Economic consequences of healthy aging

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Economic Consequences of Healthy Aging

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Economic consequences of healthy aging

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Go on, go there
You can see me aging

Bonnie "Prince" Billy

Contents

Chapter 1

General Introduction

1.1 Background and research issues

Population aging: challenges and possibilities

In the coming decades the Western population will age. The number of older people will increase, both in absolute numbers as well as compared to the number of young people. Population aging is a consequence of two things: a decline in fertility rates after the post World War II babyboom, and a continuing rise in life expectancy. In 2011, about 15 % of the Dutch population was 65 years or older. In 2050, this will be more than 25 % [1]. Understandably, population aging has given rise to concerns about the sustainability of social arrangements, such as the old-age pension system and health care. Population aging will increase the number of net recipients of social arrangements while at the same time the number of net contributors will decrease. However, population aging might also be accompanied by benefits that can counter act some of the negative effects. For instance, a higher life expectancy might enable a rise in the pension age, allowing older people to remain active in the labor market for a longer period of time. Also, gains in life expectancy do not necessarily have to lead to higher health care expenditures over total lifetime, but could instead merely postpone expenditures to older ages. In both of these cases the effect of aging depends on health: when gains in life expectancy are accompanied by improvements in health, individuals might be able to continue working and individual age-specific health care costs might decrease. For these reasons, expectations on the benefits of health and active aging are high (European Commission, 2012). Health, however, is a complex concept, and more insight is needed in its longitudinal dynamics. Finding evidence on the relationship between aging and health of the older population, and its economic

[1]Data on (projected) population size and life expectancies are taken from statline.cbs.nl

consequences, namely health care expenditures and (labor) participation, is the topic of this thesis.

Living longer in better or worse health?

In this thesis, the focus lies on the relationship between health and aging. Life expectancy has shown a continuing rise over the last two centuries (Oeppen and Vaupel, 2002). In 1950, life expectancy at birth for women in the Netherlands was 73 years, while in 2011 it was 83 years. A further rise to 87 years in 2050 is expected. The relationship between health and rising life expectancy has to lie between two extreme hypotheses: gains in life expectancy are either the result of an improvement of population health, or of a decrease in mortality given the same level of health. For example, one can think of a new medical technology that enables curing a certain chronic disease compared to a technology that increases the survival probability of a certain disease without curing the disease itself. More precisely stated, life expectancy can be caused by a decrease in the age-specific prevalence of diseases (or other forms of poor health), or of a decrease in age-specific mortality without changing the age-specific onset of diseases. In the epidemiological literature these hypotheses have been named "compression of morbidity" (Fries, 1980), respectively "expansion of morbidity" (Gruenberg, 1977). Additional hypotheses have been formulated, most notably the "dynamic equilibrium" hypothesis, assuming an equilibrium between an increasing prevalence of diseases and a decreasing severity. Unfortunately, empirical evidence does not decisively point towards one of these hypotheses. Instead, evidence seems to differ between countries, and sometimes even between studies within the same country (Martin et al., 2010; Christensen et al., 2009). An important reason for these contrasting findings is the heterogeneous nature of health.

The many faces of health

Health consists of many different dimensions. As stated in the official WHO definition, "health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" [2]. Health of the older population is especially heterogeneous (Lafortune et al., 2009). Relevant dimensions of health include the presence of (chronic) diseases, cognitive functioning, physical functioning, and self-perception of health. An important related aspect is disability, or the way in which health problems limit the ability of individuals to perform daily activities and participate in society. In empirical research, the heterogeneous nature of health is reflected in the availability of large sets of different health indicators. Although the relevance of certain health indicators depends on the particular topic of research, in many cases

[2] Preamble to the Constitution of the World Health Organization as adopted by the International Health Conference, New York, 19-22 June, 1946; signed on 22 July 1946 by the representatives of 61 States (Official Records of the World Health Organization, no. 2, p. 100) and entered into force on 7 April 1948.

a single indicator does not suffice. One major reason for this, is that time trends of different health indicators do not have similar patterns. In the Netherlands, for example, lifeyears spent with one or more chronic diseases seem to be rising, while at the same time years spent with poor self-perceived health are declining (Van der Lucht and Polder, 2010). The inconclusive findings on the relationship between longevity and health can be partially explained by a lack of consistent treatment of the different dimensions of health across studies.

The multidimensionality of health also poses modeling challenges. On the one hand, researchers have to make use of a broad concept of health, and include many of the different dimensions of health. On the other hand, they often have to rely on data with a relatively small sample size or scope, limiting the number of health variables and interactions that can be included in a model. Therefore methods are needed that can capture relationships between different health dimensions in a parsimonious way. One way to achieve both goals is to combine different health indicators into a new variable that summarizes the relevant relationships between the original indicators. Methods like factor analysis and latent class analysis have been commonly used for this purpose (Manton et al., 2007; Cutler and Landrum, 2012; Lafortune et al., 2009). This thesis is concerned with two related issues that have received less attention. First, the use of a combined measure of health as an explanatory variable for other outcomes, such as health care expenditures and labor participation. Second, the analysis of longitudinal dynamics in combined measures of health.

Modeling the relationship between health and health care expenditures

Surprisingly, one of the areas where use of health variables has largely been limited to a single indicator of health, is research on the relationship between age(ing) and health care expenditures. Traditionally, projections of future health care expenditures have been based on a combination of current age profiles of health care expenditures with projected population numbers. Given the rise in the number of older people, these projections show sharply increasing health care expenditures due to population aging. This traditional projection method does not take into account the fact that population aging is partly the result of a rise in life expectancy. Changes in life expectancy are related to changes in health, and thus also health care use. Therefore, the future age profile of health care expenditures will differ from the current one. Time-to-death studies, that correct for this changing age profile by including proximity to death as an explanatory variable, indeed find a much smaller effect of population aging on health care expenditure growth (Zweifel et al., 1999). Instead, expenditures seem to be merely postponed to later ages. In time-to-death models, mortality functions mostly as a proxy for health.

Whether time-to-death is a good proxy for health depends on the relationship between the health dimension of interest and mortality. Wong et al. (2012), for instance, find that the relationship between time-to-death and health care expenditures differs strongly between diseases. Considering that trends in health can differ from the trend in life expectancy it seems better to directly include health indicators in health care expenditure models. With some exceptions like Goldman et al. (2005), few studies include direct measures of health in projection models. Results do show that different health dimensions are relevant for different types of care. For instance, De Meijer et al. (2011) find that for long term care, disability, and not chronic diseases or other aspects of health, is the most important predictor of use. Also, more generally, the choice of a single health indicator has been found to have a large influence on estimated relationships between health and other covariates like income (Frijters and Ulker, 2008). These findings warrant the use of a combined measure of health. Such measures have been applied in some studies, like (Manton et al., 2007; Portrait et al., 2000; McNamee, 2004), but in general the use of combined health measures for the analysis of health care expenditures has been limited.

Longitudinal dynamics in health and health care expenditures

Longitudinal dynamics in individual health play an important role in explaining the influence of health on the consequences of population aging. A change in a person's current health will generally have long-term effects over the rest of his life. Most notably, health changes are related to the expected number of remaining lifeyears. One of the key questions in determining whether health improvements can help contain health care expenditures, is whether improvements in current health lead to a longer life in better health, or instead to a mere postponement of poor health, and expenditures, to later ages. This question is strongly related to the contrasting hypotheses of compression versus expansion of morbidity. In a seminal study, Lubitz et al. (2003) have found that for the U.S., health differences between older individuals of the same age do not lead to substantial differences in health care costs over remaining lifetime. The costs made in the additional lifeyears seem to compensate initial savings due to better current health. However, individuals in good initial health were expected to spend more years in good health. These kind of effects have also been found in other studies, most notably by Goldman et al. (2005), but most results are based on a single indicator, or a limited set of health indicators.

Given the complex interaction between different health dimensions and life expectancy and health care expenditures, longitudinal analysis based on a broader definition of health is desired. The analysis of health dynamics is an area still in development (Halliday, 2011). The analysis of longitudinal dynamics in combined measures of health has been especially limited (Lange and McKee, 2011). The same is true for the joint analysis of longitudinal dynamics in combined measures of health and health care expenditures. To assess the influence of health on the effect of population aging on collective health care expenditure growth, findings on an individual level have to be aggregated to a population level. Goldman et al. (2005) for instance use a microsimulation model, based on individual transition probabilities between different health states, to analyze the effect of health scenarios on health care expenditures in the U.S.

