happen or may never occur. The cumulative incidence function is the probability of observing a specific type of event before a given time, and is a function of both cause-specific hazards, that is, a function of diabetes-caused mortality and any other cause mortality.

An additive hazards model has been used. Compared with Cox proportional hazards model, the covariate effects in the additive hazards model are assumed to be additive instead of multiplicative to the baseline hazard function (Lu & Liang, 2008). Parametric survival models with a Gompertz distribution for the baseline hazard (Hosmer & Lemeshow, 1999; Rosero-Bixby and Antich, 2010) were used to describe diabetes-caused mortality. Follow-up time starts at the date each individual entered the CRELES study. Respondent's vital status was traced in a longitudinal fashion by linking the CRELES dataset with the National Vital Registration System (the Death Index).

The event of interest is diabetes-caused mortality, and mortality due to any cause other than diabetes competes with the event of interest. For individuals that could not be linked to the Death Index because of matching problems with their identification numbers, censoring occurs when individuals are lost to follow-up. For the rest of individuals, censoring occurs at the end of follow-up in December 31, 2010. Age was the only covariate used in this competing risks model.

The Death Index includes the International Classification of Diseases (ICD-10) codes for the primary cause of death, which -along with death date- was linked to the CRELES database. Date and cause of death from the descendent questionnaire interview, which was applied when a respondent was deceased by wave 2 or wave 3, were also linked to the CRELES database when the event had not yet been registered in the Death Index.

Diabetes as primary cause of death underestimates the real mortality burden. Classification of diabetes as the declared cause in death certificates has validity limitations (Gordis, 2004). That is, the use of primary cause in death certificates has a limited ability to distinguish between whose death was caused by diabetes and whose death was caused by any other condition.

In different countries, death certificates are known to omit diabetes or to include it only as a secondary cause when actually being the primary cause of death (Laclé-Murray, 2012). Usually, causes in death certificates -issued by medical doctors- are checked and recoded by national statistics bureaus before primary causes of death are included in a national death index. After analyzing the quality of death certificates and causes recorded in the death index for a cohort of Costa Rican diabetic adults, Laclé-Murray (2012) found that diabetes as the primary cause of death was omitted in 58.6% of cases. For the most part, diabetes-caused mortality was recorded as mortality due to cardiovascular disease in this cohort of diabetic individuals in Costa Rica.

Although the aforementioned results refer only to a specific urban cohort in Costa Rica and cannot be extrapolated to the rest of the country, diabetes-caused mortality based on the Costa Rican Death Index is clearly a floor estimation of the real mortality burden of the disease.

For those deaths that had not yet been registered in the Death Index, using the cause of death as declared in the descendent questionnaire interview has some limitations. Reliability of primary cause of death (Gordis, 2004) would be compromised if the primary cause of death reported by descendents of a former participant is not the same that will be reported by the Death Index. Still, this is an ancillary source of data that allows capturing death events even when they have not yet been included in the Death Index.

3.8. Current economic burden of diabetes on health care services

The economic costs associated with the prevalence of diabetes in terms of hospitalizations, outpatient consultations, and drugs were estimated in this study. The patterns of use of the health care services and the costs they have for the public health care system were used to estimate the economic cost that diabetes in the elderly population has for the health care system. Mean costs for these services as reported by the Costa Rican Social Security Fund (CCSS) were used to input the economic cost each individual represented for the public health care system according to his reported volume of utilization.

Each individual's reported volume of utilization of hospitalizations, outpatient consultations, and medications was multiplied by the corresponding average cost of the service to estimate the individual's total cost for the CCSS.

Two-part models were used to analyze the effect of individual covariates on the costs of each of these three healthcare services. These models are useful to distinguish the factors that affect the propensity to use any services from factors that affect volume of utilization once the person makes use of the services. This is a common tool used in health economics applications in which the outcomes are measures of health care utilization (Diehr et al., 1999). It basically assumes that the probability of the outcome being greater than 0 given a set of covariates is governed by a binary probability model. That is part one, and is usually modeled as a logistic regression, as is the case in this study. It also assumes that the expected logarithm of the outcome given that the outcome is greater than 0, and given the same covariates, is a linear function of those covariates. That is part two, and has been modeled as a generalized linear model for the three health care services analyzed in this study.

The generalized linear models (GLM) are used with data such as length of stay during hospitalizations and utilization of health care services. The main characteristics of these data are that the outcomes are positive numeric values, there is an important fraction of zeros, and the non zero outcomes are positively skewed. The GLM models estimate directly the logarithm of the expected value of the dependent variable given the covariates. In this modeling one specifies a mean and variance function for the observed raw-scale dependent variable, conditional on the covariates (Manning and Mullahy, 2001). A gamma stochastic distribution with a log link has been used to estimate the parameters associated to each covariate in the part-2 of the models estimated in this study. Using the gamma distribution is common in models to explain health care services utilization and costs (Diehr et al., 1999).

The expected levels of use of each of these three services were estimated by multiplying the estimates of part-1 and part-2 of the two-part models. That is, each individual's estimated cost is his probability of having any use multiplied by the expected cost conditional on being a user. The probability of having any use is estimated from the logistic regression equation. The expected cost, given some use, is estimated from the GLM regression equation.

Economic cost is the dependent variable in each of the three models. Costs are inputted for each individual based on their volume of utilization of each of the following services: hospitalizations over a calendar year, outpatient visits over a calendar year, and medications currently taken.

3.9. Projection of diabetes prevalence in the elderly

The estimates of prevalence, incidence and mortality were used to project the expected size and proportion of diabetic elderly population in the future. Main input was the sets of incidence and mortality rates computed for 5-year age groups ending in the open 95+ group. Migration is not taken into consideration; only incidence and mortality are allowed to affect the estimations of prevalence of diabetes in the elderly. These projections are therefore under the assumption that the underlying processes of incidence and mortality that give shape to the prevalence of diabetes in the elderly remain constant, and migration is null in the foreseeing future.

Because CRELES wave 1 ended in 2006; that was the year used as a start point for diabetic population projections. Diabetic population size in three 5-year-apart time points was computed: 1996, 2001, and 2006. As it will be further stated in this section, backwards projections to the years 1996 and 2001 were computed to estimate growth rates between two time points. Resulting growth rates were used to project up to the year 2025.

Based on the official total population size in 2006 available at http://www.ccp.ucr.ac.cr (defined as N_x in the formulas below), and age-specific prevalence rates, diabetic population size for each age group (N_x^d) was estimated. Prevalence rates for the elderly (60+) are this study's computations based on CRELES self- reports adjusted with biomarkers and medications. For the adult population (30-59) rates are the five-year age group national estimates reported by another research in Costa Rica (Roselló et al., 2004)[1].

Size of the diabetic population was computed five years backwards from the year 2006 to the year 2001, and then five years backwards again from the year 2001 to 1996 using the following formula:

[1] Based on individuals' self-reports of diagnoses only. Although there are more recent prevalence estimates for the adult population that rely on self-reports and biomarkers (Costa Rica Ministerio de Salud et al., 2010), they were not used in this study because they were based on wider age-groups (20-39 and 40-64 years), and were not nationally representative, but representative of the Metropolitan Area only.

$$N_x^{\,d} = [N_{x+t}^{\,d} - (N_x * {}_td_x)] / (1 - {}_td_x * {}_tq_x)$$

The previous formula derives from:

$$N_{x+t}^{\,d} = N_x^{\,d} + (N_x^{\,nd} * {}_td_x) - (N_x^{\,d} * {}_tq_x)$$

Given that:

$$N_x = N_x^{\,d} + N_x^{\,nd}$$

where:

N_x: Total population at age x

$N_x^{\,d}$: Diabetic population at age x

$N_x^{\,nd}$: Non-diabetic population at age x

${}_td_x$: Diabetes incidence rate for the population aged x to x+t

${}_tq_x^{\,d}$: Probability of dying for the diabetic population aged x to x+t

Incidence rates in the above formulas (${}_td_x$) are this dissertation's estimates for ages 30 and beyond based on CRELES data. Death rates for the diabetic population (${}_tm_x^{\,d}$) for ages 30-59 are assumed to be the same as all-cause mortality in the general population from National Vital Statistics. Death rates for the diabetic population for ages 60+ are this study's estimates of all-cause death rates in the diabetic elderly, based on CRELES data.

Age-specific probabilities of dying for the diabetic population ($_{t}qx$) are this study's estimations from both-sexes life tables based on the previously described $_{t}m_{x}^{d}$ and separation factors ($_{t}a_{x}$) from Coale and Demeny (1983) West model life tables.

Backwards projections of diabetic elderly population size by age-group were computed to estimate mean annualized growth rates for the 1996-2001 and 20001-2006 time periods under linear and exponential growth assumptions (Preston et al., 2002).

Under the assumption of linear growth, mean annualized growth rate was estimated with following formula:

$$\bar{r}[0,T] = \frac{N(T) - N(0)}{T * N(0)}$$

Under the assumption of exponential growth, mean annualized growth rate was estimated with following formula:

$$\bar{r}[0,T] = \frac{ln\left[\frac{N(T)}{N(0)}\right]}{T}$$

where:

N(T): Population size at time T

N(0): Population size at time 0

T: Number of years between time 0 and time T

Resulting growth rates were used to project forward the size of the diabetic population up to the year 2025. The growth rates from 1996 to 2001 were used to estimate the diabetic population size from 1997 to 2005, based on the estimated size of such population in 1996. The growth rates from 2001 to 2006 were used to estimate the diabetic elderly population size from 2007 to 2025, based on the estimated size of the diabetic population in 2006. Projected prevalence of diabetes in the elderly was the proportion of diabetic elderly individuals in the total elderly population each year.

Prevalence of diabetes up to the year 2025 was also projected in six different scenarios. Each scenario was under the assumption that growth was linear and the incidence pattern observed in the CRELES population remained constant, but with an increase or decrease in the diabetes incidence level in 25%, 50% and 75% respectively.

Diabetes is considered to be a permanent condition. That is, once an individual is diagnosed, there is no reversal to the non-diabetic condition. Transitions that occur from a state to another, - such as “non-diabetic to diabetic”, “non-diabetic to death”, or “diabetic to death” - are more usually handled by multistate models based on a system of equations that estimate the life tables corresponding to each transition (Preston et al., 2002).

Because the number of deaths occurred among diabetic individuals in this Costa Rican elderly cohort is still not large enough to have stable estimates for the “diabetic to death” transition, using this same dataset, instead of setting multistate models Brenes (2008) projected diabetes prevalence in the elderly using a variation of the cohort-component method.

As it will be further shown, although rather simple, the approach used in this dissertation to project diabetes prevalence yields remarkably similar results to those attained when using more complex methodological approaches (Brenes, 2008).

3.10. Impact of diabetes on future health care costs

Future costs of health care for the elderly population and the impact diabetes is expected to have on them were estimated using the projected prevalences of diabetes and the current mean costs of hospitalizations, outpatient consultations and medications. These costs projections were made in United States dollars of 2011[2] (USD2011) and under the assumption that current patterns of health care services utilization remain constant in the future both in the diabetic as in the non-diabetic elderly. Since prevalence projections were made under the assumptions of linear and exponential growth, the projection of costs and the impact of diabetes prevalence on those costs were estimated for both growth scenarios.

[2] Exchange rate: 1 USD=500 colones

3.11. Impact of diabetes on future life expectancy

According to United Nations (1958), a population forecast is a projection in which the assumptions are considered to yield a realistic picture of the probable future development of a population. According to Keyfitz and Caswell (2005), a forecast is a prediction of what will happen, whereas a projection describes what would happen, given certain hypotheses.

Deterministic projections are a set of different estimates according to a number of scenarios. The scenarios are those considered to be the most likely according to the forecaster's subjective judgments, sometimes buttressed with expert opinion. A deterministic forecast specifies time-changes over the forecast period in terms of deterministic (i.e., not random) equations or assumptions. In stochastic forecast, different from deterministic projections, the role of the forecaster's subjective judgment is reduced by using extrapolation to do the forecast (Lee and Miller, 2001). Although it can still be argued that they rely in the validity of model which is designed by experts.

A stochastic forecast consists of a statistical distribution of values of a single quantity, and may be described in summary by an average value and a pair of extreme values that include most of the possible outcomes. Then an interval is defined such that it contains the stochastic forecast with a determined percent probability. The main feature of stochastic forecasts is therefore that estimations can be accompanied by confidence intervals. A probability should be attached to a forecast, whereas a probability is meaningless for a hypothetical deterministic projection (Keyfitz and Caswell, 2005)

Confidence intervals associated to forecasts can be estimated if the demographic rates are treated as stochastic processes. Then the time trend of those rates and their variance can be estimated using time series analysis. This kind of estimation also allows one to extend the time trend into the future, instead of relying on experts' judgment for the future or on error measures from past forecasts (Lee, 1998).

The Lee-Carter method for mortality forecasting was used to forecast all-cause-mortality in this study. The Lee-Carter (LC) procedure is a stochastic rather than deterministic model. It therefore allows for the quantification of uncertainty in the estimates. With the LC method, the measures of uncertainty must be viewed as lower bounds of uncertainty, since there are a number of potential sources of error that are not incorporated in the method (Lee, 1992; Lee and Tuljapurkar, 1994).

Rewriting the mechanics of cohort component projections in matrix notation is a way to make easier the use of computer applications (Preston et al., 2002). The LC method uses the stochastic Leslie matrix approach. It forecasts probability distributions of age-specific death rates, using statistical time series analysis as well as mathematical and statistical demography. The method is "relational" because it involves the transformation of actual existing mortality schedules for the study population. It is also probabilistic because it involves statistical fitting of models (Lee and Miller, 2001).

The LC method is based in the following mortality model:

$$\ln[m(x,t)]=a(x) + b(x)k(t)+\varepsilon(x,t)$$

Where:

m(x,t) is the death rate at age x and time t,

k(t) is the index of level of mortality,

a(x) are age-specific constants describing the general pattern of mortality by age

b(x) are age-specific constants for the relative speed of mortality change, and

ε(x,t) is the residual.

The method consists of the base model of age-specific death rates with a dominant time component, k(t), which captures the overall time trend in ln[m(x,t)] at all ages. The relative age component, b(x), which is assumed to be fixed over time, modifies the main time trend according to whether change at a particular age is faster or slower than the main trend, and whether it is in the same or opposite direction.

The singular value decomposition is used to find the least squares solution in the estimation of b(x) and k(t). This decomposes the matrix of ln[m(x,t)] into the product of three matrices representing the age component, the singular values, and the time component. A unique solution is obtained by setting a(x) equal to the means over time of ln[m(x,t)], and by constraining b(x) to sum to unity. The k(t) values sum to zero.

Each k(t) is adjusted to reproduce annual total deaths while leaving a(x) and b(x) unchanged. The adjusted k(t), the k'(t), is obtained by using an autoregressive integrated moving average model. The age-specific death rates which are at the same time the base for the estimation of life expectancies are obtained by incorporating the extrapolated k'(t) in the base model. The probabilistic confidence intervals associated with k'(t) are obtained from the variances of two parameters in the model to estimate k'(t) (Lee and Carter, 1992).

This method has been widely adopted in the US, and it has also been used in the G7 countries and Australia (Booth and Tickle, 2003). Modifications and extensions have also proposed to the method (Booth et al., 2002; Li and Lee, 2005).

Because of great decrease in mortality rates, especially infant mortality, occurred during the sixties and seventies in Costa Rica, historical mortality rates for the seventies decade was not used in the time series for mortality forecasting purposes. Using that decade of information would have implied that such drastic mortality declines would have a chance to repeat in the future, which is not reasonable.

Mortality historical data from 1980 to 2010 was used to forecast 25 years of mortality. Mortality was forecasted up to the year 2035. Forecasts were made for general mortality as well as for all-cause-except-diabetes mortality.

Forecasts were estimated using the LCFIT software (Sprague, 2009), which produces a set of forecasted mortality rates as an output. Median mortality rates by age-group and calendar year, as well as their corresponding confidence intervals were estimated from the set of forecasted mortality rates.

Using forecasted mortality rates, life tables were estimated to determine life expectancy at age 60. Both-sexes life tables with separation factors ($_{t}a_{x}$) from Coale and Demeny (1983) West model life tables were used.

Current diabetes-caused mortality rates by age, estimated from the longitudinal competing risks model previously described, were used to estimate a set of rates adjusted for diabetes mortality. Because diabetes-caused mortality was estimated for ages 60+, mortality rates up to the age of 59 are assumed to be forecasted all-cause mortality rates. For ages 60+ adjusted rates were estimated as the sum of forecasted mortality rates in the absence of diabetes plus diabetes-caused mortality rates. That is under of the assumption that observed pattern and level of diabetes-caused mortality remains constant in the future.

Three sets of life expectancy at age 60 were therefore estimated: (1) e_{60} based on forecasted all-cause mortality, (2) e_{60} adjusted for DM2 mortality, and (3) e_{60} in the absence of DM2 mortality. Years of life lost to diabetes was estimated as the difference between forecasted life expectancy at age 60, and forecasted life expectancy at 60 after adjusting for diabetes mortality. These estimations and their corresponding confidence intervals are presented for the years 2015, 2025, and 2035.