Dynamics in health and participation

Population aging will result in a decrease of the (relative) size of the working population, and will most likely lead to pressures on the labor market. When population aging also increases health care demand, one of the sectors for which labor shortages can be expected to be an especially relevant issue is the health care sector (Kocher and Sahni, 2011). Alleviation of this burden might come from stimulating the growing number of older people to participate longer on the labor market, by for instance increasing the mandatory pension age. Population aging will also substantially increase the need for other forms of social participation, such as the provision of informal care (Colombo et al., 2011). Increasing labor participation might conflict with these other forms. Indeed, studies like those of Henz (2004) and Leigh (2010) find a negative relationship between provision of informal care and labor participation. Policies aimed at sustainability of total collective arrangements, and not just one aspect such as the labor market, therefore have to take possible negative tradeoffs between labor participation and other forms of participation into account. In enabling higher participation, health of the older population will play an important role. Again, empirical evidence on the relationship between health and participation is needed.

The same two issues discussed in relation to health care expenditures also play a role in the relationship between health and participation. First, the use of a broad concept of health is required. Just as for health care, not all dimensions of health are equally relevant for participation. For instance, one can expect that the mere presence of a chronic disease is not the determining factor in employment decisions, but instead the disabling effect of the disease. Many studies on the relationship between health and labor participation only use self-perceived health as a measure for health. This measure is often corrected for self-justification bias, but is not extended to other dimensions of health. As noted by Erdogan-Ciftci et al. (2011) there is no a priori reason to assume that self-perceived health can be considered true health for employment outcomes. Second, the dynamic relationship between health and participation is of specific importance. Continuation of work at older ages is, for example, sometimes found to be associated with better health (Lindeboom, 2012). Generally, the effects on health can take some time to materialize. Analysis of the relationship between health and participation has to take effects over longer parts of remaining life into account. Longitudinal dynamics in labor participation and health, e.g. (Cai and Kalb, 2006; Bound et al., 1998; Haan and Myck, 2009), and informal care and health (Henz, 2004) have been investigated, but a combined analysis of a more broad measure of participation has been lacking.

New data, new techniques

One of the reasons why multidimensional aspects of health and longitudinal health dynamics have been less thoroughly investigated in the past is the lack of good data. In many countries, larger datasets have become available in recent years, that do not rely on relatively small surveys. Instead, these datasets depend on individual linkage procedures to combine information from population wide registries, such as health insurance data. Together with the increasing availability of computer power, these datasets provide a powerful tool to conduct empirical research on an unprecedented level. For instance, in the Netherlands the Social Statistics Database enables linking of registries and survey data on diverse subjects such as employment, hospital use, health, and other variables. However, the wealth of data now at the disposal of social science researchers does not resolve all data issues, and induces new problems. For instance, even with today's computer power the analysis of the vast amounts of data now available often reaches reasonable time constraints. Non-parametric techniques and sampling from the original data are often required (Wong et al., 2012). In relationship to the use of many dimensions of health, the need for parsimonious models again has to be stressed.

Another issue is that linked datasets provide information on an incredibly wide number of topics, but the amount of detail is often surprisingly limited. Many population wide datasets are not designed with research in mind, and therefore lack detailed background information on individuals. In many cases, researchers still have to link the large registry datasets to considerably smaller surveys. For example, detailed longitudinal health information for the Dutch population is only available in a number of surveys, usually not larger than two or three thousand respondents. Moreover, time between waves of these surveys is often more than two years. As a result, the additional advantage of a large sample size can no longer be used. Despite these problems, combined datasets can also enrich each other. For instance, registry data can be used to make inferences about outcome variables of survey respondents during the time between survey waves. Thus, the use of large datasets, and the combination of registry and survey data, requires new statistical techniques that fully use the advantages of both: the representativeness, size, and continuous measurement of registry data with the level of detail of survey data.

1.2 Research aims

The aim of this thesis is to gain insight in the longitudinal relationship between longevity and health of the older population, and the consequences of this relationship for health care expenditures and participation. The following four specific aims can be formulated:

1. To investigate the relationship between different dimensions of health of older individuals. And to combine relevant health variables in an indicator of health, with a meaningful interpretation, that can be applied for the analysis of dynamic interactions between health and other outcome variables, and that is usable to operationalize health scenarios.
2. To model and estimate the individual longitudinal relationship between health and health care expenditures for older people, in order to investigate dynamics in health, longer life, and health care expenditures.
3. To operationalize health scenarios, based on the existing hypotheses on longevity and health, and to use the models from 2 to gain insight into population effects of these health scenarios on health care expenditures.
4. To model and estimate the longitudinal relationship between health and forms of social participation, such as labor participation and informal care provision, in the older population.

In order to fulfill these aims, econometric methods will be applied that can utilize the possibilities of combined registry and survey data to investigate dynamics in health and other outcome variables.

1.3 Outline of this thesis

Chapter 2 discusses the empirical evidence on the relationship between aging and health care expenditures. The chapter adds new insights to the aging debate by integrating diverse aspects of research on aging and health care expenditures in two respects. First, it shows how health economic research on the relationship between age(ing) and health care expenditures implicitly or explicitly assumes a dynamic relationship between longevity, health, and expenditures. It shows the consequences of these assumptions for the accuracy of expenditure projections, and it discusses how health care models can be improved by using more direct measures of health. Second, it discusses the interaction between aging, underlying health, and other societal determinants of health care expenditure growth such as national income growth and medical technology. Chapters 3, 4, and 5 are concerned with providing models and empirical evidence related to the first point. In Chapter 6, one of the interactions between aging and other societal determinants of health care expenditures, namely (labor) participation, is investigated.

Chapter 3 analyzes the relationship between baseline health and costs of hospital use in the Netherlands over a period of 8 years. By estimating the relationship between health and costs over a longer period of time, we gain some first insights in the dynamics between health, mortality, and costs: does better initial health lead to lower costs, or is the initial cross-sectional cost difference between individuals in good and poor health offset by the higher survival probability of the first group? The analysis is performed using four different indicators of health and disability, to attain insight in the relevance of different health dimensions in explaining hospital expenditures, and to find possible interactions between the longitudinal dynamics and choice of health indicator. A discrete survival model is employed to make full use of the data: repeated cross section health survey data linked to longitudinal registry data on hospital use.

Chapter 4 develops a latent Markov model for health and health care expenditures. The chapter builds on the two points of Chapter 3: longitudinal cost effects of differences in health, and the use of different health indicators. The relationship between a latent discrete health variable and hospital and long-term care expenditures over remaining lifetime is investigated. By combining different health indicators in a latent variable that is directly related to health care expenditures, combinations of health dimensions that are most relevant for explaining health care expenditures can be obtained. Dutch longitudinal panel data on health of the older population is combined with registry data on hospital and long-term care use. By including hospital expenditures in the definition of the latent variable, inference about the state of the latent variable can be made in years in which health data is not available.

Chapter 5 again focuses on the relevance of accounting for the multidimensionality of health and including longitudinal dynamics in health and expenditures, but now from a population perspective. The chapter addresses the need to account explicitly for changing relationships between health and longevity when making expenditure projections, as discussed in Chapter 2. Based on the model developed in Chapter 4, the influence of different scenarios of the relationship between health and longevity on health care expenditures is investigated. By comparing different life expectancy scenarios, as well as different health scenarios leading to the same life expectancy, the relative influence of aging on health care expenditure growth is reassessed.

Chapter 6 explores the interactions between health of older individuals and participation. Two dynamic models, one of health and work, and one of health and a broader measure of participation, are specified. To enable the inclusion of different dimensions of health, health is again modeled as a latent discrete variable based on observed health indicators. Results are used to investigate patterns of health, work, and participation over remaining working life.

Chapter 7 discusses the main results and the strengths and limitations of this thesis. It reflects on the research aims, as well as the data and econometric techniques that are used. Suggestions for policy as well as research are formulated.

Chapter 2

Aging Perspectives on Growth in Health Care Expenditures - Myths, Facts, and Forecasts

Abstract

Although the consequences of population aging on growth in health care expenditures (HCE) have been widely investigated, research on this topic is rather fragmented and therefore these consequences are not fully understood. We provide a first step towards a more integrated analysis. Based on a conceptual model of health care use distinguishing between individual and societal determinants, we first analyse research on the direct relationship between age and HCE to provide insight into the consequences of population aging on HCE. Second, we discuss the interaction between population aging and the main societal drivers of HCE, as population aging is likely to influence growth in HCE growth indirectly, through its influence on these societal determinants. We find that the direct effect of aging depends strongly on underlying health and disability. Commonly used approximations of health, such as age or mortality, cannot sufficiently capture complex dynamics in health. Population aging moderately increases expenditures on acute care and strongly increases expenditures on long-term care. The most important drivers of HCE growth are the societal determinants national income and medical technology. However, these drivers interact strongly with age and health, e.g. population aging reinforces the influence of medical technology on HCE and vice versa. Therefore, population aging will remain in the centre of policy debate and more integrated approach on its consequences is needed.

Chapter 2. Aging Perspectives on Growth in Health Care Expenditures - Myths, Facts, and Forecasts

Based on
De Meijer, C., Wouterse, B., Polder, J.J., Koopmanschap, M. (2013). The effect of population aging on health expenditure growth: a critical review. *European Journal of Ageing*, in press.
Koopmanschap, M., De Meijer, C., Wouterse, B., & Polder, J.J. (2010). Determinants of health care expenditure in an aging society. *Panel Paper 22*, Netspar: Tilburg.

2.1 Introduction

The societal consequences of population aging, the increasing share of older people in the population, are the subject of extensive public and scholarly debate in many different fields. In health economics, the focus has mainly been on the effect of population aging on health care expenditure (HCE) growth (see Payne et al. (2007) for a review). In OECD countries, average expenditures increased from approximately 5 percent of GDP in 1970 to nearly 10 percent in 2009 (OECD, 2011). The relationship between old age and HCE has therefore raised serious concerns for the financial sustainability of health care systems around the world. Despite the extensive research on the effect of population aging to HCE growth, consensus on its role has not yet been achieved. Instead, two contra posing views coexist. Some people, especially policy makers, view population aging as the major cause of the rapid growth in HCE. Others, mainly consisting of health economists but also scholars of other fields, have argued that population aging is largely irrelevant for the growth in HCE (Reinhardt, 2003). The main reasons why these views are able to coexist is a lack of research that: (1) integrates epidemiological insights on the relationship between health and aging with health economic research, and (2) links findings on the relationship between age(ing) and HCE to the effects of other major drivers of HCE on a societal level.

First, it seems obvious that the relationship between age and HCE depends on health. As individuals age, their health generally decreases and this in turn leads to increasing utilization of health care. Less clear, however, is how expected increases in longevity relate to health, and to HCE. Epidemiological research on the relationship between longevity improvements and health can be broadly characterized by three hypotheses proposed in the 1980s: expansion, compression, and postponement of morbidity (Gruenberg, 1977; Kramer, 1980; Fries, 1980; Olshansky et al., 1991; Payne et al., 2007). The expansion hypothesis assumes that longevity gains will increase the period of time lived with morbidity or disability. The compression hypothesis assumes that this period will shrink. In the postponement, or dynamic equilibrium, hypothesis longevity gains are expected merely to shift the period with morbidity or disability to an older age, while its duration remains constant. Projections of the consequences of aging on HCE have traditionally been based solely on age, and thus on the implicit assumption that gains in longevity are not related to changes in health. During the last two decades, HCE models have been developed that do allow for changes in the age profile of HCE, most notably by controlling for proximity to death (Zweifel et al., 1999). Generally, this type of research finds a much smaller effect of aging on HCE than the traditional age-based studies. However, most of these models do not make the link between health and longevity gains explicit, and only a few include direct measures of health.

Second, macroeconomic studies on HCE growth generally find that population aging is only one of the driving forces behind HCE, and that other factors are more important. More specifically, there is a growing consensus that medical technology combined with economic growth is the most important driving factor of HCE growth (Bodenheimer, 2005). This conclusion seems to provide weight to the view that population aging is largely irrelevant for HCE growth. However, the indirect effects of aging should not be overlooked. Medical technological progress, for instance, is strongly interrelated with aging. Not only can the introduction of new technologies lead to an increase in longevity, population aging could also lead to an increased societal demand for medical technology aimed at older people (Zweifel et al., 2005). Therefore, while the direct effect of population aging might be relatively small compared to other factors, the broader effect of population aging, as it interacts with other determinants, could be much more significant. These interactions have been somewhat neglected, because of the difficulty to assess the influence of age in macro studies, that miss a link between the individual health factors and age.

In this paper, we aim to improve understanding of the consequences of population aging for HCE by offering a first step towards a more integrated approach that combines insight on (1) the role of age(ing) for individual HCE with epidemiological research on the relationship between health and longevity, and (2) interactions between aging and societal determinants of HCE. Section 2 starts with a conceptual model of individual and societal determinants of HCE. We use this model to clarify the related roles of age and health in explaining HCE, which is essential to understand the health economic research on the direct effect of aging. We also use the model to describe the possible indirect effects of aging, through its impact on the main societal determinants found to be major drivers of aggregated HCE growth in macroeconomic research. In Section 3, we discuss the ways in which health economic research has developed from age-based models of HCE towards models that incorporate dynamics between age, health and HCE. The aim of this section is not to provide a complete overview of the very extensive aging literature, but to present the main lines of thought, findings and seminal papers to readers not familiar with the research. Also, we discuss here the, often implicit, relationship between longevity and health in these models. In Section 4, we briefly discuss empirical evidence on the role of the main societal determinants of HCE. Our aim here is to highlight the, still rather limited, empirical literature on interactions between population aging and these determinants, and to give an indication of the magnitude of the indirect effects of population aging on HCE growth. Finally, in the last section we discuss the insights that a more integrated approach brings to the two opposing views on the role of aging for HCE growth, and we point towards further possibilities for integrated research and policy.

2.2 Conceptual framework

Figure 2.1 provides an overview of the different factors that influence individual HCE. The figure is largely based on the behavioural model of health service use developed

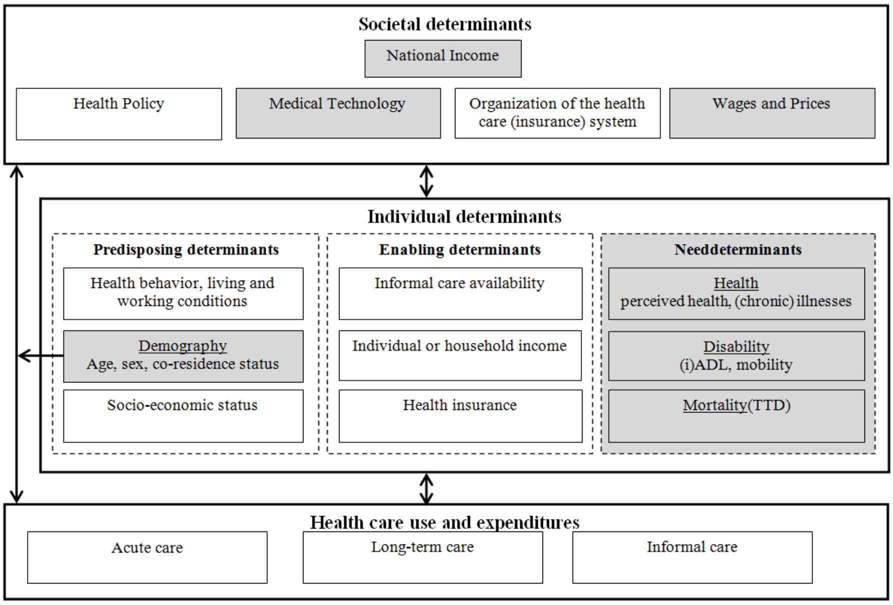

Figure 2.1: Conceptual model of individual health care expenditures.

by Andersen and Newman (Andersen and J.F., 1973). Since Andersen and Newman focused on health care use rather than expenditure, we added links between for instance medical technology, wages and prices, and HCE. Although not all elements of the model are relevant for our discussion of the role of aging, the model is useful to put aging and the related individual and societal determinants into context. Two main features of the model are especially relevant for a discussion of the role of population aging. First, the classification of individual determinants clarifies the relationship between age, health and HCE. Second, the model distinguishes between societal and individual factors that jointly determine the level of individual HCE.

The individual determinants are classified into three groups: predisposing, enabling, and need determinants. Predisposing determinants reflect the individual's "propensity toward use". These determinants influence the likelihood that an individual will use health care, without being directly responsible for it. Age, sex, marital status, co-residence status, socio-economic status, and living and working conditions are examples (Andersen, 1995). Essential for our discussion is the fact that age is classified as a predisposing determinant. Age itself is not a reason for seeking health care (Andersen, 1995). Instead, individuals in different age groups have different types and amounts of illness and consequently different patterns of health care use. The role of age as a predisposing determinant is important, because it suggests that the effect of increases in longevity, or the number of individual at older ages, depends on the relationship with the underlying need determinants. These need determinants regard the direct reasons why an individual, given the presence of predisposing and enabling determinants, seeks the use of health care: poor health and disability. Health exists of various dimensions, e.g. the presence of (chronic) diseases, self-reported health, mental- and physical illness. Disability reflects the way in which poor health limits the ability to perform (instrumental) activities of daily living and mobility. Although health and disability are related, both determinants have a different relationship to HCE. This relationship also differs between types of care, especially between acute and long-term care (LTC) (De Meijer et al., 2011). Although mortality itself cannot lead to health care use, mortality is included as a need determinant because a large part of aging research in health economics has focused on the role of proximity to death, as proxy for health, to explain HCE (Payne et al., 2007). We include mortality as a need determinant instead of a predisposing determinant, because, unlike age, death is a consequence of poor health and not the other way round. Enabling determinants concern the resources available to satisfy a need regarding health care use. Enabling determinants include the level of health insurance coverage, individual or household income, and informal care supply. Although enabling determinants play an important role in explaining health care use, they are not of direct relevance for the role of aging, and we do not discuss them further in this paper.