CHAPTER 4. Results

4.1. Descriptive information

At least one fifth of Costa Rican elderly is diabetic (table 1). This is a low estimate that considers only self-report of medical diagnosis. An adjustment of this prevalence rate using information on biomarkers and hypoglycemic drugs is presented in the next section.

More than half of Costa Rican elderly is in the 60 to 69 age group. The oldest old, aged 80+, amounts to 15% of the elderly. There is a higher proportion of female. Only about half this elderly population has complete primary school, and 4 out of 10 live with an income that is not enough to satisfy their basic needs.

Only a third of Costa Rican elderly has regular physical activity. This includes individuals who being able to exercise regularly do not do so, and those whose health condition prevent from physical activity. Out of ten individuals, 4 have family history of diabetes, and 7 have general or abdominal fat deposition that puts them at higher risk of diabetes.

The prevalence of current alcohol consumption is higher than the prevalence of current active smoking. Nevertheless, current passive smoking and active smoking is similar to the prevalence of alcohol drinking. Hyper caloric diets are not common among Costa Rican elderly.

Access to health care seems to be good for this elderly population. The great majority of them have health insurance; more than half live in the Great Metropolitan Area, where the urban conditions make health care facilities geographically more accessible; and mean time to the nearest health facility is half an hour along the country.

Chronic comorbidities are common in the elderly. Hypertension and hypertriglyceridemia are highly prevalent in Costa Rican population. Hypertension is the most common cardiovascular disease and the most common comorbid condition for diabetic elderly. Eighty-two percent of diabetic are hypertensive, as compared to 59% hypertensive among non-diabetic Costa Rican elderly. Twenty-eight percent of hypertensive elderly are diabetic, as compared to 11% among the non-hypertensive.

Table 1. Descriptive information of the CRELES Costa Rican elderly at baseline: 2004-2006 (weighted estimates).

Characteristic, *n=2827 unless otherwise noted*	**Percentage**	**95% Confidence interval**
Sociodemographics		
Age		
60-69 yrs	53.7	[51.9 - 55.6]
70-79 yrs	31.6	[29.9 - 33.3]
80+	14.7	[13.4 - 16.0]
Sex: % male	47.5	[45.6 - 49.3]
Education: % with complete primary	49.0	[47.2 - 50.8]
Low income, *2799*	40.6	[38.7 - 42.4]
Risk factors		
Regular physical activity	31.3	[29.6 - 33.0]
Family history of diabetes	39.4	[37.6 - 41.2]
Waist circumference, *2632*		
Normal	31.7	[29.9 - 33.5]
Increased	23.2	[21.5 - 24.8]
Substantially increased	45.1	[43.2 - 47.0]
Body Mass Index, *2698*		
Underweight	3.3	[2.6 - 3.9]
Normal	28.4	[26.7 - 30.2]
Overweight	42.1	[40.3 - 44.0]
Obese	26.1	[24.5 - 27.8]
Waist circumference and BMI, *2627*		
Normal WC and BMI	21.4	[19.9 - 23.0]
Normal WC, overweight or obese	10.3	[9.2 - 11.5]
Incr. or subst. incr. WC, normal weight	10.0	[8.8 - 11.1]
Incr. WC, overweight or obese	17.0	[15.6 - 18.5]
Substantially increased WC, overweight	18.0	[16.6 - 19.5]
Substantially increased WC, obese	23.2	[21.6 - 24.8]
Behavioral health risks		
Smoking, *2810*		
Never	35.7	[33.9 - 37.5]
Former active or passive smoker	38.9	[37.1 - 40.7]
Current passive smoker	13.8	[12.5 - 15.1]
Current active smoker	11.6	[10.4 - 12.8]
Alcohol, *2809*		
Never	35.8	[34.0 - 37.6]
Former alcohol drinker	29.7	[28.0 - 31.4]
Current alcohol drinker	34.5	[32.8 - 36.3]
Calorie daily consumption >=3000, *2819*	12.3	[11.1 - 13.5]

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Characteristic, *n=2827 unless otherwise noted*	Percentage	95% Confidence interval
/…Comes from previous page.../		
Access to health care		
Having health insurance	94.6	[93.8 - 95.4]
Living in the Great Metropolitan Area	53.0	[51.1 - 54.8]
Mean time to the nearest health facility (minutes), *2401*	31.0	[27.1 - 34.8]
Health condition		
Chronic morbidity		
Diabetes[3]	20.5	[19.0 - 21.9]
Hypertension, *2823*	64.5	[62.7 - 66.3]
Dyslipidemia[4], *2656*	51.2	[49.3 - 53.1]
Elevated Total/HDL cholesterol ratio, *2654*	28.5	[26.7 - 30.2]
Elevated triglycerides, *2573*	44.9	[42.9 - 46.8]
Cardiovascular disease[5]	17.6	[16.2 - 19.0]
Myocardial infarction	4.6	[3.8 - 5.3]
Ischemic heart attack (no infarction)	12.0	[10.8 - 13.2]
Stroke	3.8	[3.1 - 4.5]
Cancer	5.8	[4.9 - 6.7]
Lung disease	16.6	[15.2 - 18.0]
Arthritis	14.5	[13.2 - 15.8]
Osteoporosis	9.5	[8.4 - 10.6]
Other measures of health condition		
Poor self-perceived health, *2813*	47.3	[45.4 - 49.1]
At least 1 ADL limitation, *2808*	65.3	[63.5 - 67.0]
At least 1 IADL limitation, *2756*	23.1	[21.5 - 24.6]

[3] Diabetes refers to self-report of MD diagnosis
[4] Dyslipidemia refers to any or both: hypercholesterolemia(Total/HDL ratio) and hypertriglyceridemia
[5] Cardiovascular disease refers to at least one of: myocardial infarction, ischemic heart attack, and stroke

4.2. Prevalence of diabetes in the elderly and its determinants

Diabetes prevalence in Costa Rican elderly was 22% after adjusting for glycated hemoglobin levels (HbA1C) and hypoglycemic drugs under prescription. It was estimated 2 percent-points lower when only self-report was considered in the definition. Most of the subjects were classified as diabetic because of their self report of MD diagnosis (93%), 4% because of HbA1C levels, and the remaining 3% after evaluating their prescription drugs.

Table 2 presents weighted prevalence of both self reported diabetes and the estimate adjusted for biomarkers and medications. Prevalence estimates by age and sex are shown as well. Diabetes prevalence is significantly higher among women. It is also significantly lower among the oldest old. Women aged 70 to 79 have the highest prevalence: 27%; men aged 80+ have the lowest prevalence: 11%.

Table 2. Prevalence of diabetes in CRELES first wave, by age and sex (weighted estimates).

Characteristic	**Prevalence (%)**	**95% Confidence Interval**
Prevalence of diabetes		
Self-reported	20.50	[19.01 - 21.99]
Men	16.51	[14.48 - 18.53]
Women	24.02	[21.88 - 26.16]
Self-reported estimate adjusted for biomarkers and medications	21.86	[20.33 - 23.38]
Men	18.01	[15.91 - 20.11]
Women	25.24	[23.07 - 27.42]
Age and sex self-reported prevalence adjusted with biomarkers and medications		
60-69 yrs	21.90	[19.10 - 24.70]
Men	17.22	[13.38 - 21.06]
Women	26.38	[22.37 - 30.38]
70-79 yrs	24.91	[22.14 - 27.68]
Men	22.63	[18.80 - 26.47]
Women	26.92	[22.94 - 30.90]
80+	15.12	[12.94 - 17.29]
Men	11.34	[8.42 - 14.25]
Women	18.05	[14.93 - 21.17]

Different models of the determinants of diabetes prevalence were tested. Body mass index and central obesity showed to have an independent gradient effect on the prevalence of this condition. Even when waist circumference may be a slightly better predictor of diabetes, the substitution of body mass index by waist circumference as an indicator of risk for diabetes may be an oversimplification if both measurements are available. The model of diabetes prevalence determinants used in this study combines both general and central obesity into six categories.

The association between the diabetes prevalence and its determinants are presented in table 3. Although the associations remain similar with both definitions of diabetes, it is worth noting that when self-reports of diabetes are adjusted for the likely undiagnosed cases, sex differentials turn to be non-significant, and the categories of waist circumference and body mass index gain in terms of magnitude and significance.

Table 3. Odds ratios and confidence intervals from logistic regression models of diabetes prevalence, by definition of diabetes.

Variable	Self-report			Adjusted self-report		
	OR		(95% CI)	OR		(95% CI)
Sociodemographics						
Age	0.99		[0.98 - 1.01]	0.99		[0.98 - 1.01]
Male	0.77	*	[0.56 - 1.05]	0.80		[0.59 - 1.09]
Complete primary school	0.77	**	[0.60 - 0.98]	0.78	**	[0.61 - 0.99]
Low income	1.06		[0.84 - 1.35]	1.08		[0.86 - 1.36]
Risk factors						
Family history of diabetes	2.57	***	[2.05 - 3.21]	2.44	***	[1.96 - 3.04]
Normal WC and BMI	1.00			1.00		
Normal WC, overweight or obese	1.41		[0.86 - 2.33]	1.64	**	[1.01 - 2.67]
Incr. or subst. Incr. WC, normal weight	1.64	*	[0.98 - 2.75]	1.69	**	[1.01 - 2.82]
Incr. WC, overweight or obese	2.10	***	[1.38 - 3.21]	2.26	***	[1.48 - 3.43]
Subst. incr. WC, overweight	2.11	***	[1.36 - 3.26]	2.47	***	[1.61 - 3.79]
Subst. Incr. WC, obese	3.67	***	[2.45 - 5.48]	4.13	***	[2.78 - 6.15]
Behavioral health risks						
Never smoker	1.00			1.00		
Former active or passive smoker	1.02		[0.78 - 1.33]	1.02		[0.79 - 1.32]
Current passive smoker	1.18		[0.84 - 1.65]	1.09		[0.78 - 1.52]
Current active smoker	2.24	***	[1.54 - 3.26]	2.04	***	[1.41 - 2.96]
Never drinker	1.00			1.00		
Former drinker	0.82		[0.59 - 1.13]	0.85		[0.61 - 1.17]
Current drinker	1.06		[0.78 - 1.43]	1.10		[0.82 - 1.48]
Calorie daily consumption >=3000	0.85		[0.59 - 1.21]	0.90		[0.64 - 1.27]
Access to health care						
Has health insurance	1.05		[0.62 - 1.79]	1.09		[0.65 - 1.85]
Living in the Great Metropolitan Area	0.89		[0.71 - 1.12]	0.95		[0.76 - 1.18]
Time to the closest facility (minutes)	0.77	**	[0.62 - 0.96]	0.85	*	[0.71 - 1.03]
Comorbidities						
Hypertension	2.61	***	[1.99 - 3.43]	2.69	***	[2.06 - 3.51]
Elevated HDL/LDL cholesterol	1.28	*	[0.99 - 1.67]	1.24	*	[0.96 - 1.61]
Elevated triglycerides	0.76	**	[0.60 - 0.97]	0.81	*	[0.64 - 1.02]
Pseudo R^2=			*0.1225*			*0.1196*
Prob> Chi^2=			*0.0000*			*0.0000*

Significance levels: ***: p<0.01, **: p<0.05, *: p<0.10

The adjustment to the definition of diabetes uses a cutoff point for the HbA1C biomarker higher than the established cutoff point used for diagnosis. As stated before, it is a rather conservative definition which although does not avoid misclassification, increases sensitivity –the ability to identify correctly those who have diabetes-, while trading off some specificity –the ability to identify correctly those who do not have diabetes-. To test how sensitive the results were to this choice; prevalence rates and multivariate logistic models were also estimated using a less conservative classification. The new definition used a 6.5% cut-off point for HbA1C rather than 7%. This led to a higher prevalence of the condition (27% as compared to 22% when using the 7% criteria). Nevertheless, none of the inferences from the logistic regression model changed.

4.3.Incidence of diabetes in the adult population and its determinants

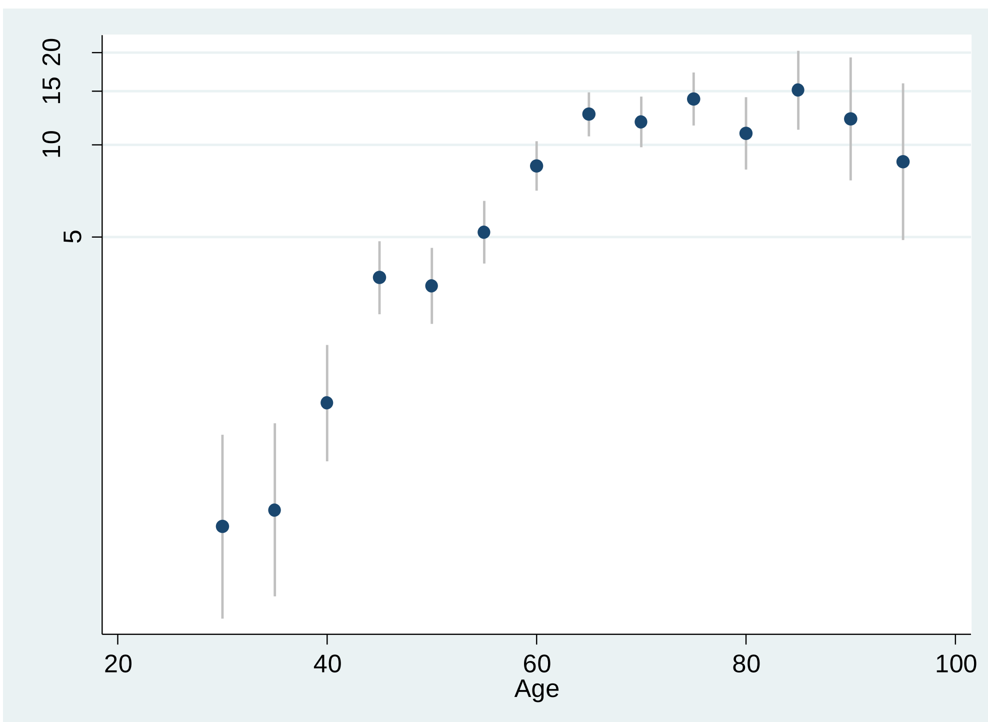
Diabetes incidence estimation according to CRELES data is at least 5.2 per 1 000 people aged 30 and above, and significantly higher in the female adult population (table 4). As shown in Graph 7, incidence rates increase with age up until the age of 65, and then it starts to decline. It is significantly higher among the female population at younger adult ages; at the age of 70 and beyond female incidence rates remain higher than male rate, but this difference is not significant anymore (Graph 8).

Table 4. Incidence[6] rate of diabetes, by sex and definition of diabetes (rates per 1000 person-years, unweighted estimates).

Population	Self-report[7]				Adjusted self-report[8]			
	Incidence rate		95% CI		Incidence rate		95% CI	
Total population	5.2		[4.9 -	5.6]	5.9		[5.5 -	6.3]
Female	6.0		[5.5 -	6.6]	6.7		[6.2 -	7.4]
Male	4.3		[3.8 -	4.9]	4.9		[4.3 -	5.4]
Incidence Rate Ratio[9]	1.4	***	[1.2 -	1.7]	1.4	***	[1.2 -	1.6]

Significance level ***: p<0.01

Graph 7. Incidence[3] rates of diabetes[8] and 95% confidence intervals, by age (rates per 1000 person-years, unweighted estimates).



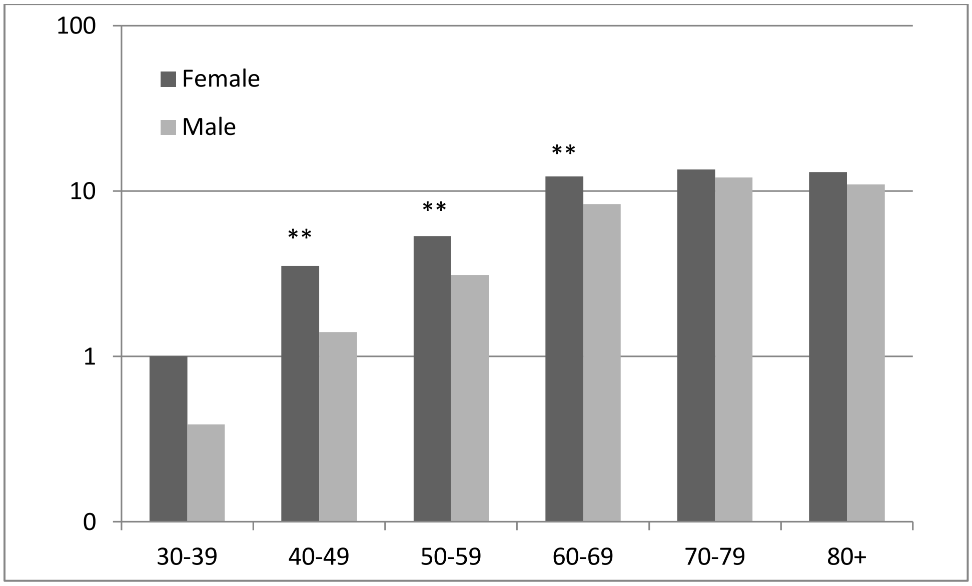
[6] Incidence estimated for adult ages 30 and above

[7] Diabetes diagnosed at age 30+ by MD as reported by the subject

[8] Diabetes diagnosed at age 30+ by MD, or taking hypoglycemic medication, or Hba1c >=7% at interviews

[9] Mantel-Haenszel estimates of the rate ratio

Graph 8. Incidence rates of diabetes[10] per 1 000 people, by age and sex (unweighted estimates).