At the top of Figure 2.1, the societal determinants of HCE are shown. Societal determinants influence HCE directly and indirectly, through their interaction with the individual determinants of health care use. National income, medical technology and wages and prices are the societal determinants that are most often found to play the largest role in HCE growth (Reinhardt, 2003; Van Elk et al., 2010). National income provides the resources for health care funding and thus has a constituting influence on the ability and willingness to pay. Medical technology influences the principles and techniques available to provide health care, and their costs. It is viewed by many as the key driver of HCE growth (e.g. Newhouse (1992); Van Elk et al. (2010); Dormont et al. (2006)). Finally, partially due to the high labour intensity of some parts of care, wages and prices are among the main driving forces of growing HCE (Van Elk et al., 2010). The relevance of the societal determinants for this paper lies in their interaction with age and health. In a collectively financed health care system, societal determinants are largely responsible for the level of collective HCE, whereas individual determinants, as age and health, are largely responsible for the distribution of collective HCE between individuals (Getzen, 2000). Therefore, societal determinants often reinforce the effect of population aging, and vice versa. For instance, new medical technology aimed at older age groups can steepen the age curve of HCE and thus strengthen the effect of an aging population (Wong et al., 2012). Also, as can be seen in Figure 2.1, interactions can go from societal determinants to individual determinants, but also the other way. A relative increase of the number of older people, for example, could increase labour shortages in health care and thus raise wages and prices. As we will discuss in Section 4, these kind of interactions between societal determinants to a great extent determine the influence of population aging on HCE growth.

The determinants that we discuss in the rest of the paper are shaded in gray in Figure 2.1. Although the paper does not summarize evidence on all potential determinants of HCE, it captures all the relevant ones needed for a discussion on the role of aging in HCE growth. In case of the individual determinants, these are age, health, disability, and mortality, on which the research on the relationship between age and HCE has been based (Section 3). In case of the societal determinants (Section 4), , these are national income, medical technology, and wages and prices, that are found most often to be major drivers of HCE growth in macro studies. Although, health policy and the organization of the health care system are important factors in determining HCE, they are not often found to be major causes of HCE growth. Also, research on their interaction with population aging is limited.

2.3 Individual determinants of health care expenditure: age, mortality, and health

2.3.1 The impact of age and mortality

Until the end of the 1980's, studies on the consequences of population aging on HCE were mostly based on the observed relationship between age and average HCE per person in a particular year. This relationship shows a strong increase of HCE with age. When cross sectional age profiles of expenditures are combined with projections of a rising number of older people, huge increases in HCE due to population aging are predicted (Longman, 1987; OECD, 1988). As pointed out in the conceptual model, age is a predisposing determinant and not in itself a reason for seeking care. Therefore, age-based projections are only valid when it is (implicitly) assumed that increases in life expectancy do not change the relationship between age and need determinants like health and disability. Or, in other words, that the relationship between age and HCE remains constant. However, studies that explicitly accounted for the high HCE in the final years of life contradict this assumption (see Payne et al. (2007) for a review).

The idea behind the latter studies is that the final years of life are responsible for the largest part of an individual's HCE. The observed rise in average costs with age can thus be explained by the fact that relatively more individuals are in their final years of life in older age groups than in younger age groups. To investigate the consequences of aging on HCE, HCE should therefore be differentiated between survivors and decedents. These so-called cost of dying (COD) studies either analysed aggregate HCE of decedents by age, or compare age-specific HCE between survivors and decedents. COD studies confirmed that HCE are considerably larger for decedents than survivors and that the magnitude of this relative difference diminished with age (Lubitz and Prihoda, 1984; McCall, 1984; Scitovsky, 1984; Hogan et al., 2001; Lubitz et al., 2003; Hoover et al., 2002; Madsen et al., 2002; Yang et al., 2003; Polder et al., 2006). For acute care expenditures, expenditures only slightly increase with age after controlling for the expensive final years of life. For LTC, expenditures still increase significantly with age (McGrail et al., 2000; Polder et al., 2006; Spillman and Lubitz, 2000; Yang et al., 2003). The fact that expenditures are largely concentrated at the end of life regardless of the age at death suggests that, "as age-specific death rates fall over time, there will be fewer people in the last year of life in any age category, and this will reduce age-specific health care expenditures" (Fuchs, 1984). Thus, predictions of future HCE should be corrected by including the change in the age pattern as a consequence of increased longevity (Fuchs, 1984; Manton, 1982).

A more refined way of making such corrections is offered by time to death (TTD) studies. Instead of comparing aggregated costs of decedents and survivors by age, TTD studies used individual data to model HCE as a function of the time away from death, allowing for in-depth analyses of the effects of approaching death on HCE over time. TTD studies consistently concluded that TTD and not age is the main demographic determinant of HCE. This finding has led Zweifel et al. (1999) to the conclusion that age is a “red herring”, a distraction from the real drivers of HCE. As in the COD studies, the effect of TTD diminishes with age (e.g. (Roos et al., 1987; Häkkinen et al., 2008; Seshamani and Gray, 2004a; Stearns and Norton, 2004; Werblow et al., 2007)). For acute care, age has no or a negative effect on decedents’ expenditures, and only a weak positive effect on survivors’ expenditures (e.g. (Häkkinen et al., 2008; Werblow et al., 2007)). For LTC, however, expenditures still increase with age, although controlling for TTD diminishes its effect (e.g. (Häkkinen et al., 2008; Roos et al., 1987; Weaver et al., 2009; Werblow et al., 2007)).

2.3.2 Reconsidering the impact of age and mortality: controlling for health and disability

COD and TTD studies recognize the role of age as a predisposing determinant, in the sense that the age pattern in HCE is shown to depend on increasing mortality rates with age. The latter relationship, however, is itself the result of deteriorating health. If mortality is indeed a proxy of morbidity in explaining HCE, the concentrated HCE at the end of life are merely due to a higher burden of disease at the end of life. For instance, Hogan et al. (2001) reported that decedents have almost 4 times more diseases than survivors. When mortality functions as a proxy of health, predictions of the effect of population aging, and specifically longevity gains, are only accurate when longevity gains do not change the relationship between mortality and health. However, as mentioned earlier, epidemiological research suggested that this relationship might not be constant (Gruenberg, 1977; Kramer, 1980; Fries, 1980; Olshansky et al., 1991; Payne et al., 2007). In such cases, models are needed that incorporate direct measures of health.

While there are many TTD studies, only a few explored the relationship between health, disability, and individual HCE. The available studies can be divided into three categories. The first category comprises studies that differentiate the effect of mortality by underlying cause-of-death. For example, decedents from cancer and respiratory diseases have significantly higher end-of-life spending than decedents from heart disease (Bird et al., 2002; Seshamani and Gray, 2004a). Furthermore, the effect of mortality on hospital expenditures is larger for highly lethal diseases compared to less lethal diseases (Wong et al., 2011b).

Second, there are studies that use both mortality and general health indicators to explain HCE. Dormont et al. (2006) analysed the growth in French HCE over the period 1992-2000. Shang and Goldman (2008) evaluated the effect of age on Medicare expenditures when further controlling for mortality and morbidity. Both studies revealed that mortality has little impact on HCE after controlling for morbidity. It seems that a large part of the effect of mortality on expenditures is due to mortality acting as an approximation of morbidity. Dormont et al. (2006) further reported that the increasing HCE by age can entirely be explained by differences in health. These and other studies further showed that the precise effect of mortality depends on the specific health problem (Wong et al., 2011b), and also on the coexistence of other health problems (e.g. (Wong et al., 2011a; Häkkinen et al., 2008)).

Third, a few studies analysed the long-term relationship between health status and HCE by examining cumulative HCE over remaining lifetime. These studies demonstrated that improvements in health lead to longer life expectancy, but generally not to lower HCE (Lubitz, 2005; Wouterse et al., 2011). For example, Lubitz et al. (2003) quantified the effect of self-reported health and disability on lifetime HCE from the age of 70 in the US. Older people with better self-reported health lived longer, but incurred similar HCE than those reporting poor health. With respect to disability, lifetime HCE of non-disabled individuals were on average $9,000 lower while they lived on average 2.7 years longer than disabled individuals.

Some studies examined the effect of need determinants specifically for LTC (De Meijer et al., 2009, 2011; Weaver et al., 2009). As for acute care, the effect of mortality turns out to depend on cause-of-death (De Meijer et al., 2011). However, there is also a significant difference: the relationship between age and LTC expenditures remains, even after extensively controlling for disability and general health. In contrast to cure, disability is an important determinant of LTC expenditures, while mortality, self-reported health, and chronic conditions are much less important (e.g. (De Meijer et al., 2009; Li et al., 2011)).