Significance level **: $p<0.05$

The association between the diabetes incidence and its determinants are presented in table 5. Although the associations remain similar with both definitions of diabetes, it is worth noting that when self-reports of diabetes are adjusted for the likely undiagnosed cases, the hazard ratios reach greater magnitudes, especially for body mass index and smoking categories.

[10] Diabetes diagnosed at age 30+ by MD, or taking hypoglycemic medication, or Hba1c >=7% at interviews

Table 5. Results from log-logistic longitudinal regression models of diabetes incidence at age 30 and above, by definition of diabetes (unweighted estimates).

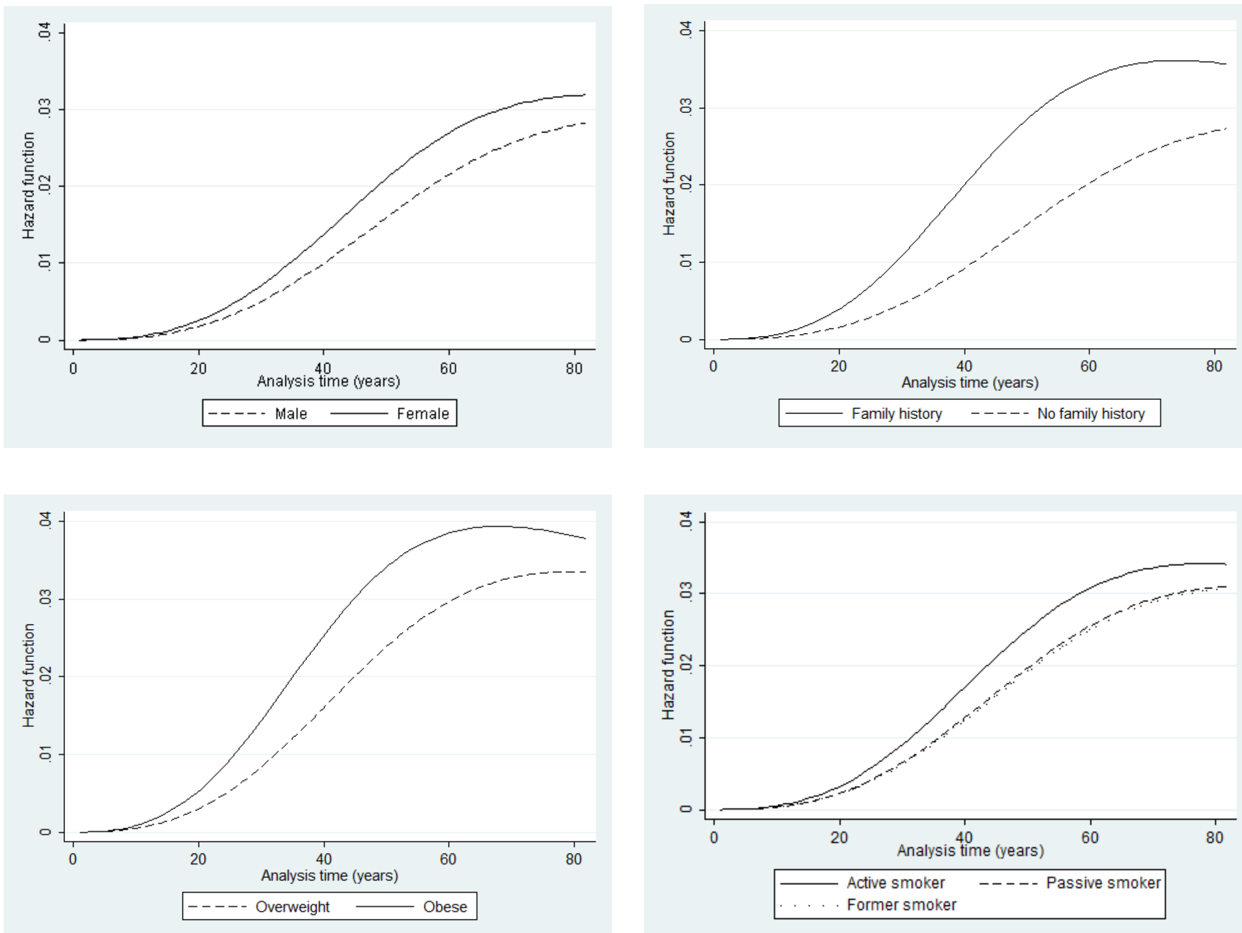
Variable	**Self-report[11]**			**Adjusted self-report[12]**		
	Coefficient		**[95% CI]**	**Coefficient**		**[95% CI]**
Sociodemographics						
Age	0.02	***	[0.02 - 0.03]	0.02	***	[0.02 - 0.03]
Male	0.11	***	[0.03 - 0.18]	0.10	***	[0.04 - 0.16]
Complete primary school	0.04	*	[0.03 - 0.10]	0.04		[0.02 - 0.09]
Risk factors						
Family history of diabetes	-0.28	***	[0.35 - 0.22]	-0.25	***	[0.31 - 0.19]
Normal BMI	1.00			1.00		
Underweight	-0.01		[0.18 - 0.16]	-0.05		[0.19 - 0.09]
Overweight	-0.10	***	[0.18 - 0.03]	-0.13	***	[0.19 - 0.06]
Obese	-0.27	***	[0.37 - 0.18]	-0.28	***	[0.37 - 0.20]
Behavioral health risks						
Non smoker	1.00			1.00		
Former active or passive smoker in wave 1	-0.01		[0.08 - 0.06]	-0.03		[0.09 - 0.03]
Passive smoker	-0.02		[0.12 - 0.07]	-0.13		[0.11 - 0.06]
Active smoker	-0.13	**	[0.24 - 0.02]	0.01	***	[0.22 - 0.03]
Non drinker	1.00			1.00		
Former drinker	0.03		[0.06 - 0.11]	0.01		[0.06 - 0.08]
Active drinker	0.00		[0.08 - 0.08]	-0.01		[0.08 - 0.06]
Log pseudolikelihood =	*-1146.4*			*-1147.4*		
Prob > chi^2=	*0.0000*			*0.0000*		

Significance levels: ***: p<0.01, **: p<0.05, *: p<0.10

[11] Diabetes diagnosed at age 30+ by MD as reported by the subject

[12] Diabetes diagnosed at age 30+ by MD, or taking hypoglycemic medication, or Hba1c >=7% at interviews

Graph 9. Predicted hazards for diabetes incidence[13] by sex, family history of diabetes, body mass index and smoking, from log-logistic longitudinal regression model.



Graph 9 shows the predicted hazard functions resulting from the longitudinal model of diabetes incidence. Incidence differentials by sex, family history of diabetes, body mass index and smoking are presented. Net of the effects of the other characteristics that are being controlled for, the hazard of diabetes incidence is higher for females, for individuals with family history of the condition, and for obese individuals. Active smokers also show greater hazards than passive and

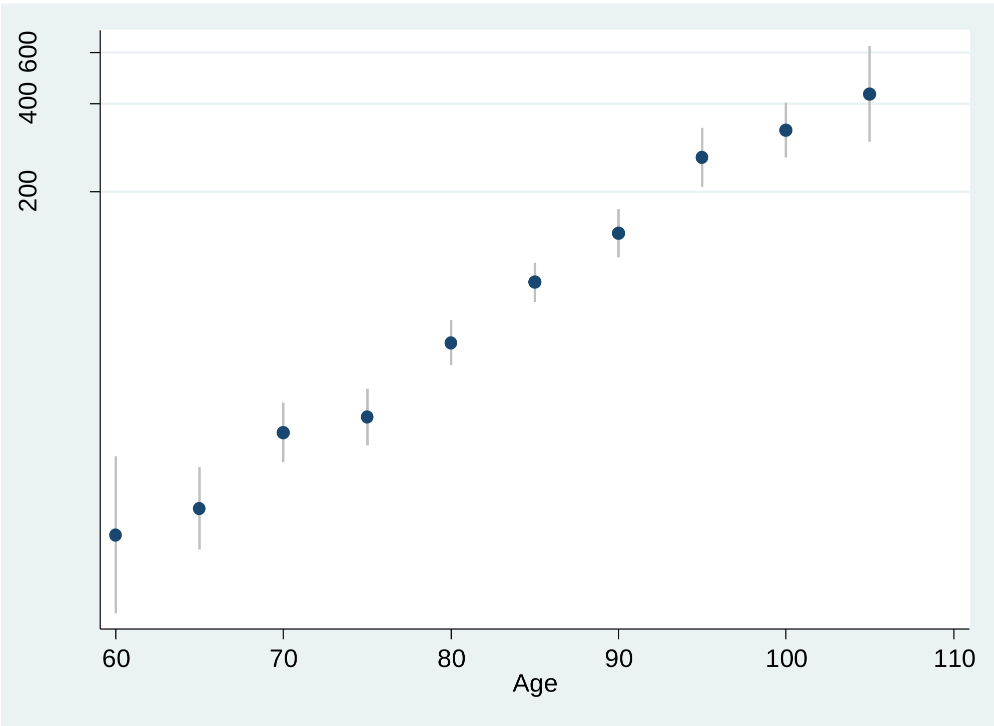
[13] Predicted hazards from the log-logistic longitudinal regression model shown in table 5, corresponding to the adjusted diabetes definition: diabetes diagnosed at age 30+ by MD, or taking hypoglycemic medication, or Hba1c >=7% at interviews

former smokers. Obesity and family history of diabetes are the two most important predictors of incidence of diabetes type 2.

4.4. Mortality

General mortality is estimated at 60.6 per 1 000 person-years in individuals aged 60 and beyond. Graph 10 shows the general mortality curve for this population. Sex crude mortality rates are not significantly different; female mortality is 57.1 and male mortality is 64.8 per 1000 person-years.

Graph 10. General mortality rates per 1 000 people, by age (unweighted estimates).



Cause specific mortality is shown in graph 11. As compared to other-causes, mortality due to diabetes has a greater share on general mortality at younger ages. Results of a longitudinal model of general mortality are shown in table 6. When controlling for sociodemographic characteristics and other chronic morbidity as the most proximate determinants of mortality, diabetes is significantly associated with general mortality. No differences are found when using self-report diabetes as compared with the adjusted definition of diabetes using biomarkers and medications.

Graph 11. Cause-specific mortality rates per 1 000 people from a competing risks longitudinal model, by age (unweighted estimates).

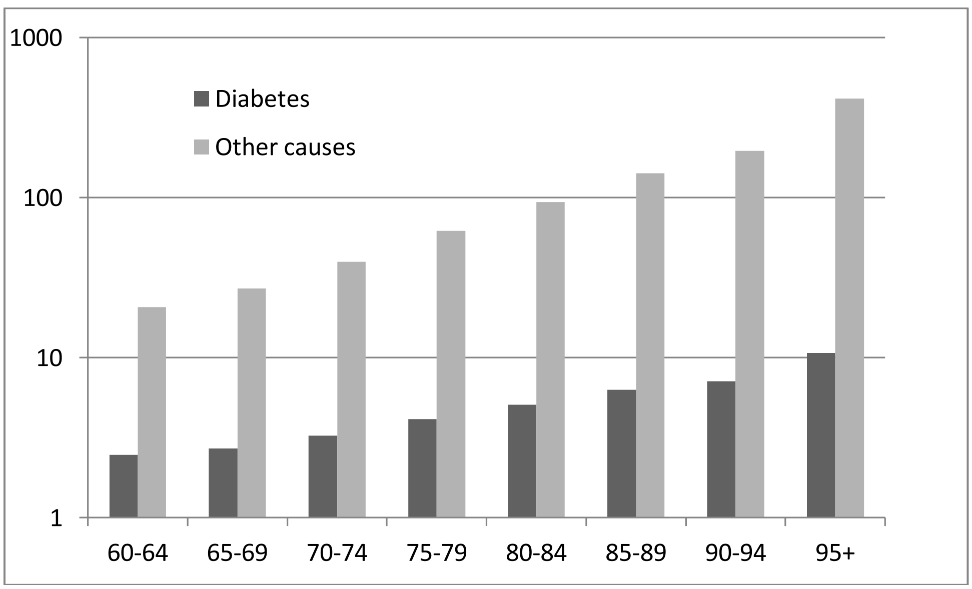


Table 6. Hazard ratios and confidence intervals from Gompertz longitudinal regression models of general mortality at age 60 and above, by definition of diabetes (weighted estimates).

Variable	Self-report							Adjusted self-report						
	Hazard Ratio		**[95% CI]**					**Hazard Ratio**		**[95% CI]**				
Sociodemographic														
Age	1.09		[	1.07	-	1.10	]	1.09		[	1.07	-	1.10	]
Male	1.31	***	[	1.08	-	1.59	]	1.31	***	[	1.08	-	1.59	]
Complete primary school	1.09		[	0.89	-	1.33	]	1.08		[	0.89	-	1.33	]
Chronic morbidity														
Diabetes	**1.40**	*******	**[**	**1.11**	**-**	**1.75**	**]**	**1.36**	*******	**[**	**1.10**	**-**	**1.70**	**]**
Cancer	2.30	***	[	1.53	-	3.45	]	2.32	***	[	1.54	-	3.48	]
Lung disease	1.41	***	[	1.13	-	1.75	]	1.41	***	[	1.13	-	1.75	]
Myocardial infarction	1.67	**	[	1.06	-	2.62	]	1.67	**	[	1.07	-	2.63	]
Ischemic heart disease (no infarction)	1.41	***	[	1.09	-	1.82	]	1.41	**	[	1.09	-	1.82	]
Stroke	1.54	**	[	1.02	-	2.35	]	1.55	**	[	1.02	-	2.35	]
Log pseudolikelihood =	*-1554.92*							*-1555.28*						
Prob > chi^2=	*0.0000*							*0.0000*						

Significance levels: ***: p<0.01, **: p<0.05, *: p<0.10

Because diabetes-caused mortality is not proportional to other-cause mortality, an age-stratified analysis of general mortality was conducted. Table 7 shows that between 60 to 69 years the hazard of mortality increases about 70% in individuals with diabetes as compared to individuals with no diabetes (p<0.05). In the 70-79 age group, mortality hazard is about 35% higher in individuals with diabetes as compared to those with no diabetes (p<0.10). Elderly individuals who have ever been diagnosed with cancer, or have ever had a myocardial infarction, or a stroke, have the lowest survival probabilities as compared to their corresponding counterparts (Graph 12).

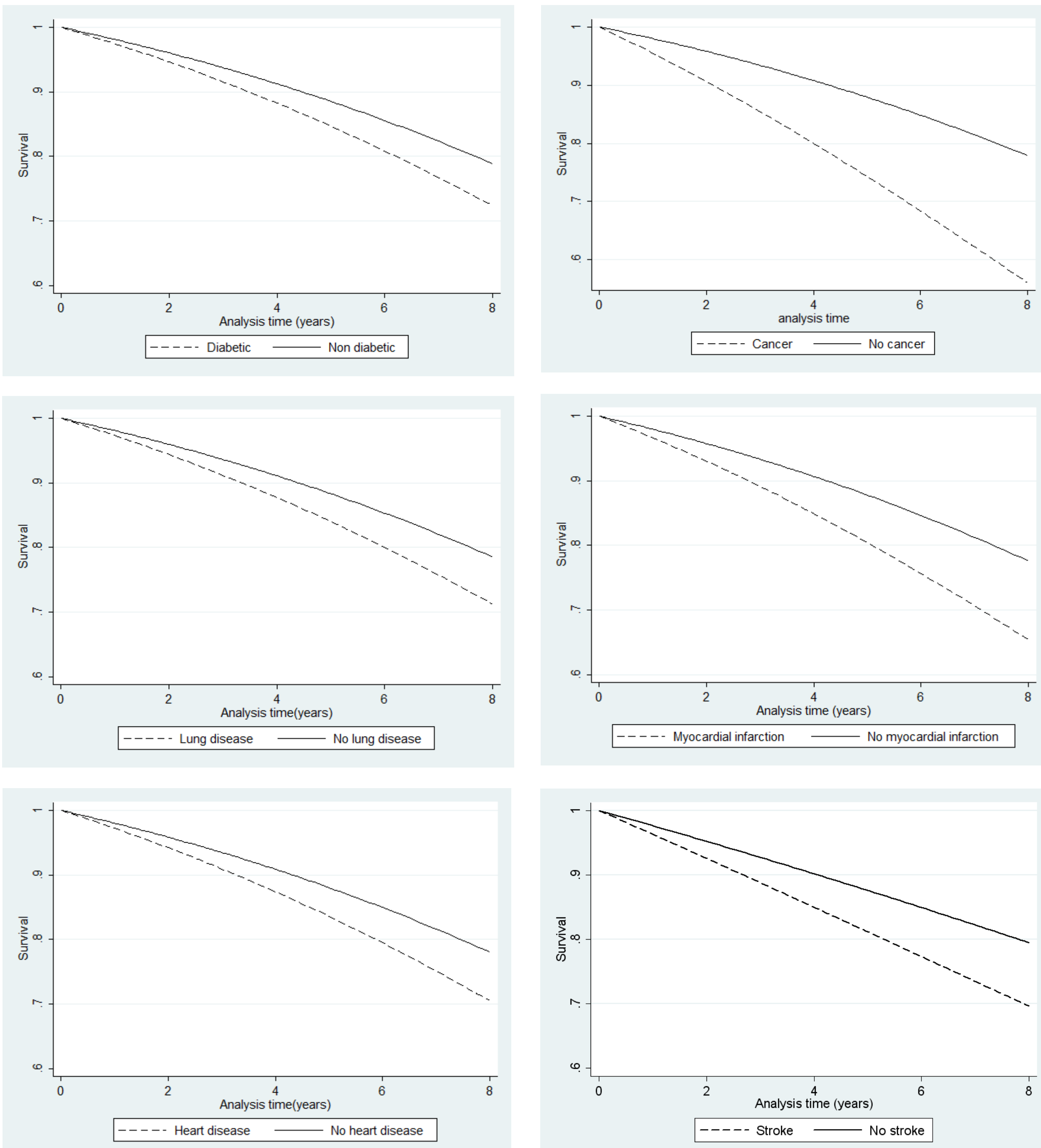
Table 7. Hazard ratios of death from Gompertz longitudinal regression models of general mortality, by age group (weighted estimates).

Variable	Hazard Ratios					
	60-69 years		70-79 years		80+	
Sociodemographics						
Male	1.36		1.39	**	1.25	
Complete primary school	1.25		0.94		0.94	
Chronic morbidity						
Diabetes[14]	**1.68**	**	**1.36**	*	**1.11**	
Cancer	4.83	***	2.13	**	1.38	
Lung disease	1.34		1.29	**	1.55	***
Myocardial infarction	1.95		2.02	**	1.13	
Ischemic heart disease (no infarction)	1.58		1.52	**	1.31	*
Stroke	2.68		0.99		1.66	**
Log pseudolikelihood =	*-551.08*		*-547.19*		*-463.41*	
Prob > chi2=	*0.000*		*0.0001*		*0.0000*	

Significance levels: ***: p<0.01, **: p<0.05, *: p<0.10

[14] Diabetes diagnosed at age 30+ by MD, or taking hypoglycemic medication, or Hba1c >=7% at interviews

Graph 12. Survival curves for general mortality from Gompertz longitudinal regression models, by diagnosed chronic conditions. (Adjusted self-report of diabetes[15])



[15] Diabetes diagnosed at age 30+ by MD, or taking hypoglycemic medication, or Hba1c >=7% at interviews

4.5.Current economic burden of diabetes on health care services

Following the Andersen's model of access to medical care the economic burden of diabetes on the public health care system was estimated by modeling the costs of hospitalizations and outpatient care over a year, as well as the medications currently taken by this elderly Costa Rican population.

Controlling for predisposing characteristics, enabling resources and need; the probability of hospitalization and its cost is higher for diabetic individuals, although not statistically significant (table 8). Mean hospitalization costs are 50% higher for diabetic elderly, 1 124 USD2011 a year for diabetic elderly as compared to 745 USD2011 for non-diabetic elderly. Non-diabetic individuals aged 60 to 69 have the lowest hospitalization costs, and diabetic elderly aged 80 and beyond have the greatest hospitalization costs (table 9).

Table 8. Results from a two-part regression model of the cost of hospitalizations along one calendar year in the elderly population (weighted estimates).

Determinants	Part 1- Logistic		Part 2- GLM	
	Odds Ratios		**Exp(β)**	
Predisposing characteristics				
Age	1.00		1.00	
Female	0.61	***	0.85	
Live in the Metro Area	0.72	**	1.32	
Married or in union	0.84		0.48	***
Retired	1.10		1.21	
Enabling resources				
Personal				
Complete primary school	1.08		0.64	**
Low income	0.79		1.40	*
Contextual				
Mean time to nearest health facility	1.05		1.06	
Need				
Poor self-perceived health	1.90	***	0.97	
At least 1 ADL limitation	1.51	**	1.18	
At least 1 IADL limitation	2.06	***	1.17	
Diabetes	1.24		1.09	
Hypertension	1.35	*	1.39	
Dyslipidemia	0.70	**	1.03	
Cardiovascular disease	1.58	***	0.96	
Lung disease	0.84		1.01	
Cancer	1.75	**	1.01	
Arthritis	1.48	**	0.85	
Osteoporosis	0.92		1.34	
Pseudo R^2=	*0.0841*			
Prob> Chi^2=	*0.0000*			
AIC			*29.69*	
BIC			*-1043.17*	

Significance levels: ***: p<0.01, **: p<0.05, *: p<0.1

Table 9. Individual mean cost of hospitalizations along one calendar year, by age and diabetes condition. Predicted costs from a two-part regression model (weighted estimates, USD 2011)

Characteristic	Mean cost	95% Confidence Interval				
Total population	827	[	763	-	891	]
Non-diabetic	745	[	683	-	807	]
Diabetic	1,124	[	930	-	1,318	]
Age and diabetes condition						
60-69 yrs	570	[	521	-	620	]
Non-diabetic	493	[	447	-	538	]
Diabetic	841	[	693	-	988	]
70-79 yrs	952	[	846	-	1,058	]
Non-diabetic	852	[	726	-	979	]
Diabetic	1,280	[	1109	-	1,452	]
80+	1,634	[	1404	-	1,863	]
Non-diabetic	1,503	[	1323	-	1,683	]
Diabetic	2,424	[	1195	-	3,654	]

The probability of outpatient consultation and its cost is significantly higher for diabetic individuals. Once diabetic individuals make use of outpatient care, they have an 11% higher volume of utilization than their non-diabetic counterparts (table 10). Mean cost of outpatient care for the elderly population is 337 USD2011, and it is about 24% higher for the diabetic elderly, 404 as compared to 319 USD2011 for the non-diabetic elderly (table 11).

Table 10. Results from a two-part regression model of the cost of outpatient care along one calendar year in the elderly population (weighted estimates).

Determinants	**Part 1- Logistic**		**Part 2- GLM**	
	Odds Ratios		**Exp(β)**	
Predisposing characteristics				
Age	1.01		1.00	
Female	2.02	***	1.06	**
Live in the Metro Area	1.29		1.00	
Married or in union	1.30		1.13	***
Retired	2.13	***	1.04	
Enabling resources				
Personal				
Complete primary school	1.18		1.07	**
Low income	1.13		0.91	***
Contextual				
Mean time to nearest health facility	1.06		1.01	
Need				
Poor self-perceived health	1.37	*	1.10	***
At least 1 ADL limitation	1.48	**	1.05	
At least 1 IADL limitation	0.89		1.08	**
Diabetes	3.08	***	1.11	***
Hypertension	1.18		0.97	
Dyslipidemia	0.64	***	0.98	
Cardiovascular disease	7.91	***	1.16	***
Lung disease	2.99	***	1.06	*
Cancer	1.23		1.03	
Arthritis	1.46		1.09	**
Osteoporosis	1.54		1.04	
Pseudo R^2=	*0.1461*		-	
Prob> Chi^2=	*0.0000*		-	
AIC	-		*27.43*	
BIC	-		*-14345.83*	

Significance levels: ***: p<0.01, **: p<0.05, *: p<0.10

Table 11. Individual mean cost of outpatient care along one calendar year, by age and diabetes condition. Predicted mean costs from a two-part regression model (weighted estimates, USD 2011)

Characteristic	**Mean cost**	**95% Confidence Interval**				
Total population	337	[	334	-	341	]
Non-diabetic	319	[	316	-	322	]
Diabetic	404	[	398	-	410	]
Age and diabetes condition						
60-69 yrs	328	[	323	-	334	]
Non-diabetic	308	[	303	-	314	]
Diabetic	398	[	388	-	407	]
70-79 yrs	347	[	342	-	352	]
Non-diabetic	328	[	323	-	333	]
Diabetic	409	[	400	-	418	]
80+	355	[	349	-	360	]
Non-diabetic	343	[	337	-	348	]
Diabetic	427	[	414	-	440	]

Medications utilization and costs are also significantly higher for diabetic elderly individuals (table 12). Once diabetic individuals make use of medications, they have a 28% higher volume of utilization than their non-diabetic counterparts (table 12). Mean cost of medications for the diabetic elderly is almost twice the cost for non-diabetic elderly, 31 as compared to 17 USD of 2011. Costs presented in table 13 are particularly low for medications. This is because they refer to the mean cost of a single drug prescription, which is the way the Costa Rican Social Security Fund (CCSS) provides mean costs of drugs.

Table 12. Results from a two-part regression model of the cost of medications currently being taken at interview in the elderly population （weighted estimates).

Determinants	Part 1- Logistic		Part 2- GLM	
	Odds Ratios		Exp(β)	
Predisposing characteristics				
Age	1.03		1.00	
Female	1.73	***	1.10	**
Live in the Metro Area	1.97		1.10	
Married or in union	1.42		1.07	***
Retired	1.80	***	1.05	
Enabling resources				
Personal				
Complete primary school	1.39		1.06	**
Low income	0.74		1.02	***
Contextual				
Mean time to nearest health facility	1.00		1.01	
Need				
Poor self-perceived health	1.68	*	1.13	***
At least 1 ADL limitation	1.26	**	1.09	
At least 1 IADL limitation	1.47		1.12	**
Diabetes	3.44	***	1.28	***
Hypertension	3.42		1.42	
Dyslipidemia	0.85	***	0.97	
Cardiovascular disease	3.52	***	1.36	***
Lung disease	1.96	***	1.05	*
Cancer	0.70		1.01	
Arthritis	1.75		1.15	**
Osteoporosis	2.88		1.06	
Pseudo R^2=	*0.2559*		-	
Prob> Chi^2=	*0.0000*		-	
AIC	-		*21.31*	
BIC	-		*-12381.65*	

Significance levels: ***: p<0.01, **: p<0.05, *: p<0.10

Table 13. Individual mean cost of drug prescriptions currently taken, by age and diabetes condition. Predicted mean costs from a two-part regression model (weighted estimates, USD of 2011)

Characteristic	**Mean cost**	**95% Confidence Interval**				
Total population	20	[	20	-	20	]
Non-diabetic	17	[	16	-	17	]
Diabetic	31	[	31	-	32	]
Age and diabetes condition						
60-69 yrs	18	[	18	-	19	]
Non-diabetic	15	[	14	-	16	]
Diabetic	30	[	29	-	31	]
70-79 yrs	22	[	21	-	22	]
Non-diabetic	18	[	18	-	19	]
Diabetic	33	[	31	-	34	]
80+	23	[	23	-	24	]
Non-diabetic	21	[	21	-	22	]
Diabetic	36	[	34	-	38	]

4.6. Projection of diabetes prevalence in the elderly

Using the information on diabetes prevalence at CRELES first wave, as well as 5-year-age-group incidence and mortality rates, the size of the diabetic population was estimated backwards from year 2006 (the end of CRELES wave 1) to the years 2001 and 1996. Input data used for this estimation is shown in table 14.

Table 14. Input data used in the retrospective projection of diabetes prevalence in Costa Rica from year 2006 back to 1996 and 2001.

Age-group	**Total population**			**Diabetes prevalence rates**[16]	**Diabetes incidence rates**[17] $_td_x$	**Death rates**[18] **for the diabetic population**		**Probability of dying**[19] **for the diabetic population**	
	1996	**2001**	**2006**			$_tm_x^d$ **1996**	$_tm_x^d$ **2001**	$_tq_x^d$ **1996**	$_tq_x^d$ **2001**
30-34	301,836	309,449	316,985	0.0060000	0.0005667	0.0012788	0.0011666	0.0063746	0.0058180
35-39	263,358	306,657	310,010	0.0210000	0.0006392	0.0014847	0.0012946	0.0073975	0.0064541
40-44	208,677	265,885	306,105	0.0280000	0.0014295	0.0022954	0.0019106	0.0114095	0.0095096
45-49	156,590	209,213	264,019	0.0520000	0.0021560	0.0033591	0.0029587	0.0166551	0.0146864
50-54	117,663	155,909	206,521	0.0830000	0.0045127	0.0045299	0.0041306	0.0223964	0.0204439
55-59	95,160	115,886	152,634	0.1210000	0.0051787	0.0077659	0.0067998	0.0380905	0.0334317
60-64	77,384	92,049	111,963	0.2216049	0.0085090	0.0223628	0.0223628	0.1058947	0.1058947
65-69	65,209	72,840	86,693	0.2157768	0.0111045	0.0242239	0.0242239	0.1142038	0.1142038
70-74	46,941	58,648	66,273	0.2559249	0.0136088	0.0328731	0.0328731	0.1518829	0.1518829
75-79	31,068	39,413	50,098	0.2364293	0.0140838	0.0379725	0.0379725	0.1734034	0.1734034
80-84	22,312	23,463	30,644	0.1519971	0.0110055	0.0561725	0.0561725	0.2462794	0.2462794
85-89	11,003	14,162	15,171	0.1750931	0.0144459	0.1163086	0.1163086	0.4505403	0.4505403
90-94	4,351	5,098	7,175	0.1156294	0.0127762	0.0944012	0.0944012	0.3818803	0.3818803
95+	1,068	1,857	2,390	0.0871720	0.0085480	0.2452316	0.2452316	1.0000000	1.0000000

[16] Prevalence rates for ages 30-59 are the national estimates reported by Roselló et al. (2004). Prevalence rates for ages 60+ are this study's national estimates based on CRELES data.

[17] Incidence rates are this study's national estimates based on CRELES data.

[18] Death rates for the diabetic population ($_tm_x^d$) for ages 30-59 are assumed to be the same as all-cause mortality in the general population from National Vital Statistics. Death rates for the diabetic population for ages 60+ are this study's estimates of all-cause death rates in the diabetic elderly, based on CRELES data

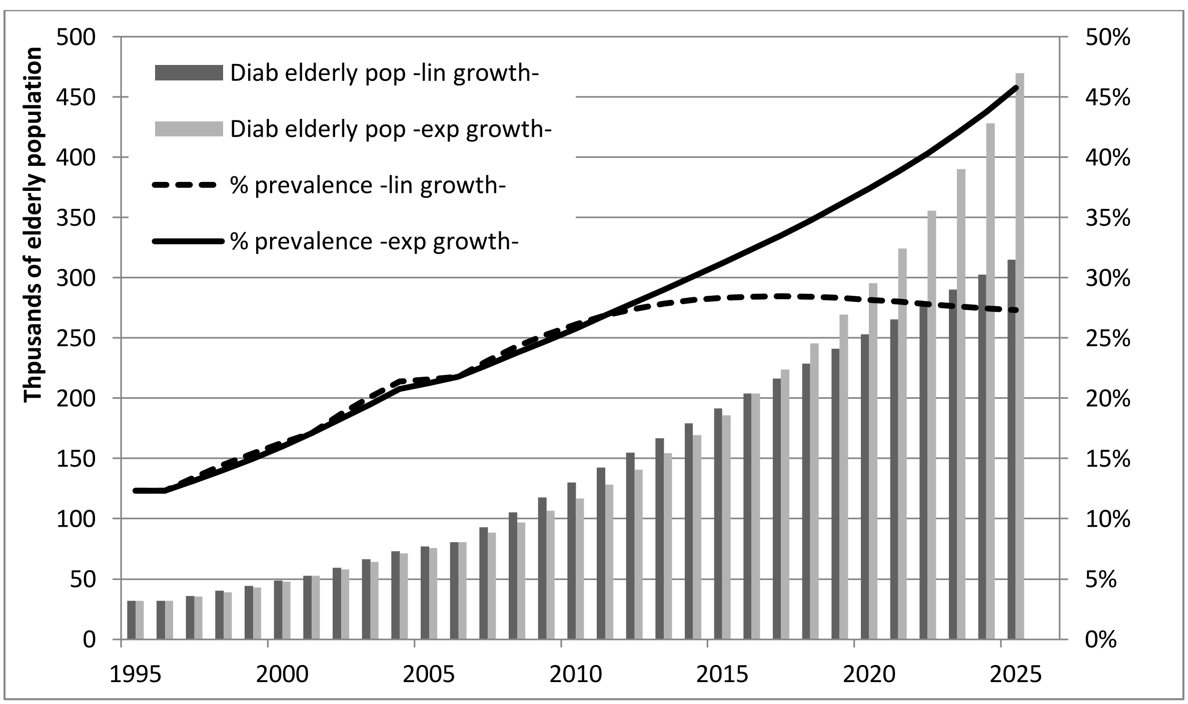
[19] Probability of dying $_tq_x$ is this study's estimation from both-sexes life table with separation factors ($_ta_x$) from Coale and Demeny (1983) West model life tables.

As a result, mean annualized growth rates for the 1996-2001 and 2001-2006 periods were estimated under the assumptions of linear and exponential future growth of the elderly diabetic population up to the year 2025. Results are shown in table 15.

Table 15. Retrospective projection of diabetes prevalence in the Costa Rican elderly for the years 1996, 2001, 2006; and mean annualized growth rates for the 1996-2001 and 2001-2006 periods.