2.3.3 Predictions of HCE growth based on individual determinants (age, mortality, and health)

Different types of expenditure models also lead to different predictions of the effect of population aging on future HCE. Predictions from age-based models (models that do not account for mortality or health) implicitly assume that gains in longevity do not influence the relationship between age and HCE and therefore adhere to the compression of morbidity hypothesis. Instead, mortality models assume that the high HCE during the final years of life shifts equivalently with longevity gains. Thus, mortality based projections adhere to the postponement of morbidity hypothesis: the period spent in poor health is assumed to be merely postponed to a later age. Population aging has therefore a significantly lower impact on future HCE when accounting for mortality instead of age only.

Total annual real growth of HCE is approximately 4-5 percent per year. Studies on annual HCE growth rates found a rate roughly between 0.5-1.7 percent due to population aging without accounting for decreasing mortality rates and a 0.1-0.5 percentage point lower growth rate when accounting for reductions in mortality rates. In Switzerland, Steinmann et al. (2007) found an annual increase of 0.7 percent between 2005 and 2030 for an age-based projection and 0.55 percent when shifts in mortality were taken into account. Miller (2001) used a relatively long prediction period (1997-2070) and found somewhat higher average annual growth rates for the US: 1.3 (1.1) percent for an age-based (mortality) model. Shang and Goldman (2008) report an expected annual growth rate of Medicare expenditures during 2000-2080 due to population aging of 1.7 (1.5) percent for an age-based (mortality) model. For the Netherlands, Polder et al. (2006) predicted a 0.7 percent (age-based) and 0.61 percent (mortality) annual growth between 2000 and 2020 due to population aging. The extent of the variations in prediction between age-based and mortality models also depends on the service under consideration. The difference between age-based and mortality models is particularly large for hospital expenditures and much less for primary care and pharmaceutical expenditures (e.g. (Seshamani and Gray, 2004b; Serup-Hansen et al., 2002; Häkkinen et al., 2008; Kildemoes et al., 2006)).

Although mortality models adhere to the postponement of morbidity hypothesis, recent evidence seems to support the compression hypothesis, although not unambiguously (Martin et al., 2010; Christensen et al., 2009). Evidence on health trends vary by country, and sometimes even within countries (Lafortune and Balestat, 2007; Mackenbach et al., 2008; Parker and Thorslund, 2007). Despite divergent results, the tendency seems to be that the number of years spent with a chronic disease is rising, whereas the time spent with (severe) disability remains constant or is shrinking (De Hollander et al., 2006; Parker and Thorslund, 2007). Population aging had therefore a significantly lower impact on future HCE in models that do account for disability instead of only age or mortality.

However, few projections of future HCE controlling for trends in disability have been made. Manton et al. (2006, 2007) investigated how the observed decline in disability among US elders between 1982 and 1999 affected future Medicare costs. Although their projections are outdated (2004 and 2009), the results are still worth mentioning, as they demonstrated that projections accounting for the recent disability decline approached the actual amount spend most accurately. For the 2009 projection, the annual growth of Medicare expenditures between 2004 and 2009 was estimated to be 9.80 percent based on a model that assumed stable disability prevalence and 6.49 percent based on a model with disability decline. De Meijer et al. (2011) demonstrated the importance of omitting important determinants by projecting homecare expenditures for the Dutch 50+ population between 2004 and 2040. Extrapolating recent declines in severe disability resulted in an estimated annual growth rate of 0.6 percent versus 2.1 percent for constant disability rates and 1.8 percent according a postponement of disability hypothesis (e.g. mortality model).

In conclusion, the discourse on the impact of aging on health expenditure has moved from age-based models towards more sophisticated analyses of TTD and most recently of disability. Since age is a predisposing determinant of HCE, it is not age as such that matters, but the (age-specific) prevalence of disease, disability and comorbidity in a certain year, or even over the whole life span. Predictions that account for mortality and morbidity generally result in significantly lower estimates of the effect of population aging. However, the impact of population aging differs between acute care and LTC. For acute care, differences in health can explain the age pattern of expenditures almost completely. In LTC, a strong age effect remains present. Still, annual HCE growth attributed to population aging is found to be up to 1%, which is far from trivial. Also, although health based models of HCE can better cope with the complex relationship between health and longevity, empirical evidence about this relationship is not decisive.

2.4 Societal determinants: national income, technology and wages

The analysis of the relationship between age and HCE in the previous section shows that population aging as such accounts for an annual real growth of HCE of 0.5-1.0 percent. As total annual real growth is around 4-5 percent, population aging is not the only important determinant of HCE growth (Burner et al., 1992; Reinhardt, 2003; Richardson and Robertson, 1999). Societal factors, such as national income growth, technological development, and rises in wages and prices, are at least equally important. However, as explained in the conceptual model, there might be strong interaction effects between population aging and these factors. In this section, we briefly discuss the main evidence on the role of income, medical technology, and wages and prices for HCE growth. We focus on research that explicitly takes into account interactions with population aging. Then, we turn to empirical evidence describing changes in the age-HCE relationship that can be caused by developments in these societal determinants.

2.4.1 Income

In general, income reflects the ability and willingness to pay for health (care). It is often assumed that health is a luxury good: when income grows, a larger share of it is spent on health care. Based on this reasoning, Hall and Jones (2007) predicted that HCE can rise to 33 percent of national income in the U.S. by the middle of the 21st century. However, empirical evidence on the role of income depends strongly on the level of analysis. In the framework of Figure 2.1 income appears twice: once as an individual enabling determinant, in the form of individual income, and once as a societal determinant, in the form of national income. On a national level, income growth is often found to be strongly positively correlated with HCE growth (Newhouse, 1977; Gerdtham et al., 1992; OECD, 2006; Van Elk et al., 2010). On the individual level, however, income is found to have a very small impact (Van Doorslaer et al., 2004; Getzen, 2000; Van Ourti, 2004). This apparent paradox can be resolved as follows: in the presence of health insurance, the marginal price of health care is typically (near) zero. Therefore, on individual level income differences do not play a large role in explaining differences in HCE among individuals belonging to the same group of insured (in many cases the total population). In contrast, collective or national income is a strong explanatory factor when explaining differences between groups (countries, insurance groups) where it does reflect a societal willingness to pay for health care (Getzen, 2000). In line with the conceptual model, we could say that the political willingness to pay and the societal ability to pay eventually largely accommodates the level of total HCE, whereas the distribution of collectively-financed care between individuals is determined mostly by individual determinants other than individual income.

The interaction between population aging and income growth is a complex one. First, there is a dual causal relationship between life expectancy and income. On the one hand, the rise in life expectancy during the last centuries has had a strong effect on income growth (e.g. (Fogel, 1997; Bloom et al., 2010)). For instance, Fogel (1997) estimated that approximately 30 percent of the economic growth in the UK during the last two centuries can be attributed to better nutrition and health. Therefore, the additional HCE caused by national income growth, are partially made possible by longevity gains in the past. On the other hand, health spending can have a positive effect on longevity and health. For long periods of time, the role of health care in decreasing mortality has been found to be small compared to other factors such as nutrition and public health measures (McKeown, 1976; Szreter, 1988). However, for recent decades a much stronger effect of health care on longevity has been found

(Bunker et al., 1994; Mackenbach, 1996; Cutler et al., 2006; Mackenbach et al., 2011). When increases in HCE indeed reflect an increasing willingness to pay for additional health, gains in life expectancy can partly be attributed to income growth. Second, given that the distribution of collectively financed health care is determined by individual need determinants, additional health care spending caused by income growth will largely be distributed towards older age groups. When this is the case, the age profile of HCE will steepen, and the effect of the increase in the number of older people will be reinforced. Third, as population aging will shift the demographic composition of the population towards the older age groups, one would expect that the societal value of health care aimed at those groups will increase. Indeed, Murphy and Topel (2006) have shown that "aggregate willingness to pay for progress against a particular disease will be highest when the age distribution of the population is near, but before, the typical onset of the disease". Therefore, the aging of the wealthy baby boom generation will likely raise the social value of treatments aimed at diseases at higher ages. This could again lead to a steepening of the age profile of HCE.

2.4.2 Medical technology

Although it is sometimes stated that development of new medical technology is a result of increasing willingness to pay for health, medical progress itself is often mentioned as the most important driver of HCE growth, in particular of acute expenditures (e.g. (Newhouse, 1992; Weisbrod, 1991)). In fact, technological progress has two contrasting effects on HCE: technological progress can mitigate expensive care and reduce costs, but tends to increase use (Cutler and McClellan, 2001; Cutler, 2007). Or, intuitively stated by Jones (2002): "Medical advances allow diseases to be cured today at a cost that could not be cured at any price in the past". In general, the second effect prevails resulting in a rise in total HCE (Bodenheimer, 2005). Although intuitively strong, direct evidence on the impact of technological progress is relatively scarce. For instance, Newhouse (1992) reached his conclusion about the importance of medical technology by eliminating other explanatory factors, not by direct evidence. In terms of cost effectiveness, medical spending (Cutler, 2007) and pharmaceuticals spending in particular (Civan and Koksal, 2010; Lichtenberg, 2007) generally seems to provide value for money, although budget impact and costs per additional life year vary substantially among new innovations (Goldman et al., 2005). Cost-effective innovations, however, generally raise HCE.