	1996	**2001**	**2006**
Diabetic elderly population size	31,909	52,634	80,676
Prevalence (%)	**12.3**	**17.1**	**21.8**
Annualized period growth rates			
Linear growth	0.1298982	0.1065556	
Exponential growth	0.1000934	0.0854164	

Graph 13. Projection of diabetic population size and prevalence rate in the elderly under linear growth and exponential growth assumptions. Costa Rica: 1996-2025.



Diabetes prevalence is estimated to be at least 27% in year 2025. Under this conservative scenario of linear growth, the size of the diabetic elderly population will double between the years 2010 and 2025. If diabetic elderly population followed an exponential growth, the size of the diabetic elderly in 2025 would be four-fold the size in 2010 and 46% of the individuals would be diabetic. An exponential growth of the diabetic elderly population may be used as an upper limit of what the prevalence would be like in the years to come (graph 13).

Considering projection is made 15 year further, linear growth is a more realistic assumption than exponential. In another research using this same dataset Brenes (2008) projected diabetes prevalence in the elderly based on a variation of the cohort-component method. The approach used in this dissertation to project diabetes prevalence yields remarkably similar results to those attained when using more complex methodological approaches: 27% as compared to 28% diabetes prevalence in the year 2025.

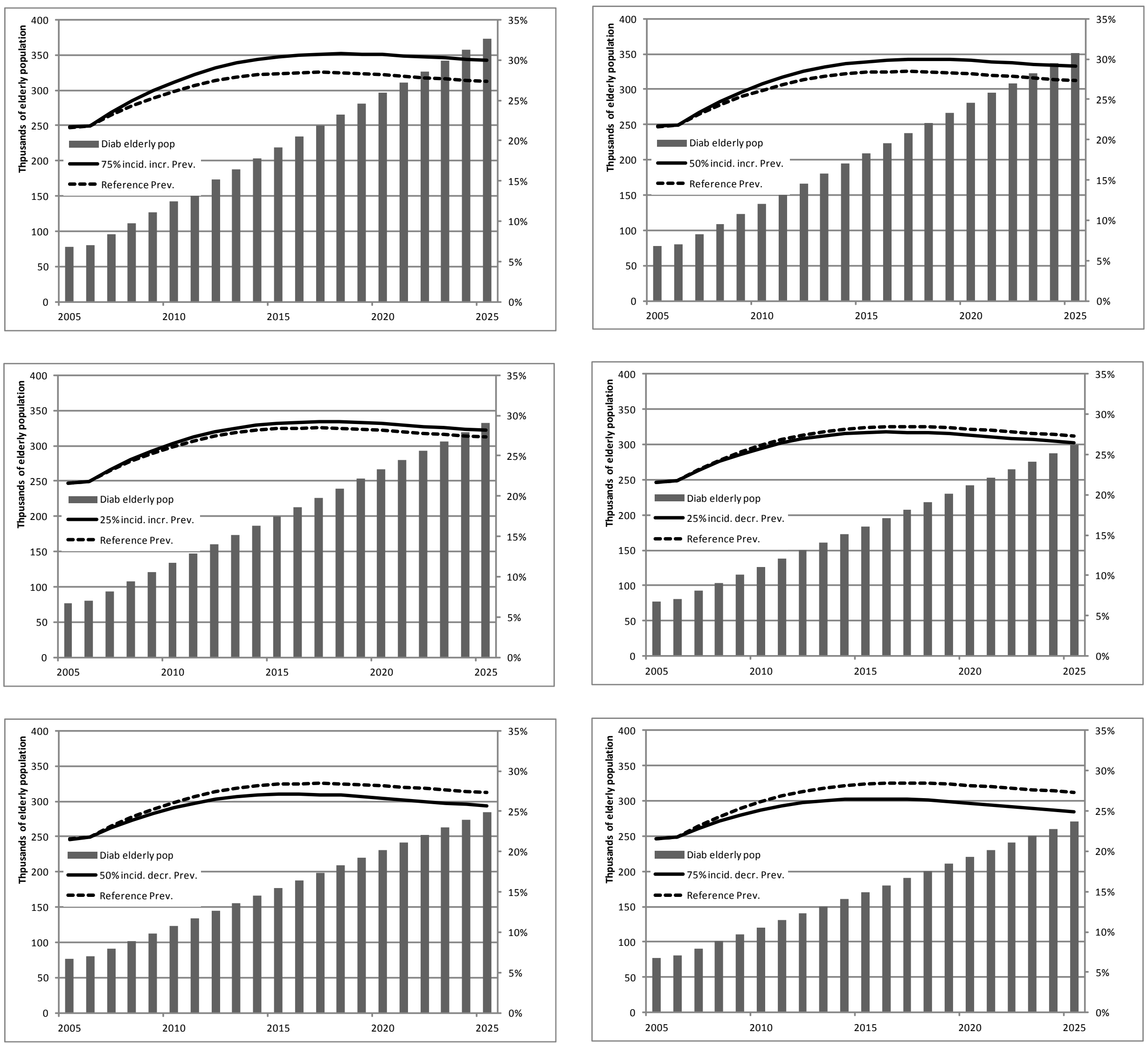
Prevalence of diabetes for the year 2025 was also projected in six different scenarios. Each scenario was under the assumption that growth was linear and the incidence pattern prevailed, but with an increase or decrease of incidence level in 25%, 50% and 75%. Prevalence is expected to double by the year 2025, even in the most optimistic scenario of a 75% decrease in incidence level (table 16).

Projected diabetic elderly population size under each of the six scenarios and a comparison between projected prevalence if pattern and level of incidence remain constant (reference) and the projected prevalence if level increases or decreases is shown in graph 14.

Table 16. Projection of diabetes prevalence in the elderly under the assumptions of linear growth and different incidence level scenarios. Costa Rica: 2025

Scenarios	**Diabetic elderly population size**	**Prevalence (%)**	**Prevalence ratio years 2010/2025**
Incidence pattern prevails, but level increases:			
75%	372,870	30	2.62
50%	351,697	29	2.55
25%	332,472	28	2.49
Reference: Observed incidence pattern and level prevail	**314,939**	**27**	**2.42**
Incidence pattern prevails, but level decreases:			
25%	298,885	26	2.36
50%	284,128	26	2.30
75%	270,519	25	2.24

Graph 14. Projected diabetic elderly population sizes and prevalence under different incidence level scenarios. Costa Rica: 2005-2025.



4.7. Impact of diabetes on future health care costs

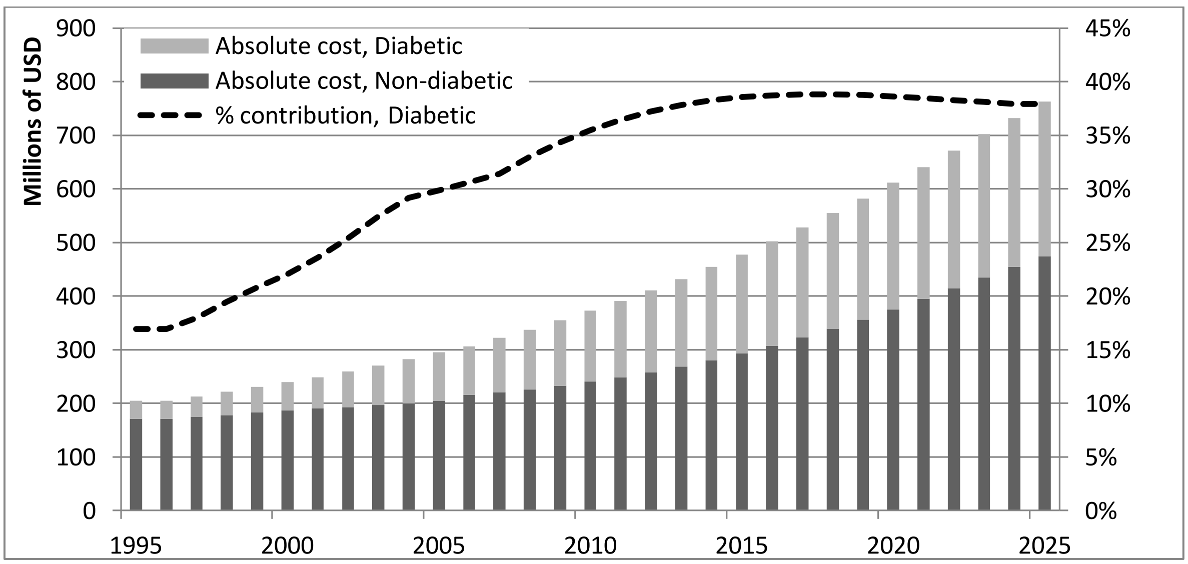
Because of the ongoing aging process itself, Costa Rican public health care system will face raising costs in the provision of services for the elderly. Even under the most conservative assumption of diabetes prevalence growing at a linear constant rate, total cost of health care will double between 2010 and 2025. Under the assumption of diabetes prevalence growth at an exponential constant rate, costs would be up to 2.5 times higher in 2025 as compared to 2010.

The impact of diabetes prevalence on future health care costs was estimated based on the increase in mean individual costs. Under a linear growth rate assumption, prevalence reaches a 27% rate in 2025. Costs associated with the hospitalization of diabetic elderly are projected to have a 38% share on total costs of hospitalizations in the elderly in the year 2025, 8 percentage points higher as compared to 20 years back, in 2005 (graph 14). Outpatient consultations are projected to represent 34% of total consultation costs in the elderly in 2025, which is 8 percentage points higher than in 2005 (graph 15).

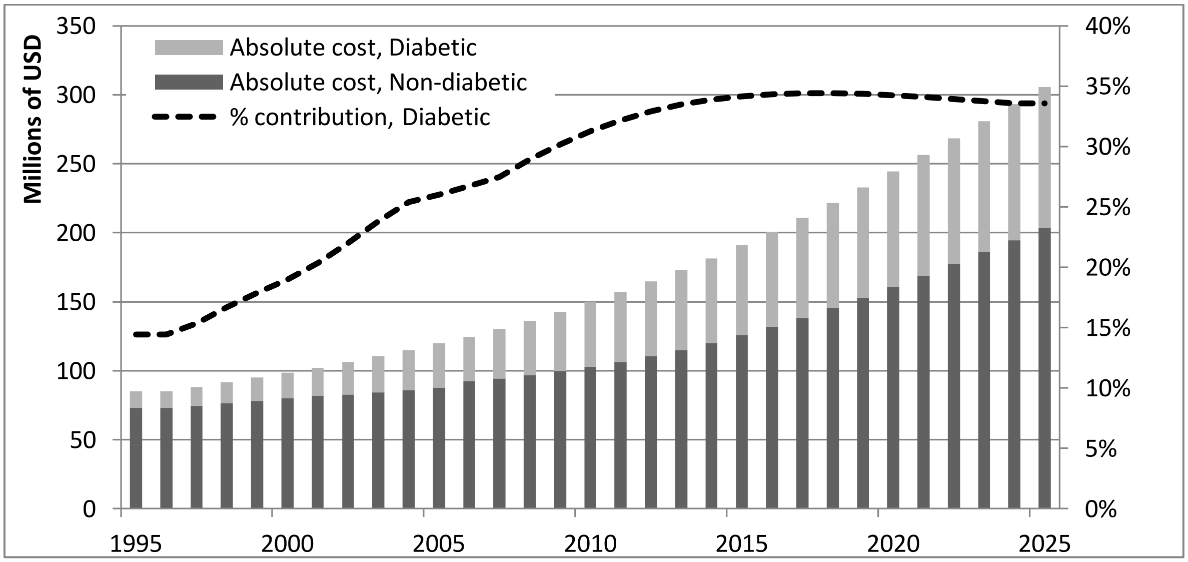
The highest share diabetic individuals have on total cost of healthcare services occurs in medications. Medications for the diabetic elderly population are projected to have a 43% share on total costs of medications for the elderly in 2025, and it was estimated they represented a 34% in 2005 (graph 16).

Because this elderly population will double during this 20-years time period (elderly population size in 2025 will be 2.6 times the size in 2005), the final net effect is a proportional increment in the global health care costs, which is slightly higher in medications.

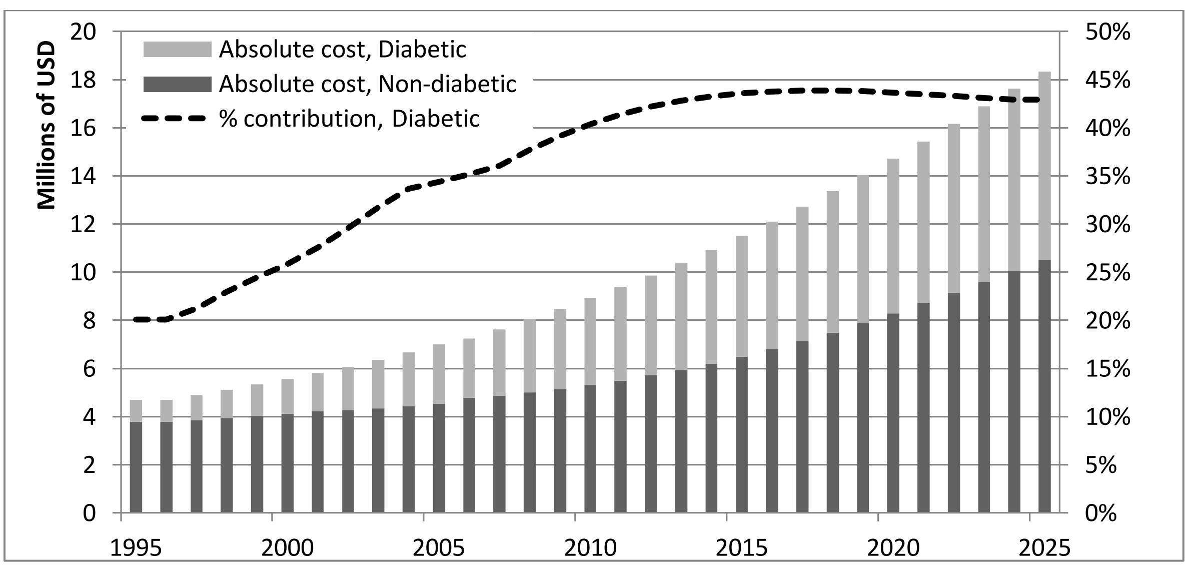
Graph 14. Projected annualized mean individual costs of hospitalization of the Costa Rican elderly population under the assumption of linear growth of diabetes prevalence (USD2011).



Graph 15. Projected annualized mean individual costs of outpatient consultations of the Costa Rican elderly population under the assumption of linear growth of diabetes prevalence (USD2011).



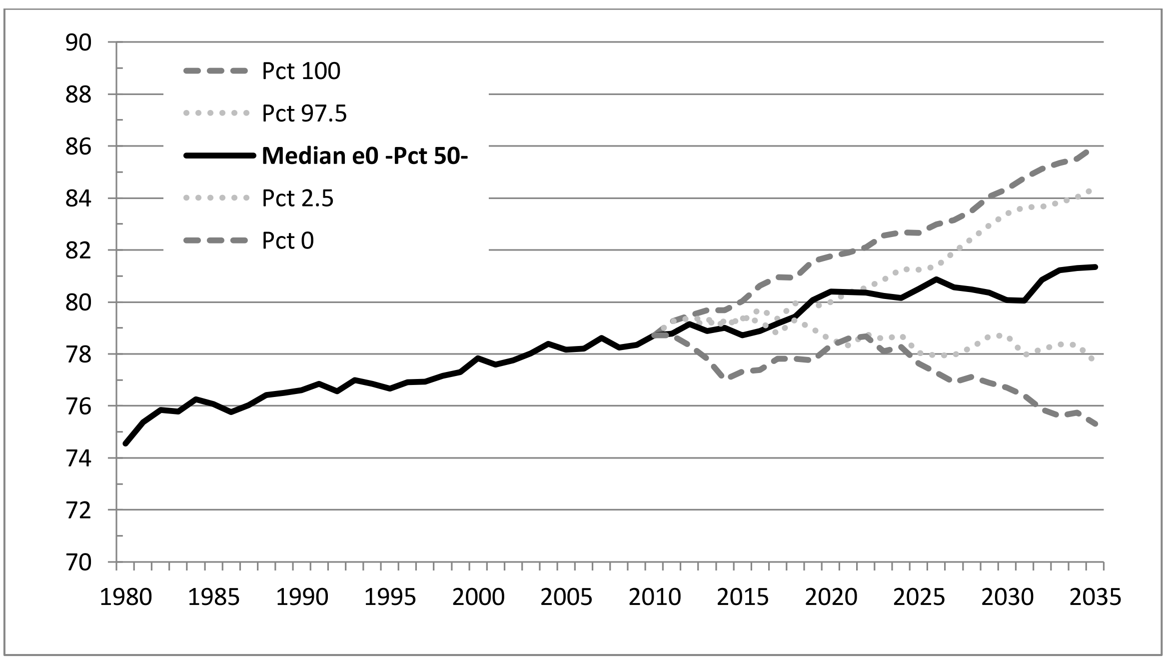
Graph 16. Projected mean individual costs of drug prescriptions of the Costa Rican elderly population under the assumption of linear growth of diabetes prevalence (USD2011).