A number of studies have attempted to analyze the role of technological progress explicitly (Breyer and Ulrich, 2000; Dormont et al., 2006; Goldman et al., 2005; Jones, 2002; Okunade and Murthy, 2002; Suen, 2005; Westerhout, 2006). Using macro data for Western Germany for the period 1970-1995, Breyer and Ulrich (2000) estimated that technological progress increased per capita HCE by 0.8-1.4 percent annually. Suen (2005) showed for the US that the rising trend in HCE and the significant increase in life expectancy during the second half of the twentieth century can be explained by medical technological progress and higher incomes. Okunade and Murthy (2002) approximated medical progress by total R&D spending and health-specific R&D spending in the US, finding a significant effect on HCE for the period 1960-1997. Westerhout (2006) found an additional 0.6 percent annual growth in HCE due to medical progress. Dormont et al. (2006) examined the relative contributions of changes in demography, morbidity and health care practices to the HCE growth in France over the period 1992-2000. Their conclusion was that "changes in medical practices were the main driver in the increase in expenditures", especially for pharmaceutical expenditures.

The interaction between aging and medical technology is again firstly determined by the influence of technological progress on life expectancy. Moreover, new medical technologies will most likely be developed to improve current treatment or to treat currently not treatable diseases. Although there are examples of medical innovations aimed at age groups with relatively small health problems, older people are likely to disproportionally benefit from medical innovations. For instance, improved anaesthesiology and surgical techniques (e.g. angioplasty, laser and arthroscopic surgery) increased the probability of successful surgery resulting in additional patients (especially older people) becoming eligible for treatment (Polder et al., 2002). For the Netherlands, Wong et al. (2012) have investigated the effect of medical patents on age-specific hospital use. They find that the influence of innovations is largest at older ages. Goldman et al. (2005) use simulations to estimate the effects of ten key technologies, most likely to affect the health of older people positively in the future, on HCE in the US. They find that all of these innovations will lead to an increase in HCE. This finding is largely due to the life extending effect of most of these innovations, resulting in a shift of HCE to older age groups (Lubitz, 2005). That medical innovations are targeted more at older people also seems to be suggested by the fact that during the last few decades, life expectancy at age 65 grew faster than at other ages (Christensen et al., 2009).

2.4.3 Prices and wages

HCE growth is also determined by an increasing relative price of health care compared to other sectors in the economy, a phenomenon also known as Baumol's disease (Baumol, 1967). Health care tends to be relatively labour intensive and part of this labour cannot easily be substituted by technology, especially in LTC. As a result, labour productivity in health care tends to develop more slowly compared to other industries. Since health care workers earn an income comparable to that in other sectors, the relative price of health care increases. Okunade et al. (2004) have found an increase of relative prices of health care in OECD countries over most of the 1968-1997 period. Baumol's disease increased the price of health care, but also lowered the demand. Although study findings vary (Murillo et al., 1993; Murthy and Ukpolo, 1994; Okunade et al., 2004), it seems most likely that Baumol's disease leads to higher HCE and a somewhat smaller volume of health care use (Hartwig, 2008; Van Elk et al., 2010). The size of the Baumol effect on HCE approaches the magnitude of the contribution of population aging. The interaction between population and income and medical technology lies mostly in changes in health care use, but through wages population aging also influences the price of health care. The number of people in working age will decrease, while the number of people in need of care will increase. Population aging is expected to lead to serious labour shortages in health care, resulting in an upward pressure on wages in the health care sector (Dixon, 2003; Simoens et al., 2005).

2.4.4 Changes in the age profile of HCE

As the discussion in the previous paragraphs has shown, the influence of societal determinants is not age-neutral, and additional HCE is likely targeted at older age groups. As a result, the age-profile of HCE might steepen over time. Indeed, between 1963 and 1987 medical expenditures of older people in the US rose more quickly than expenditures for younger age groups (Meara et al., 2004). After 1987, however, HCE growth has been somewhat higher for adults than for older people (e.g. (Hartman et al., 2008; Meara et al., 2004)). This finding seems to be related to policy changes, especially in Medicare (Meara et al., 2004). For Germany, Buchner and Wasem (2006) have found a steepening of the age curve of HCE during the period 1979-1996. Dormont et al. (2006) demonstrate that HCE in France grew disproportionally for age 60+ during 1992-2000. For Switzerland, Felder and Werblow (2008) find that, after controlling for mortality changes, HCE has increased more strongly for age groups between 65 and 90 (Breyer et al., 2010).

In conclusion, although national income growth, technological development, and changes in the relative price of health care have a comparable or even a larger effect on HCE growth as population aging, all these societal determinants interact with individual determinants. As a result the age profile of HCE seems to be steepening over time.

2.5 Discussion and conclusion

2.5.1 Aging in perspective

In this paper we have tried to provide a first step towards a more integrated approach towards the effect of population aging on HCE growth. We have, first combined insights from health economics and epidemiology to gain insight into the individual relationship between aging and HCE, and second, discussed evidence on the interactions between population aging and the main societal determinants deemed to be responsible for HCE growth. We started out with two opposing views: population aging either is the main factor behind the rapid growth in HCE, or instead is largely irrelevant for this growth. What has our approach added to these views?

First, we have showed the value of explicitly considering health-related causes of the relationship between age and HCE. As discussed in the conceptual model, age is a predisposing determinant that is not directly responsible for utilization of health care. Instead, it is the relationship between age and need determinants such as health and disability that explain the age pattern of HCE. Predictions that account for health, either directly or by using mortality as a proxy, generally find that population aging only moderately contributes to the growth in HCE. The results therefore seem to support the second view. However, the effect of population aging is much stronger for LTC compared to cure. In fact, annual HCE growth attributed to population aging is found to be up to 1 %, which is far from trivial.

Second, in discussing the effect of societal determinants on HCE growth, we have found that the direct effect of population aging is modest in comparison to total HCE growth that amounts to 4-5 percent (Burner et al., 1992; Reinhardt, 2003; Richardson and Robertson, 1999). National income growth, medical technology, and price and wage rises are found to be the main drivers of HCE growth on the aggregated level. However, there is a strong and complex interaction between population aging and these determinants. Whereas the level of collective HCE is to a large extent driven by societal determinants, its distribution is largely determined by health and disability. Medical innovations and additional growth in HCE are therefore more often targeted at older people, reinforcing the effect of population aging. There is indeed evidence for a steepening of the age profile of HCE.

Instead of taking one of the two extreme positions, more shades of grey are needed in the aging debate. Population aging is certainly not the only major force behind HCE growth, its direct, and also indirect, effects are still of major importance. In the next two sections, we will discuss what further steps in an integrated approach could look like, and what policy lessons can be learned from our discussion.

2.5.2 Future research

Our discussion of the role of aging for HCE growth points towards two directions for future research. One is the improvement of models for individual health care use by including additional health information. The other is a further synthesis between micro research on individual determinants and macro research on societal determinants. As we have shown in Section 3, the inclusion of detailed information on health improves understanding of the relationship between age and HCE. The use of age or proxies of health, such as mortality, has sometimes been motivated by a lack of good information on health. However, more detailed data on health of the older population is becoming available. This data is often longitudinal and can be linked to other sources containing information on HCE. Therefore, for many countries it is now possible to analyse dynamics in health and expenditures over time. Challenges are combining large sets of different health indicators into measures that are relevant for HCE, and accurately dealing with prediction uncertainties due to diverging time trends between health indicators.

Although there is a distinction in purpose and methods between micro and macro studies of determinants of HCE, both types of studies can benefit from a further synthesis. On the micro side, an especially relevant issue is that most studies that project HCE, based on trends in mortality and need determinants, assume that these trends are exogenous. Longevity gains and improvements in morbidity and disability, however, may themselves be partly a result of HCE growth. This reversed relationship can lead to endogeneity issues. A first proxy of the effect of changes in aggregated HCE can be obtained by including calendar year dummies in micro models using more than one year of data. We discussed findings on changing age patterns of HCE over time, and in fact most studies do include these dummies. However, findings on calendar year effects are seldom explicitly discussed, and models that allow for interactions between these effects and health are scarce. For an even better understanding of the effect of macro level changes on individual health care use, researchers should try to make use of natural experiments caused by policy changes. For instance, Mackenbach et al. (2011) suggest that the rapid acceleration of Dutch life expectancy growth after 2001 is largely associated with a relaxation of health care budgets, resulting in higher health care use by the older population. If such changes in policy are used as quasi natural experiments, dual causal relationships between HCE and health can be identified.

On the macro side, models could also benefit from the inclusion of more detailed health information. Often, empirical macro models only include very crude proxies of health such as the share of people aged 65 and older. Studies that relate HCE growth to the increasing willingness to pay for health, due to income growth, often concentrate only on life expectancy (Hall and Jones, 2007; Breyer et al., 2010). Since part of HCE growth, especially in LTC, is aimed at improvements in health or functioning not directly related to extension of life, these studies do not fully capture the relationship between HCE and willingness to pay for health. As a result, interactions between population aging, underlying health, and societal determinants are not fully understood. Although age-specific data on health or quality of life over time might be harder to obtain than data on survival, the use of broader measures of health is therefore needed..

2.5.3 Policy implications

The discussion of the role of population aging has showed that population aging has an effect on future HCE growth, but that its direct effect is less dramatic than expected by some. However, policy makers should keep in mind the interaction between population aging, health, income growth, technological developments and wages/prices. Although HCE growth might reflect a collective willingness to pay for health, we have discussed evidence that increased HCE is to a relatively large extent beneficial to the older age groups, which are growing in relative size. In a collectively financed health care system, where a substantial part of health care premiums are paid by the working force population, this might strain intergenerational solidarity. Baicker and Skinner (2011) find that OECD countries with higher tax burdens in 1979 experienced slower HCE growth in subsequent decades. This observation seems to suggest that there are limits to what individuals are willing to pay for collectively financed health care. Depending on societal preferences for equality between individuals and generations, policy makers should therefore be selective in what kinds of health care they want to fund by public resources.

The findings on the relatively large role of age and disability for LTC expenditures suggest that prioritizing medical innovations aimed at improvement of quality of life and functioning over those aimed at postponement of death might be a promising approach to contain costs. (Medical) technology that allows people to remain living at home, even with chronic diseases, might lead to substantial savings in LTC. Additionally, improved functioning could improve labour participation at older ages, and increase the (health care) workforce.

2.5.4 Conclusion

HCE will continue to rise in the coming decades. Although the direct effect of population aging is modest, age and aging remain important factors in the debate on HCE growth. Many drivers of HCE growth - health, national income growth, technological progress, wages and prices - interact with population aging. Future HCE is likely to be targeted more towards the older population. If increases in HCE reflect an increasing willingness to pay for health and solidarity, HCE growth may not necessarily be a problem. However, the larger extents to which HCE will be used by older people, in combination with a financing system that distributes costs over the entire population, can strain intergenerational solidarity. Therefore, population aging will remain in the centre of policy debate and a more integrated approach of individual and societal determinants is warranted, in research as well as in policy-making.

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Chapter 3

The longitudinal relationship between baseline health and costs of hospital use

Abstract

In this paper, we investigate the relationship between baseline health and costs of hospital use over a period of eight years. We combine cross sectional survey data with information from the Dutch national hospital register. Four different indicators of health (self-perceived health, long-term impairments, ADL limitations and comorbidity) are considered. We find that for ages 50 to 70, differences in hospital costs between good health and bad health are substantial and persist during the whole time period. However, for higher ages expected hospital costs for individuals in bad health decline rapidly and become lower than those for people in good health after about six to seven years. The higher mortality rate among people in bad health is the primary cause here. Our results are confirmed for all four health indicators. We conclude that relying on better health to contain health care expenditures is too optimistic, and the interaction between health and mortality should be taken into account when projecting health care costs. Healthy ageing is important, but more for health gains than for cost savings.

Based on
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3.1 Introduction

The ageing of the population in most Western countries is an important issue in policy debate. The increase of the share of elderly in these countries, as a result of decreased fertility rates and increasing life expectancy, will put pressure on public finances. Health care use is highly correlated with age, therefore the budgetary effects of ageing are especially relevant in the health care sector. Because it has often been suggested that a part of the cost raising effects of ageing can be offset by an increase in general health, insight in the longitudinal relationship between health and costs of health care use is needed. The influence of health on costs of health care comprises two opposing components: better health is associated with lower costs per life year but also with additional costs associated with a higher remaining life expectancy. There is strong evidence of increasing trends in life expectancy, but the findings on trends in health and prevalence of chronic diseases are much less clear (Robine and Michel, 2004; Fries, 2005; Luepker, 2006; De Hollander et al., 2006; Mackenbach et al., 2008).

The influence of trends in health on costs of health care use are assessed in a number of studies (Singer and Manton, 1998; Westerhout and Pellikaan, 2005; Manton et al., 2007; Goldman et al., 2008). However, the relationship between health status, mortality and costs of health care use is seldom directly taken into account. Lubitz et al. (2003) do estimate this relationship using multistate lifetable techniques. They find that at 70 years of age, individuals with limitations in activities of daily living have a considerably lower life expectancy than individuals in good health, but the cumulative health care expenditures over their remaining life are almost equal. This result seems to indicate that better health will not necessarily lead to lower cost of health care use. Instead, the role of a longer life expectancy and postponement of costs to a later age may be more important.

This paper investigates the longitudinal relationship between health status and costs of hospital use in the Netherlands. We aim to provide the following contributions: First, we investigate the relationship between health and costs of hospital use over a time period of eight years. We use survival analysis to relate initial health status to costs of hospital use in following yearly periods. In contrast, Lubitz et al. (2003) and Goldman et al. (2008) first relate costs of hospital use to current health status and then use Markov techniques to model transitions in health state. By directly estimating costs as a function of initial health we avoid the possibly restrictive Markov assumption of duration independent transitions. There is evidence that the probability of returning to good health is smaller if the time spent in bad health is longer, and that transitions in health are indeed not independent of duration (Crimmins et al., 1994; Burchardt, 2000; Cai et al., 2006).

Second, we look at the relationship between health status and hospital costs for different age groups of people older than 50. Lubitz et al. (2003) focus on health care expenditures for individuals at the age of seventy, but cost differences between health states at other ages might well show different results. The effect of initial health on mortality and hospital use, especially over a longer period of time, can be age- and sex-dependent. For example, at higher ages initial health state might be less informative of future hospital costs, because the probability of becoming less healthy is higher than at lower ages.

Third, we estimate the relationship between health and hospital costs for different indicators of health (self-perceived health, long-term impairments, ADL and co-morbidity). The relationship between health and costs may depend on the chosen measure. For instance, Cesari et al. (2008) find differences in performance between physical functioning and self-rated health in predicting mortality. The differences between indicators could also be age- and sex-specific and duration dependent.

We use eight years of Dutch cross sectional health survey data and link this data to the Dutch National Medical Registration and the Causes of Death Statistics over the same period. This linkage allows us to estimate the relationship between health status and hospital use and mortality over a maximum period of eight years. We use a three-part model, modeling the probability of survival, the conditional probability of hospital use and the conditional costs of hospital use separately. Although there are a number of studies that use two- or three-part models for (semi-) continuous data, for example (Olsen and Schafer, 2001; Tian and Huang, 2007; Liu, 2009), to our knowledge this is the first implementation of such a model in a discrete survival context.

3.2 Methods

3.2.1 Three part model

We want to relate health status and background characteristics of an individual at a certain time t_0 to costs of hospital use in the following consecutive yearly periods after t_0. Let $h_{i,k}$ be the total costs of hospital care use of individual i during period $t_k \leq t < t_{k+1}$, where $k = 0, 1, .., K$ coincides with yearly time intervals. To relate $h_{i,k}$ to survival probability and health status, we start from a two part model (Duan et al., 1983) in which the probability of hospital use is modeled separately from the conditional costs of hospital use. This two part model is extended with an additional part, modeling the probability of survival up to time t_k. This modeling strategy is used for two reasons: First, it allows us to separately identify the relationship between health and survival, health and probability of hospital use, and health and costs of hospital use. Second, modeling the probability of hospital use and costs of hospital use separately accounts for excess zeros: the number of people not using any hospital care during a particular year is so large that the observed number of zeros is many times higher than is consistent with, for example, a Poisson distribution.

The aim of our study is to estimate the overall influence of differences in health status on longitudinal hospital costs. Therefore we use a marginal modeling framework (Lu et al., 2004) for the three part model. The resulting estimates provide population averaged effects, in the sense that they show the average difference in hospital costs between individuals in different health states. This is often the relevant viewpoint from a policy or societal perspective (Liu et al., 2010). It can be expected, for example based on the well known relationship between time to death and health care expenditures, that the different parts of the three part model are correlated. The use of the marginal model implies that we do not model that correlation. An alternative model specification, which does take this inter-part correlation into account, would be a random effects model with correlated random effects between the different parts, for example applied by Liu (2009). As noted by Albert (2005) the marginal model and the correlated random effects model can yield different parameter estimates, when correlation between the parts indeed exists. Which model is correct again depends on the aim of the study. For example, the marginal model estimates of the third part of our three part model for period k, are estimates of the influence of health status on the conditional hospital costs for the individuals who actually went to the hospital in period k. Instead, the random effects estimates provide the effect of health status on conditional expenditures for an average individual from the total population. In accordance with the societal perspective of our study, the marginal model seems justified. For the same reason, we opt for the two-part model framework instead of a heckit model, because we consider the zeros to be actual outcomes and not censored "potential" outcomes. As argued by Dow and Norton (2003), such an independent two-part model is often more appropriate for estimating real outcomes than inflated zero- or heckit models.