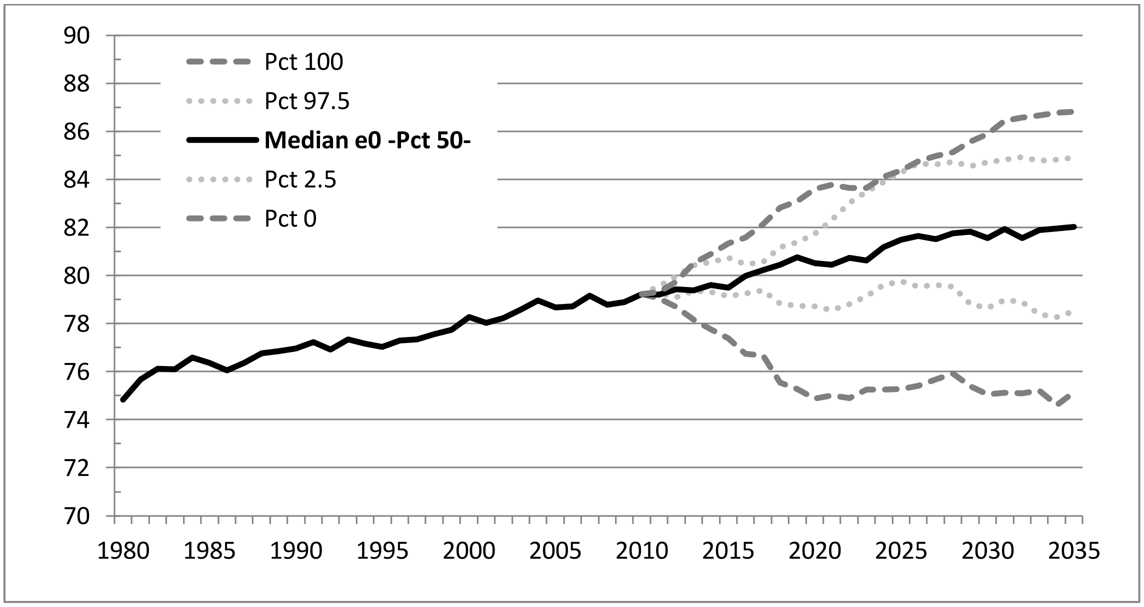
4.8.Impact of diabetes on life expectancy

Current total life expectancy in Costa Rica is 79 years. Based on historical mortality, life expectancy was forecasted 25 years using the Lee-Carter method. As a result, it is expected to have a life expectancy at birth of 80 years in 2025 (graph 17). When making the exercise of deleting diabetes as a cause of death in the historical data, forecasted life expectancy at birth is one year higher (Graph 18).

Graph 17. Lee-Carter forecasts of life expectancy at birth. Forecasts based on all-cause mortality. Costa Rica: 1980-2035.



Graph 18. Lee-Carter forecasts of life expectancy at birth. Forecasts based on mortality in the absence of diabetes. Costa Rica: 1980-2035.



Life expectancy at age 60 was estimated from forecasted mortality rates for years 2015, 2025 and 2035. The impact of diabetes on future life expectancy at age 60 is estimated in 7 months of life lost in year 2025 and the same estimation holds for year 2035 (table 17).

Table 17. Lee-Carter forecasts of life expectancy at age 60 (e_{60}) for years 2015, 2025 and 2035

Forecast	**2015**	**2025**	**2035**
e_{60}	23.66 [23.64 - 23.69]	24.33 [24.28 - 24.38]	24.97 [24.90 - 25.04]
e_{60} adjusted for DM2 mortality[20]	23.05 [23.03 - 23.08]	23.73 [23.68 - 23.77]	24.37 [24.30 - 24.43]
e_{60} in the absence of DM2 mortality	24.11 [24.08 - 24.14]	24.84 [24.79 - 24.89]	25.54 [25.47 - 25.61]
Years of life lost to diabetes[21]	**0.611 [0.605 - 0.612]**	**0.602 [0.600 - 0.605]**	**0.597 [0.592 - 0.603]**

[20] Based on forecasted mortality rates in the absence of DM2 plus DM2-caused mortality rates from a competing risks regression model using CRELES

[21] Based on the difference between e_{60} adjusted for DM2 mortality and forecasted e_{60}

CHAPTER 5. Discussion

Diabetes is a highly prevalent condition in the elderly. More than a fifth of Costa Rican elderly has this condition. Based on retrospective information on these individuals, incidence of diagnosed diabetes for adults aged 30 or beyond is estimated to be at least 5 per 1 000 person-years. Type 2 diabetes has shown to be significantly associated with an increased premature mortality, especially between 60 to 69 years when diabetic individuals have 68% more probability of dying of any cause than non diabetic individuals.

Chronic comorbidities are common. Hypertension is the most common comorbid condition for diabetic elderly, and its prevalence is much higher in the diabetic population than in their non-diabetic peers (Barceló, 2000). Similar to what has been reported in other countries such as Mexico (Velázquez-Monroy et al., 2003), in Costa Rica the odds of diabetes are increased in the hypertensive elderly, and the odds of hypertension are increased in the diabetic elderly. In this Costa Rican cohort, as it has also been reported by Velázquez-Monroy et al. (2003), the prevalence of diabetes increases as obesity and smoking habits increase.

Latin America as a region has adopted health and nutrition problems of western nations (Albala, 2001). Metabolic conditions, hypertension and diabetes included, have common risk factors. Although subjacent genetic factors play a role, environmental risk factors play a key role.

Obesity, which has come partly as a consequence of changing lifestyles, is one of the most important risk factors for metabolic conditions.

The prevalence of diabetes is higher at younger ages, and decreases with age. This holds not only for Costa Rica, but to Latin America at large. The same age pattern of prevalence has been observed in most of seven Latin American cities, where the prevalence of diabetes increased between 60 to 69 years of age and slightly declined thereafter (Barceló et al., 2006).

This age trend can be explained as a result of survival bias. Healthier people tend to live longer and are less likely to be diabetic than more disadvantaged individuals. Diabetes itself is associated with premature mortality, which contributes to lower prevalence at older ages.

An alternative explanation to this decrease of prevalence at older ages may be the presence of birth cohort effects. Currently observed patterns may result from cohort effects that have occurred over time (Szklo & Nieto, 2004). It may be hypothesized for example, that individuals from older cohorts might have been exposed in a lower degree to risk factors such as physical inactivity or high fat diets than individuals from younger cohorts who are now experiencing higher rates of diabetes prevalence. The CRELES study interviewed 2 827 elderly individuals and then went back to the same participants for a second and third wave of interviews. Different from some panel studies, cohorts of individuals in this study were not renewed within each wave. As a result, a large enough sample size of individuals within cohorts is not feasible. Because of this limitation, birth cohort effects were not assessed in this dissertation.

Using a definition of diabetes that relies on biomarkers and drugs leads to higher prevalence and incidence estimates than using a definition based solely on self-report. Difference between self-reports and biomarkers is an indication of the undiagnosed diabetes in the elderly population. Undiagnosed diabetes is very likely for a number of reasons. One of them is that due to lack of symptoms of hyperglycemia, it has been estimated that diagnosis of diabetes is often late with an average delay of 5 years following to the first manifestation of hyperglycemia (Hauner et al., 2008).

Incidence on the other hand, is lower at younger ages, increases up to the age of 60 and then flattens at older ages. This pattern of the diabetes incidence curve has been observed in populations from developed countries, but it has not been described for populations in developing countries. Laclé-Murray and Valero (2008) estimated the incidence of diabetes for an adult population with diabetes risk factors in Costa Rica, but did not describe an incidence curve by age. Rockwood et al. (2000), based on a sample from the Canadian Study of Health and Aging, found that the incidence of diabetes decreased with age in Canada, especially among the oldest old. A reasonable explanation to this flattening or even fall of diabetes incidence among the oldest old is that competing risks cause death in those who would otherwise be susceptible to diabetes (Rockwood et al., 2000).

Because of survival bias, this is a rather conservative estimation of the real incidence. Assuming that those who did not survive to the age of 60 had a less favorable health status, these results are most likely an underestimation. With the information available, incidence rates were adjusted for ages 60 and beyond using biomarkers and drugs information, but because of lack of information no adjustment was feasible at younger ages. Using this adjustment of incidence rates for ages 60 and beyond results in an estimation of total incidence of 6 per 1 000 person-years in Costa Rica; which would still be considered, as aforementioned, a conservative estimation of the incidence in the adult population aged 30 or beyond.

Diabetes prevalence has reported to be higher in men than in women in the elderly of the United States and some cities of Latin America and the Caribbean (Barceló et al. 2007). In Costa Rica, however, male prevalence is lower than female diabetes prevalence. According to world estimations there is not a consistent trend in the frequency of this condition for one or another sex (Ávila-Curiel et al., 2007).

Costa Rican elderly men have a lower crude prevalence than women in all 10-year age-groups. After controlling for other sociodemographic characteristics, risk factors, behavioral health risks, and access to health care, men are 23% less likely to have a diabetes diagnosis than women.

Nonetheless, this male apparent advantage in terms of prevalence seems to be explained by a higher proportion of undiagnosed cases. Male population seems to be diagnosed later in their lives. Prevalence of diabetes is very similar between ages 60-69 and 70-79 in the female population (26% vs. 27%), whereas it is significantly different in the male population for the same age groups (17% vs. 23%). This age differential in male prevalence is probably related to late diagnoses, since prevalence is higher between 70 and 79 years than between 60 to 69 years for males.

When the prevalence of diagnosed diabetes is modeled controlling for sociodemographic variables, risk factors, behavioral health risks, and access to health care characteristics, men show a marginally significant lower prevalence than women. Furthermore, once the prevalence model includes a definition of diabetes adjusted with biomarkers and use of medications, no significant difference in the prevalence between men and women is observed. This is an indication of a higher prevalence of undiagnosed diabetes in the male population, since after correcting for likely undiagnosed cases, sex differentials in prevalence are not observed anymore.

Incidence rates are also an indication of female population having earlier diagnoses of the condition than male. Women have a significantly higher incidence of diagnosed diabetes at younger ages. Sex differentials are clearly larger in the youngest age groups. No adjustment can be made on the estimates of incidence during adulthood since biomarkers and drugs use are only available for this elderly cohort now they are elder. Part of this sex incidence differential may therefore be the result of a diagnosis differential by sex.

In Costa Rica, as well as many other Latin American countries, male have lower utilization rates of health care services, especially at younger ages, and they use consultation and hospitalization services less periodically than female do (Castro, 1996). Six out of 10 outpatient consultations in the Costa Rican elderly are made by a woman (Chaves & León, 2010). It is likely that diabetes goes undiagnosed or is diagnosed later in the male population. Undiagnosed or lately diagnosed diabetes has premature mortality as one of its side effects. Individuals who have the condition, but do not have a medical diagnosis, do not control their disease and are at risk of greater morbidity and premature mortality.

Education is one of the social determinants of health that in general acts as a protective factor. The odds of being diabetic, presented in the prevalence models, are about 20% lower for individuals who have at least complete primary school, and this effect remains significant after adjusting the definition of diabetes. The hazard of becoming diabetic is also lower for those with higher education. This is coincident with other populations in which lower incidence of diabetes is associated with higher education, and people with higher levels of education are more likely to be diagnosed and to adhere to treatment (Whiting et al., 2010).

An association between low income and the odds of being diabetic was not found to be significant in Costa Rica. This is worth to mention because, contrary to what is expected in other contexts, (Venkat-Narayan et al., 2006) no socioeconomic status gradient seems to model elderly health status in Costa Rica. The absence of a clear SES gradient in the country has been previously described (Rivera, 2009; Rosero & Dow, 2009). Universal health insurance and high coverage of the primary healthcare network are possible explanations for no SES gradient in Costa Rica.

The elderly who had known family history of diabetes more than doubled the odds of being diabetic and the hazard of becoming diabetic, as compared with their counterparts with no family history of the disease. This association is highly significant and holds for diabetes prevalence and incidence no matter what definition of diabetes is used. There is a prevailing hypothesis regarding the influence of family history; environmental factors, such as excessive calorie intake and a sedentary lifestyle, which may be superimposed on a familial genotype of susceptibility lead over time to type 2 diabetes (Karter et al., 1999; Venkat-Narayan, 2006).

The association between BMI or waist circumference and diabetes is well established among middle-aged populations. But the associations between BMI and health outcomes among the elderly have been inconsistent. This could be explained by BMI not being a good measure of fat mass in older adults. It may not reflect the muscle mass loss that occurs with aging, or the effect of comorbidities -such as subclinical cancer- that affect fat content or body composition. It has been argued that the increase in abdominal adiposity and its association with metabolic risk may be better reflected by waist circumference measures in the elderly (Barceló et al. 2007, Chang et al., 2012; Kyle et al., 2001).

Although waist circumference does not differentiate between subcutaneous fat and visceral fat, central obesity -where visceral adipose tissue is stored- has been associated with decreased glucose tolerance. Visceral adipose tissue is known to generate diabetogenic substances (Bonora et al., 2004). Clinical evidence suggests that the association of diabetes with central obesity is stronger than the association with general fat (Vazquez et al. 2007; Wang and Beydoun, 2007).

A clear gradient effect has been shown in this research from individuals with normal BMI and waist circumference, up to those who are obese and have a substantially increased waist circumference. When making the estimations only with diagnosed individuals, prevalence odds ratios range from a 41% increase to a three-fold probability of being diabetic in the highest risk category. When using the adjusted definition of diabetes, prevalence odds ratios range from 64% increase to a four-fold probability of being diabetic.

The first category after the reference, -individuals who are overweight or obese but with a normal waist circumference- have significantly higher odds of being diabetic when using the adjusted definition of diabetes, but not when using the definition that relies solely in diagnosis of the condition. Similarly, individuals with normal weight but increased or substantially increased waist circumference –the second category after the reference- have more highly significant odds of being diabetic when using the adjusted definition of diabetes in the analysis than when using only self-report of medical diagnosis. This is an indication that the use of biomarkers and medications help in the detection of a population that is in early stages of overweight or obesity but have not been diagnosed with diabetes yet.

No information on waist circumference before the age of 30 was available for this elderly sample. But data on BMI at the age of 25 and at every wave was available from the CRELES data. Therefore, for the incidence model only BMI was used. A gradient was also observed. The hazard of becoming diabetic was significantly higher for overweight and obese individuals; and the magnitude of these hazards was greater when the adjusted definition of diabetes was used.

Costa Rican elderly have a significant two-fold probability of being diabetic if they are active smokers; and the hazard of becoming diabetic is also higher for active smokers as compared to non-smokers. An association between active smoking and increased risk of diabetes has been previously described, but it has not yet been established whether this association is causal or it is confounded or mediated by other factors. Nonetheless some possible mechanisms that relate smoking to oxidative stress, systemic inflammation, and endothelial dysfunction have been proposed in the scientific literature (Willi et al., 2007; Zhang et al., 2011).

Passive smoking has more recently been described to have an association with diabetes (Kowall et al., 2010). But, in tandem with active smoking, it has not yet been established whether this association is causal or it is confounded or mediated by other factors. The prevalence of passive smokers in Costa Rican elderly is a conservative one. It only includes information on whether or not each individual's partner was a smoker. Exposure to environmental tobacco smoke can certainly come from other sources. Although not statistically significant, a slight direct association between passive smoking and diabetes prevalence was observed in this Costa Rican population.

A J-shaped association between alcohol consumption and diabetes has been described in the literature. It has been found that moderate alcohol consumption is protective for type 2 diabetes, but binge drinking is a risk factor for diabetes (Baliunas et al., 2009; Beulens et al., 2005; Nakanishi, 2003; Pietraszek et al., 2010). No significant association was found between alcohol drinking or hyper calorie diets and the prevalence of diabetes. Alcohol drinking was not found to be significantly associated with diabetes incidence in this Costa Rican population either.

Having health insurance was not found to have a significant association with diabetes prevalence. As previously mentioned, this may be explained by the fact that Costa Rica has a universal health care system with no co-payments associated to the use of services, which makes heath care affordable to the entire population.

Living in the Great Metropolitan Area of Costa Rica was not found to have a significant association with diabetes prevalence. But longer mean times to the nearest health care facility were associated with a decreased probability of having a medical diagnose of diabetes. People are less likely to have a medical diagnosis of diabetes the longer it takes them to get to the nearest facility.

This is evidence of geographical barriers to health care that translate into a lower probability of diabetes diagnosis in the elderly. A previous study by Brenes-Camacho and Rosero-Bixby (2008a) had reported differential access to care in this same elderly population since individuals not living in the Great Metropolitan Area of Costa Rica had a lower probability of having their diabetes controlled.

Inequalities in access to diabetes care can result from various factors including the geographical distribution of health services and therefore the distance needed to travel to have access to them (Whiting et al., 2010). In Costa Rica, having health insurance or the economic costs of attention do not pose a barrier to health care, but the location of facilities relative to population is an important determinant of health care access (Rosero-Bixby, 2004).

Diabetes-caused mortality rates increase with age, but they are not proportional to the mortality due other causes. Diabetes causes premature mortality. Diabetes cause-specific mortality has a greater share of general mortality at younger ages in the elderly. As individuals age, mainly at 80 years and beyond, mortality-caused diabetes has a smaller share on total mortality.

Diabetes, as it has also been shown in other studies, is associated with increased risks of death from all causes (Hu et al., 2007). In Costa Rican elderly, the 60-69 years age group, where most of premature death occurs, cancer and diabetes are the only morbidities with a significant death hazard. After controlling for sociodemographic characteristics and chronic morbidity, the risk of mortality is 68% higher in diabetic elderly aged 60 to 69, and 36% higher in the 70-79 diabetic elder, as compared to their non-diabetic counterparts. At the age of 80 and beyond diabetes makes no difference in terms of general mortality.

Costs of health care in the diabetic elderly are significantly higher than in the non-diabetic elderly. There are some factors that affect the propensity to use any services, whereas there are some others that affect the volume of utilization once the person makes use of the services. In terms of hospitalizations, diabetes is more likely to affect the propensity of using the service rather than the volume of utilization, although these associations did not reach statistical significance. The propensity of using outpatient consultation services and prescription drugs is significantly higher in the diabetic elderly. Although volume of utilization of both outpatient consultations and medications has also a significant association with diabetes, higher costs in the diabetic elderly are clearly driven by the probability of using outpatient services and medications as compared to their non-diabetic counterparts.

Controlling for other predisposing characteristics, enabling resources and need; female elderly have lower costs of hospitalizations, but higher costs in terms of outpatient care and prescribed drugs. Female population has a significantly lower propensity to use hospitalization services. Both propensity to use and volume of utilization of outpatient consultation and medications are significantly higher in the female as compared to the male elderly. This adds to the evidence of women having higher volumes of health care utilization that somehow prevents them from major health problems, which clearly results in the lower hospitalization rates.

In general, patterns of use and costs of hospitalization and outpatient care share similarities. Predisposing characteristics such as sex or retirement are more associated with propensity to use outpatient care services and medications. Enabling resources such as education or income are more significantly associated with the volume of utilization of health care services. Need has a clear association with propensity to use hospitalizations. Whereas, regarding outpatient consultations and medications; need is almost equally associated with both propensity and volume of use.

Medications are widely available in all the levels of healthcare attention in Costa Rica, and without any co-payment involved. The latter is probably related to the fact that predisposing characteristics, enabling resources, and need are significantly associated with both propensity of use and volume of utilization of medications. Polipharmacy -the use of multiple medications by a patient- is important in this elderly population. Propensity to use medications is 3 times as high in diabetic individuals as compared to non-diabetic, and 3 times as high in hypertensive elderly as compared to non-hypertensive.

Diabetes prevalence will continue to rise in the elderly. This increased prevalence is the main responsible for the growing burden of diabetes not only in developing but also in developed countries (Sloan, 2008). A 27% of the elderly population is projected to be diabetic by 2025 in Costa Rica. This diabetes prevalence projection is remarkably similar to a previous estimation by Brenes (2008) using a different methodological approach. It had been estimated a 28% prevalence of diabetes in the elderly for the same year (Brenes, 2008).

Diabetic elderly population size will double between 2010 and 2025, and so will the total costs of the elderly hospitalizations, outpatient consultations and medications. The impact of diabetes on future life expectancy at age 60 around the year 2025 is estimated to lead to a loss of about 7 months of life.

Diabetes prevention, or at least delaying its onset is possible. This would reduce the impact of the diabetic epidemic in the elderly population. Previous studies have shown that in individuals at high risk, a combination of weight loss, physical activity and dietary advice leads to a significant reduction in incidence (Whiting, 2010). Prevention using life style interventions as a strategy lead to higher cost-effective reductions in incidence among people at high risk than strategies that use drugs -such as metformin- for prevention (Venkat-Narayan et al., 2006).

Because it is also expected that a substantial proportion of diabetes will arise in individuals not identified as being at high risk, broader strategies are also necessary. These strategies include public policy to modify the obesogenic environment in which populations live (Unwing et al., 2010).

Although problematic, having common risk factors for a number of metabolic conditions, diabetes included, is also a window of opportunity. Lifestyles are modifiable and although this is clearly not an easy task, public policies can direct efforts to do so. Controlling population nutritional status with strategies intervening not only individuals but also their environments, would bring the benefits of preventing more than one condition.

The most highly effective interventions to reduce morbidity, premature mortality and the incidence of complications that derive from diabetes are both education for lifestyle change, and the creation of environments in which individual behavioral initiatives can succeed. As stated by Yach et al. (2006) overweight and obesity have become to diabetes what tobacco is to lung cancer. Acting on diabetes preventable risk factors is therefore mandatory.

CHAPTER 6. Conclusions and public policy implications.

This study adds to the literature an estimation of the impact diabetes mellitus type 2 has on a developing country that has already started the population aging process. Although data refers to Costa Rica, results may be applicable to other aging developing countries in the Latin American and Caribbean region.

Diabetes is associated to a greater probability of premature mortality. Evidence of this is the age mortality differential that affects more heavily diabetic individuals aged 60 to 69. Furthermore, it is estimated that in the next 15 years, diabetes will have an impact on life expectancy at age 60 of about 7 months.

Besides the impact diabetes epidemic has on life expectancy, this condition clearly puts under pressure the public health care system. Diabetic elderly is more expensive in terms of hospitalizations, outpatient care and medications. Nearly 27% of the Costa Rican elderly will be diabetic in 2025. Costs of health care for the diabetic elderly are projected to have a growing share on total healthcare costs to the system.

The costs of health care will increase for the elderly population because of the population aging process itself. But the impact of diabetes on these costs can be reduced if risk factors are attenuated in the population and earlier diagnoses of the condition are attained, especially in the male population. Policies to reduce risk factors will not affect diabetes incidence in the short term, but will in the mid and long term. Programs to improve detection and management of diabetes would reduce the burden in a shorter term as a result of a slower progression to complications.

Directing public funds at treating diabetes and its complications is important. Nonetheless, the rapid escalation of expected numbers of elder with diabetes in the near future demands urgent action on prevention. Not directing funds at prevention would have the perverse effect of increasing economic costs due to premature morbidity and mortality from diabetes that would absorb much of the health care budgets. And this likely scenario is applicable not only to Costa Rica, but also to other developing countries.

Diabetes mellitus along with comorbid conditions such as hypertension, elevated cholesterol, and elevated triglycerides increase the risk of premature mortality and contribute to several of the leading causes of death. These conditions share common risk factors such as obesity and lack of exercise. The challenge for public programs of prevention is to develop and evaluate ways of addressing the underlying factors that make individuals vulnerable to the condition.

Strategies to tackle obesity might be incorporated into other existing health promotion programs. But strategies should be framed in contexts that reduce obesogenic environments. Educational strategies may lead to a better diet in individuals, but sustainable changes occur in the population when supporting environments for these behavior shifts are also part of the equation.

As Zimmet (2000) has described, one of the myths of the modern world is that health is determined largely by individual choice. Nevertheless it must acknowledged that along with globalization not only human behavior and lifestyle has changed, but also pronounced changes in the human environment have occurred, which have had an impact on human health. Type 2 diabetes, more than just a disease, should be seen according to Zimmet as one of the effects on human health of environmental and lifestyle changes.

ANNEX 1

Table 1. Body Mass Index (kg/m^2) of CRELES participants at baseline, by sex and silhouette selected by the participant in the Figure Rating Scale

Silhouette	Male Mean BMI (Std Dev)	Female Mean BMI (Std Dev)
1	21.0 (3.0)	20.8 (3.7)
2	22.4 (3.0)	23.4 (4.9)
3	23.8 (2.4)	25.1 (3.2)
4	24.9 (3.5)	26.2 (3.0)
5	27.3 (3.1)	29.0 (4.0)
6	28.9 (3.2)	31.0 (4.2)
7	30.2 (3.6)	34.4 (5.2)
8	31.8 (4.4)	35.3 (6.0)
9	32.2 (3.3)	36.6 (13.8)

Table 2. Proposed silhouette ranges and their mean body mass index, by BMI and sex

BMI category	Male		Female	
	Silhouette range	Mean BMI (kg/m^2)	Silhouette range	Mean BMI (kg/m^2)
Normal	[1-4]	23.3	[1-3]	23.3
Overweight	[5-6]	27.9	[4-5]	27.8
Obese	[7-9]	30.6	[6-9]	32.8

REFERENCES

Albala, C., Vio, F., Kain, J., & Uauy, R. (2001). Nutrition transition in Latin America: The case of Chile. *Nutrition Reviews, 59*(6), 170-176.

American Diabetes Association. (2011). Diagnosis and classification of diabetes mellitus. *Diabetes Care, 34,* 62-69.

American Diabetes Association. (2012). Diagnosis and classification of diabetes mellitus. *Diabetes Care*, *25,* S64-S71.

Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter? *Journal of Health and Social Behavior, 36,* 1-10.

Andrade, F. C. D. (2006). *Functional disability and health inequality among elderly Latinos: The diabetes mellitus burden*. (Doctoral dissertation, University of Wisconsin-Madison). Available from ProQuest Dissertations and Thesis database. (UMI No. 3245628).

Ávila-Curiel, A., Shamah-Levy, T., Galindo-Gómez, C., Cuevas-Nasu, L., Moreno-Macías, H., & Chávez-Villasana, A. (2007). La diabetes mellitus en estratos socioeconómicos bajos de la ciudad de México. Un problema relevante. *Revista de Investigación Clínica, 59*(4), 246-255.

Baliunas, D.O., Taylor, B.J, Irving, H., Roerecke, M., Patra, J., Mohopatra, S., & Rehm, J. (2009). Alcohol as a risk factor for type 2 diabetes. A systematic review and meta-analysis. *Diabetes Care*, *32*(11), 2123-2132.

Barceló, A. (2000). Diabetes and hypertension in the Americas. *West Indian Med J, 49*(4), 262-265.

Barceló, A., Aedo, C., Rajpathak, S., & Robles, S. (2003). The cost of diabetes in Latin America and the Caribbean. *Bulletin of the World Health Organization, 81*(1), 19-27.

Barceló, A., Peláez, M., Rodríguez-Wong, L., & Pastor-Valero, M. (2006). The prevalence of diagnosed diabetes among the elderly of seven cities in Latin America and the Caribbean. *Journal of Aging and Health, 18*(2), 224-239.

Barcelo, A., Gregg, E., Pastor-Valero, M., & Robles, S. (2007). Waist circumference, BMI and the prevalence of self-reported diabetes among the elderly of the United States and six cities of Latin America and the Caribbean. *Diabetes Research & Clinical Practice, 78*(3), 418-427.

Bennett, C.M., Guo, M., & Dharmage, S. C. (2007). HbA1c as a screening tool for detection of type 2 diabetes: A systematic review. *Diabetic Medicine*, *24*, 333-343.

Beulens, J.W.J., Stolk, R.P., Van Der Schouw, Y.T., Grobbee, D. E., Hendriks, H. F. J., & Bolts, M. L. (2005). Alcohol consumption and risk of type 2 diabetes among older women. *Diabetes Care 28*(12), 2933-2938.

Bonora, E., Kiechl, S., Willeit, J., Oberhollenzer, F., Egger, G., Meigs, J. B., et al. (2004). Population-based incidence rates and risk factors for type 2 diabetes in white individuals: The Bruneck study. *Diabetes*, *53*(7), 1782-1789.

Booth, H., Maindonald, J., & Smith, L. (2002). Applying Lee-Carter under conditions of variable mortality decline. *Population Studies, 56*, 325-336.

Booth, H., & Tickle, L. (2003). The future aged: New projections of Australia's elderly population. *Australasian Journal on Ageing*, *22*(4), 196-202.

Brenes, G. (2008). The effect of early life events on the burden of diabetes mellitus among Costa Rican elderly: Estimates and projections. (Doctoral dissertation, University of Wisconsin-Madison). Available from ProQuest Dissertations and Thesis database. (UMI No. 3314166).

Brenes-Camacho, G., & Rosero-Bixby, L. (2008a). Diabetes mellitus en adultos mayores costarricenses. *Población y Salud en Mesoamérica, 5*(1), Artículo 2.

Brenes-Camacho, G., & Rosero-Bixby, L. (2008b). Metabolic control in a nationally representative diabetic elderly sample in Costa Rica: patients at community health centers vs. patients at other health care settings. *BMC International Health and Human Rights*, *8,* 5. doi:10.1186/1472-698X-8-5.

Brenes-Camacho G., & Rosero-Bixby, L. (2009). Differential by socioeconomic status and institutional characteristics in preventive service utilization by older persons in Costa Rica. *Journal of Aging and Health*, *21*(5), 730-758.

Brenes, G., Fernández-Rojas, X., & Rosero-Bixby, L. (2006). *Uso del Estimador Intrínseco y medidas antropométricas para explorar efectos de cohorte en la mortalidad y morbildad por diabetes mellitus.* Paper presented in the II Latin American Population Association Meeting, Guadalajara, Mexico.

Brown, J.E. (2008). *Nutrición en las diferentes etapas de la vida.* 3ª Edición. McGraw Hill. México.

Caldwell, J. (1986). Routes to Low Mortality in Poor Countries. *Population and Development Review*, *12*(2), 171-220.

Cardinal, T. M., Kaciroti, N., & Lumeng, J.C. (2006). The Figure Rating Scale as an Index of Weight Status of Women on Videotape. *Obesity, 14*, 2132–2135. doi: 10.1038/oby.2006.249

Castro, V., Gómez, H., Negrete, J., &Tapia, R. (1996). Las enfermedades crónicas en personas de 60-69 años. *Salud Pública de México, 38*(6), 438-447.

Chang, S., Beason, T., Hunleth, J. & Colditz, G. (2012). A systematic review of body fat distribution and mortality in older people. *Maturitas, 72*(3), 175-191.

Chaves, O. & León, M. (2010). *Acceso y uso de los servicios de salud de la Caja Costarricense de Seguro Social por parte de la población adulta mayor*. Dirección de Compra de Servicios de Salud, Gerencia División Administrativa, Caja Costarricense de Seguro Social. Documento preparado para el II Informe estado de situación de la persona adulta mayor en Costa Rica, UCR/CONAPAM.

Cleves, M., Gould, W., Gutierrez, R., & Marchenko, Y. (2010). *An Introduction to Survival Analysis Using Stata*. Third edition. StataCorp LP.

Coale, A., & Demeny, P., with Vaughan, B. (1983). Regional model life tables at very low levels of mortality. *Population Index, 55*(4), 613-643.

Costa Rica Ministerio de Salud, Instituto Costarricense de Investigación en Nutrición y Salud, Caja Costarricense de Seguro Social, Organización Panamericana de la Salud. (2010). *Encuesta de diabetes, hipertensión y factores de riesgo de enfermedades crónicas, Área Metropolitana, San José, 2004*. Iniciativa centroamericana de diabetes CAMDI.

Danaei, G., Finucane, M. M., Lu, Y., Singh, G., Cowan, M., Paciorek, C. J., et al. (2011). National, regional, and global trends in fasting plasma glucose and diabetes prevalence since 1980: Systematic analysis of health examination surveys and epidemiological studies with 370 country-years and 2.7 million participants. *The Lancet, 378*(9785), 31-40. doi:10.116/S0140-6736(11)60679-X

Dankner, R., Abdul-Ghani, M. A., Gerber, Y., Chetrit, A., Wainstein, J., Raz, I., et al. (2007). Predicting the 20-year diabetes incidence rate. *Diabetes Metabolism Res Rev, 23*, 551-558.

Davidson, M. B., Schriger, D. L., Peters, A. L., & Lorber, B. (1999). Relationship between fasting plasma glucose and glycosylated hemoglobin: Potential for false-positive diagnoses of type 2 diabetes using new diagnostic criteria. *JAMA, 281*, 1203–1210.

Diehr, P., Yanez, D., Ash, A, Hornbrook, M. & Lin, D. Y. (1999). Methods for analyzing health care utilization and costs. *Annual Review of Public Health, 20*,125-144.

Droumaguet, C., Balkau, B., Simon, D., Caces, E., Tichet, J., Charles M. A., et al. (2006). Use of HbA1c in predicting progression to diabetes in French men and women. Data from an epidemiological study on the Insulin Resistance Syndrome (DESIR). *Diabetes Care, 29*(7), 1619-1625.

El-Sohemy, A., Baylin, A., Ascherio, A., Kabagambe, E., Spiegelman, D., & Campos, H. (2001). Population-based study of alpha- and gamma-tocopherol in plasma and adipose tissue as biomarkers of intake in Costa Rican adults. *Am J Clin Nutr, 74*(3), 356-363.

Gordis, L. 2004. *Epidemiology*. 3rd edition. Elsevier Saunders. USA.

Grundy, S. M., Benjamin, I. J., Burke, G. L., Chait, A., Eckel, R. H., Howard, B. V., et al. (1999). Diabetes and cardiovascular disease: A statement for healthcare professionals from the American Heart Association. *Circulation*, *100*, 1134-1146.

Gulliford, M., Figueroa-Munoz, J., Morgan, M., Hughes, D., Gibson, B., Beech, R., et al. (2002). What does 'access to health care' mean? *J Health Serv Res Policy*,*7*(3),186-188.

Hauner, H., Hanish, J., Bramlage, P. Steinhagen-Thiessen, E., Schunkert, H., Jöckel, K. H., et al. (2008). Prevalence of undiagnosed type-2-diabetes mellitus and impaired fasting glucose in German primary care: Data from the German Metabolic and Cardiovascular Risk Project (GEMCAS). *Exp Clin Endocrinol Diabetes, 116*,18-25.

Hidalgo, J., Rosero-Bixby, L., & Antich, D. (2007). Mejora de la calidad y disminución de costos de censos y encuestas utilizando computadores de mano (PDA). Una aplicación en Costa Rica. *Población y Salud en Mesoamérica, 5*(1), informe técnico 2.

Ho, S. C., Chen, Y. M., Woo, J. L. F., Leung, S. S. F., Lam, T. H., & Janus, E. D. (2001). Association between simple anthropometric indices and cardiovascular risk factors. *International Journal of Obesity, 25,* 1689-1697.

Hosmer, D.W., & Lemeshow, S. (1999). *Applied survival analysis*. New York: John Wiley & Sons.

Hu, F. B., Manson, J. E., Stampfer, M. J., Colditz, G., Liu, S., Solomon, C. G. et al. (2001). Diet, lifestyle and the risk of type 2 diabetes in women. *New England Journal of Medicine, 345*, 790-797.

Hu, F.B., Stampfer, M. J., Solomon, C. G., Liu, S., Willett, W. C., & Speizer F. E. (2007). The impact of diabetes mellitus on mortality from all causes and coronary heart disease in women. 20 years of follow-up. *Arch Intern Med, 161*, 1717-1723.

International Diabetes Federation. (n.d.). *Diabetes Atlas 5th Edition*. Retrieved from: http://www.idf.org/diabetesatlas/

International Expert Committee. (2009). International Expert Committee Report on the role of the A1c assay in the diagnosis of diabetes. *Diabetes Care 32*(7), 1327–1334.

Kabagambe, E. K., Baylin, A., Allan D. A., Siles, X., Spiegelman, D., & Campos, H. (2001). Application of the method of triads to evaluate the performance of food frequency questionnaires and biomarkers as indicators of long-term dietary intake. *Am J Epidemiol, 154*(12), 1126-1135.

Karter, A. J., Rowell, S. E., Ackerson, L. M., Mitchell, B. D., Ferrara, A., Selby, J. V., et al. (1999). Excess maternal transmission of type 2 diabetes: The northern California Kaiser permanent diabetes registry. *Diabetes Care*, *22*(6), 938-943.

Keyfitz, N., & Caswell, H. (2005). *Applied Mathematical Demography*. Third Edition. Springer.

Kowall, B., Rathmann, W., Strassburger, K., Heier, M., Holle, R., Thorand B, et al. (2010). Association of passive and active smoking with incident type 2 diabetes mellitus in the elderly population: the KORA S4/F4 cohort study. *European Journal of Epidemiology, 25*(6), 393-402.

Kyle, U. G., Genton, L., Hans, D., Karsegard, L., Slosman, D. O. & Pichard, C. (2001). Age-related differences in fat-free mass, skeletal muscle, body cell mass and fat mass between 18 and 94 years. *European Journal of Clinical Nutrition*, *55*(8), 663-672.

Laclé-Murray, A. & Valero L. F. (2008). Incidencia de diabetes tipo 2 en un área urbano marginal de Costa Rica. *Acta Médica Costarricense, 50*(1), 29-34.

Laclé-Murray, A. & Valero L. F. (2009). Prevalencia de nefropatía diabética y sus factores de riesgo en un área urbano marginal de la meseta Central de Costa Rica. *Acta Médica Costarricense, 51*(1), 26-33.

Laclé-Murray, A. (2012). Causas de muerte en una cohorte de diabéticos tipo 2 de Costa Rica y la calidad de su certificado de defunción. *Acta Médica Costarricense, 54*(1), 23-30.

Lee, R. D., & Carter, L. (1992). Modeling and forecasting US mortality. *Journal of the American Statistical Association*, *87*(419), 659-671.

Lee, R, D., & Miller, T. (2001). Evaluating the performance of the Lee-Carter method for forecasting mortality. *Demography, 38*(4), 537-549.

Lee, R. D., & Tuljapurkar, S. (1994). Stochastic population forecasts for the United States: Beyond high, medium, and low. *Journal of the American Statistical Association*, *89*(428), 1175-1189.

Lee, R. D. (1998). Probabilistic approaches to population forecasting. *Population and Development Review, 24*, 156–190.

Lee, R. D. (1992). Stochastic demographic forecasting. *International Journal of Forecasting*, *8,* 315-327.

Li, N., & Lee, R. (2005). Coherent mortality forecasts for a group of populations: An extension of the Lee-Carter method. *Demography, 43*(3), 575-594.

Llanos, A., Morera-Salas, M., Barber-Pérez, K., Xirinach-Salazar, Y., & Vargas, J. R. (2009). Factores relacionados con la utilización de servicios de salud en Costa Rica. *Revista de Salud Pública, 11*(3), 323-335.

Lo, W., Ho, S., Wong, B., Mak, K., & Lam, T. (2011). Validity and test-retest reliability in assessing current body size with figure drawings in Chinese adolescents. *International Journal of Pediatric Obesity*, *6*(2-2), E107-E113.

Lu, W., & Liang, Y. (2008). Analysis of competing risks data with missing cause of failure under additive hazards model. *Statistica Sinica, 18,* 219-234.

Manning, W., & Mullahy, J. (2001). Estimating log models: to transform or not to transform? *Journal of Health Economics, 20,* 461-494.

McDonald, M., Hertz, R. P., Unger, A. N., & Lustik, M. B. (2009). Prevalence, awareness, and management of hypertension, dyslipidemia, and diabetes among United States adults aged 65 and older. *The Journals of Gerontology, 64A*(2), 256-63.

Méndez-Chacón, E., Rosero-Bixby, L., Fernández-Rojas, X., & Barrantes-Jiménez, K. (2007). Comparación de los resultados de pruebas de laboratorio seleccionadas de un estudio poblacional de adultos mayores de Costa Rica. *Población y Salud en Mesoamérica, 5*, artículo 4.

Méndez-Chacón, E., Santamaría –Ulloa, C., & Rosero-Bixby L. (2008). Factors associated with hypertension prevalence, unawareness and treatment among Costa Rican elderly. *BMC Public Health, 8*, 275. doi:10.1186/1471-2458-8-275

Ministerio de Salud, Instituto Costarricense de Investigaciones en Nutrición y Salud, Caja Costarricense del Seguro Social, Instituto Nacional de Estadística y Censos, & Instituto Costarricense sobre Drogas. (2009). *Encuesta Nacional de Nutrición Costa Rica, 2008-2009. Antropometría*. Retrieved from: http://www.ministeriodesalud.go.cr

Morice, A., Roselló, M., Aráuz, A. G., Sánchez, G., & Padilla, G. (1999). *Diabetes mellitus en Costa Rica: un análisis interdisciplinario.* Instituto de Investigación y Enseñanza en Nutrición y Salud. (Inciensa). Serie de documentos técnicos. Tres Ríos, Costa Rica.

Nakanishi, N., Suzuki, K., & Tatara, K. (2003). Alcohol consumption and risk for development of impaired fasting glucose or type 2 diabetes in middle-aged Japanese men. *Diabetes Care, 26*(1), 48-54.

Palloni, A., Wong, R., & Peláez, M. (2006). The tide to come. Elderly health in Latin America and the Caribbean. *Journal of Aging and Health*, *18*(2), 180-206.

Pan American Health Organization. (2011). *Informe sobre el estado de situación financiera del seguro de salud de la Caja Costarricense del Seguro Social*. Situación reciente y proyecciones. Versión preliminar. 12 de julio de 2011. Retrieved from: http://portal.ccss.sa.cr/html_portal/transparencia/informe_ops/estado_situacion_financiera_seguro_de_salud_ccss.zip

Pietraszek, A., Gregersen, S., & Hermansen, K. (2010). Alcohol and type 2 diabetes: A review. *Nutrition, Metabolism and Cardiovascular Diseases*, *20*(5), 366-375.

Popkin, B. (2007).The world is fat. *Scientific American, 297*(3), 88-95.

Population Reference Bureau. (2011). *2011 World Population Data Sheet*. Washington, DC. Population Reference Bureau.

Prentice, A. (2001). Fires of life: the struggles of an ancient metabolism in a modern world. *Nutrition Bulletin, 26*, 13-27.

Preston, S. H., Heuveline, P., & Guillot, M. (2002). *Demography: measuring and modeling population processes*. Oxford, UK: Blackwell Publishers Ltd.

Rehkopf, D., Dow, H., & Rosero-Bixby, L. (2010). Differences in the association of cardiovascular risk factors with education: A comparison of Costa Rica (CRELES) and the USA (NHANES). *Journal of Epidemiology and Community Health*, *64*(9): 821–828. doi: 10.1136/jech.2009.086926

Rivera, C. (2009). *Impacto de la diabetes mellitus en el bienestar socioeconómico de los adultos mayores costarricenses*. Trabajo Final de Graduación. Maestría en Estadística. Universidad de Costa Rica. San José, Costa Rica.

Rockwood, K., Awalt, E., MacKnight, C., McDowell, I. (2000). Incidence and outcomes of diabetes mellitus in elderly people: Report from the Canadian Study of Health and Aging. *Canadian Medical Association Journal*, *162*(6), 769-772.

Roselló, M., Aráuz, A. G., Padilla, G. (2004). Prevalencia de diabetes mellitus autorreportada en Costa Rica, 1998. *Acta Médica Costarricense, 46*(4), 190-195.

Rosero-Bixby, L. (1991). Socioeconomic development, health interventions, and mortality decline in Costa Rica. *Scandinavian Journal of Social Medicine*, *Supplement N 46*, 33-42.

Rosero-Bixby, L. (1996). Adult mortality decline in Costa Rica. In: *Adult Mortality in Latin America*. Chapter 9. Edited by Timaeus, I.M., Chackiel, J., & Rusicka, L. Clarendon Press. Oxford.

Rosero-Bixby, L. (2002). *Tendencias en la mortalidad y esperanza de vida*. *Costa Rica 1970-2001*. Proyecto Estado de la Nación. San José, Costa Rica.

Rosero-Bixby, L. (2004). Spatial access to health care in Costa Rica and its equity: A GIS-based study. *Social Science and Medicine*, *58,* 1271-1284.

Rosero-Bixby, L., Antich, D. (2010). Estudio longitudinal de mortalidad de adultos costarricenses 1984-2007. *Población y Salud en Mesoamérica, 7*(2), artículo 2.

Rosero-Bixby, L., & Dow,W.H. (2009). Surprising SES gradients in mortality, health, and biomarkers in a Latin American population of adults. *J Gerontol B Psychol Sci Soc Sci, 64B*(1), 105–117. doi: 10.1093/geronb/gbn004

Saudek, C. D., Herman, W. H., Sacks, D. B., Bergenstal, R. M., Edelman, D., & Davidson, M. B. (2008). A new look at screening and diagnosing diabetes mellitus. *J Clin Endocrinol Metab, 93*(7), 2447-2453.

Scagliusi, F. B. , Alvarenga, M., Polacow, V. O., Cordas, T.A., Queiroz, G. K. D., Coelho, D, et al. (2006). Concurrent and discriminant validity of the Stunkard's figure rating scale adapted into Portuguese. *Appetite, 47*(1): 77-82. doi: 10.1016/j.appet.2006.02.010.

Szklo, M. & Nieto, F. J. (2004). *Epidemiology: Beyond the basics*. Jones and Bartlett Publishers, Inc.

Shaw, J., Sicree, R., & Zimmet, P. (2010). Global estimates of the prevalence of diabetes for 2010 and 2030. *Diabetes Research & Clinical Practice, 87*(1), 4-14.

Sloan, F.A., Bethel, M.A., Ruiz, D., Shea, A. H., & Feinglos, M. N. (2008). The growing burden of diabetes mellitus in the US elderly population. *Arch Intern Med, 168*(2),192-199.

So, W. Y., Yang, X., Ma, R. C. W., Kong, A. P. S., Lam, C. W. K., Ho, C. S., et al. (2008). Risk factors in V-shaped risk associations with all-cause mortality in type 2 diabetes-The Hong Kong Diabetes Registry. *Diabetes Metabolism Research and Reviews, 24,* 238-246.

Solli, O., Jensen, T., & Kristiansen, I. S. (2010). Diabetes: cost of illness in Norway. *BMC Endocrine disorders, 10,* 15. doi:10.1186/1472-6823-10-15

Sprague, W. (2009). *LCFIT*. Web based software for estimating the Lee-Carter method for modeling and forecasting mortality, with extensions to Coherent Forecasts of Li and Lee, and Lee-Carter method with sparse and incomplete data. Retrieved from: http://lcfit.demog.berkeley.edu/. Last visited on November 30, 2012.

StataCorp. (2011). *Stata Statistical Software: Release 12.0*. College Station, TX. Stata Corporation.

Sorensen, T. I., Stunkard, A. J., Teasdale, T. W., & Higgins, M. W. (1983). The accuracy of reports of weight: children's recall of their parents' weights 15 years earlier. *Int J Obes., 7,* 115–122.

Stunkard, A. J., Sorensen, T. I., & Schulsinger, F. (eds). (1983). *Use of the Danish Adoption Register for the Study of Obesity and Thinness*. Raven Press: New York.

Suh, D. C., Kim, C. M., Choi, I. S., & Plauschinat, C. A. (2008). Comorbid conditions and glycemic control in elderly patients with type2 diabetes mellitus, 1988 to 1994 to 1999 to 2004. *Journal of the American Geriatric Society, 56*, 484-492.

Unger, J. P., De Paepe, P., Buitrón, R., & Soors ,W. (2008). Costa Rica: Achievements of Heterodox Health Policy. *American Journal of Public Health, 98*(4), 636-646.

United Nations. (1958). *Multilingual Demographic Dictionary*. United Nations Population Studies. No 29.

Unwing, N., Whiting, D., & Roglic, G. (2010). Social determinants of diabetes and challenges of prevention. *Lancet, 375,* 2204-2205.

Vazquez, G., Duval, S., Jacobs, D.R., & Silventoinen, K. (2007). Comparison of body mass index, waist circumference, and waist/hip ratio in predicting incident diabetes: A meta-analysis. *Epidemiologic Reviews, 29,* 115-128.

Velázquez-Monroy Ó., Rosas-Peralta M., Lara-Esqueda A., Pastelín-Hernández, G., Grupo ENSA 2000, Sánchez-Castillo, C., et al. (2003). Prevalencia e interrelación de enfermedades crónicas no transmisibles y factores de riesgo cardiovascular en México: Resultados finales de la Encuesta Nacional de Salud (ENSA) 2000. *Archivos de Cardiología de México, 73*(1), 62-77.

Venkat-Narayan, K. M., Zhang, P., Kanaya, A. M., Williams, D. E., Engelgau, M. M., Imperatore, G., et al. (2006). Diabetes: The pandemic and potential solutions. In: Jamison DT et al., eds. *Disease control priorities in developing countries*. Washington, DC/New York, World Bank, Oxford University Press: 591-604.

Wang, Y., & Beydoun, M. A. (2007). The obesity epidemic in the United States-Gender, age, socioeconomic, racial/ethnic, and geographic characteristics: A systematic review and meta-regression analysis. *Epidemiologic Reviews, 29*, 6-28. doi: 10.1093/epirev/mxm007.

Whiting, D., Unwin, N., & Roglic, G. (2010). Diabetes: Equity and social determinants. In: Blas E and Sivasankara Kurup A, eds. *Equity, social determinants and public health programmes*. World Health Organization: 77-94.

Willi, C., Bodenmann, P., Ghali, W. A., Faris, P. D., & Cornuz, J. (2007). Active smoking and the risk of type 2 diabetes. A systematic review and meta-analysis. *JAMA, 298*(22), 2654-2664.

Woo, J., Ho, S.C., Yu, A. L. M., & Sham, A. (2002). Is waist circumference a useful measure in predicting health outcomes in the elderly? *International Journal of Obesity*, *26*, 1349-1355.

World Health Organization. (1999). *Definition, diagnosis and classification of diabetes mellitus and its complications: Report of a WHO Expert Consultation. Part 1: Diagnosis and classification of diabetes mellitus*. Geneva: WHO Department of Noncommunicable Disease Surveillance. Document # WHO/NCD/NCS/99.2.

World Health Organization. (2000). *Obesity: preventing and managing the global epidemic: Report of a WHO consultation*. Geneva, Switzerland. 2000. Technical Report Series no. 894.

World Health Organization. (2006). *Definition and diagnosis of diabetes mellitus and intermediate hyperglycemia. Report of a WHO/IDF Consultation.* Geneva, Switzerland. WHO Document Production Services.

World Health Organization. (2006). *Preventing chronic diseases- a vital investment*. Geneva, Switzerland.

Yach, D., Stuckler, D., & Brownell, K.D. (2006). Epidemiologic and economic consequences of the global epidemics of obesity and diabetes. *Nature Medicine, 12*(1), 62-66.

Zhang, L., Curhan, G. C., Hu, F. B., Rimm, E. B., & Forman, J. P. (2011). Association between passive and active smoking and incident type 2 diabetes in women. *Diabetes Care, 34,* 892-897.

Zimmet, P. (2000). Globalization, coca-colonization and the chronic disease epidemic: can the doomsday scenario be averted? *Journal of Internal Medicine, 247,* 301-310.

Zimmet, P., Alberti, K. G., & Shaaw, J. (2001). Global and societal implications of the diabetes epidemic. *Nature, 414*, 782-787.