In the data, survival is observed in discrete time intervals. Therefore, we apply a discrete survival analysis approach to the three part model. The first part of the model concerns the probability of being alive at time t_k. Let T_i be the duration of the time an individual is alive, then we use the following discrete-time transition model (Cameron and Trivedi, 2006) for the probability of being alive up to time t_k:

$$P(T_i \geq t_k | T_i \geq t_{k-1}, x_{i,t_k}) = F_1(x'_{i,t_k}\beta_{t_k}). \tag{3.1}$$

For F_1, we use the logistic cumulative density function. We condition the probability of being alive at t_k on being alive at time t_{k-1}, which means that we model the probability of surviving during period $t_{k-1} \leq t < t_k$. The parameters as well as the x vectors have time subscript. This time dependence is discussed in Section 3.2.3. Equation (3.1) can be estimated by using a stacked data design: separate observations are constructed for each discrete time period during which individual i is alive and one observation for the period in which he or she dies. A dummy variable is added, indicating whether individual i stays alive or dies during the period under consideration.

We formulate the second part of the model, the probability of hospital use, as

$$P(h_{i,k} > 0 | T_i \geq t_k, x_{i,t_k}) = F_2(x'_{i,t_k}\beta_{t_k}). \tag{3.2}$$

The probability of hospital use during $t_k \leq t < t_{k+1}$ is expressed conditional on being alive up to time t_k. For F_2 we again use the logistic cdf. The third part of the model is the expected hospital use given any hospital use in period k. For this part, a generalized linear model is used:

$$E(h_{i,k}|h_{i,k} > 0, x_{i,t_k}) = g(x'_{i,t_k}\beta_{t_k}). \tag{3.3}$$

The function $g(.)$ links the linear relationship between the covariates $x'_{i,t_k}\beta_{t_k}$ to expected hospital use. The choice of this link function is discussed in Section 3.2.2.

The three parts of the model can be combined to get the unconditional expectation of costs of hospital use in period $t_k \leq t < t_{k+1}$:

$$E(h_{i,k}|x_{i,t_k}) = E(h_{i,k}|h_{i,k} > 0, x_{i,t_k}) \times P(h_{i,k} > 0|T_i \geq t_k, x_{i,t_k}) \times S_i(t_k, x_{i,t_k}). \tag{3.4}$$

$S_i(t_k|x_i)$ is the survival function, the probability of surviving up to time t_k. This survival function is constructed by multiplying the probabilities from Equation (3.1) for $t = 0, 1, .., t_k$ to get

$$S_i(t_k|x_{i,t_k}) = \prod_{j=1}^{k} P(T_i \geq t_j|T_i \geq t_{j-1}, x_{i,t_j}). \tag{3.5}$$

Expected cumulative costs over longer discrete periods of time can be calculated by summing over the yearly periods. Let $H_{i,k}$ be the cumulative costs over the period 1 to k, then

$$E(H_{i,k}|x_{i,t_k}) = \sum_{j=0}^{k} E(h_{i,k}|x_{i,t_k}). \tag{3.6}$$

To obtain confidence intervals for predicted survival, probability of hospital use, conditional- and unconditional costs of hospital use, we use bootstrapping. To preserve the correlation between longitudinal observations of the same individuals, we perform the bootstrap procedure with clustering observations on an individual level. The models for each indicator and their three separate parts are all estimated within the same sample. We use 1000 bootstrap runs.

3.2.2 Choosing the functional form

The third part of our model, concerning the conditional costs of hospital care in period k, is formulated as a generalized linear model (GLM). The reason for this formulation, is that we expect the data to have thick right tails. Instead of log transforming the data, the GLM approach avoids transformation issues by directly modeling $E(y)$ as a possibly non linear function of x. For notational convenience, let

$y_{i,t_k} \equiv E(h_{i,k})|(h_{i,k} > 0, T_i \geq t_k)$ and $g^* = g^{-1}$ so that we can rewrite Equation (3.3) as

$$g^*(y_{i,t_k}|x_{i,t_k}) = x'_{i,t_k}\beta_{t_k}. \tag{3.7}$$

The GLM approach requires the choice of the link function $g^*(.)$ as well as a function for the variance of y_i. The link function determines the transformation of y_{i,t_k}. For example, the log-link models a linear relationship between $\log(y_{i,t_k})$ and $x'_{i,t_k}\beta_{t_k}$:

$$g^*(y_{i,t_k}|x_{i,t_k}) = \log(y_{i,t_k}|x_{i,t_k}) = x'_{i,t_k}\beta_{t_k}. \tag{3.8}$$

To determine the appropriate link function, we use a Box-Cox test. We limit our choice of variance functions to the class of power-proportional variance functions, which describe the relationship between $Var(y_i)$ and the mean as

$$Var(y_{i,t_k}) = y^m_{i,t_k}, \tag{3.9}$$

where m is an integer. Different values of m coincide with well known functional forms: For example, $m = 1$ is equivalent to a Poisson distribution and $m = 2$ is equivalent to a Gamma distribution. We use the modified Park test described by Manning and Mullahy (2001) to determine m.

3.2.3 Duration dependence

The formulation of the three part model allows for time varying covariates as well as parameters. In case of the covariates, we use the values at time t_0. The reason for keeping the values at their initial level, is that the model is forward looking or predictive: it estimates expected costs of hospital use in following periods based on information on current health status. We do correct for calendar year effects, caused by changes in budget constraints imposed by the government and other autonomous influences, by including calendar year dummies.

The effect of the health variables is allowed to change over time, by using duration dependent parameters. The parameters of the other background variables are kept constant. In regard to the time dependence of the covariates and the parameters, the x-vector can be split up into three parts

$$x_{i,t_k}\beta_{t_k} = x^{a'}_{i,t_0}\beta^a_{t_k} + x^{b'}_{i,t_0}\beta^b + x^{c'}_{t_k}\beta^c, \tag{3.10}$$

where the covariates x^a have time varying parameters $\beta^a_{t_k}$ and x^b have constant parameters β^b_{i,t_0}. The vector $x^c_{t_k}$ consists of the calendar year dummies.

The duration dependence of $\beta^a_{t_k}$ can be introduced by using a separate coefficient for each period. However, this would drastically increase the number of parameters in the models. To keep the model more parsimonious, we model duration dependence as an n-th order polynomial:

$$x'_{i,t_0}\beta_{t_k} = x'_{i,t_0}\beta_0 + \sum_{j=1}^{n} x'_{i,t_0}\beta_j k^j. \tag{3.11}$$

The order of the polynomial n is determined by assessment of model fit, based on AIC and BIC values and Likelihood Ratio tests. Because a stacked dataset is used, in which a separate individual observation is available for each period k, the inclusion of time dependent parameters is straightforward.

3.3 Data

3.3.1 General description of the data

The data used in this research is part of the Social Statistics Database (SSB) [1] of Statistics Netherlands (CBS). The SSB consists of a collection of several independent surveys and registrations. At the core of the SSB is the Municipal Population Registration (GBA), which contains basic information like date of birth and registered partners for everyone enlisted in a Dutch municipality. Databases which are part of the SSB, can be linked to the GBA by means of an anonymized identification key. Using this key, it is possible to link information from different sources at an individual level. We use three data sources from the SSB: the Statistics Netherlands Integrated System of Social Surveys (POLS), the Dutch Causes of Death Statistics (DO) and the Dutch Hospital Discharge Register (LMR). The POLS survey consists of a basic survey and several modules, which cover a specific subject in more detail for different parts of the total POLS population. One of these modules is the POLS health survey. This health survey is a representative sample survey containing detailed information on health and health care use for approximately 10,000 individuals per year. We use the survey years 1997-2005. The Causes of Death Statistics is a register covering all deaths in the Netherlands. The Dutch Hospital Discharge Register (LMR) is provided by the Prismant health care services institute. All university and general hospitals and most specialized hospitals participate in the LMR. Therefore, the dataset provides a nearly complete coverage of all hospital inpatient treatments in the Netherlands. All clinical and day admissions are registered based on a uniform registration system. The data include admission and discharge dates, and extensive treatment and diagnosis information on ICD-9 level.

We construct our dataset by linking a particular POLS health survey year to consecutive years of the DO and LMR registers up to 2005. Linkage of POLS to the Causes of Death Statistics and LMR enables us to estimate mortality and hospital use

[1] http://www.cbs.nl/nl-NL/menu/informatie/onderzoekers/ssb/ssb-info-medio-07.htm

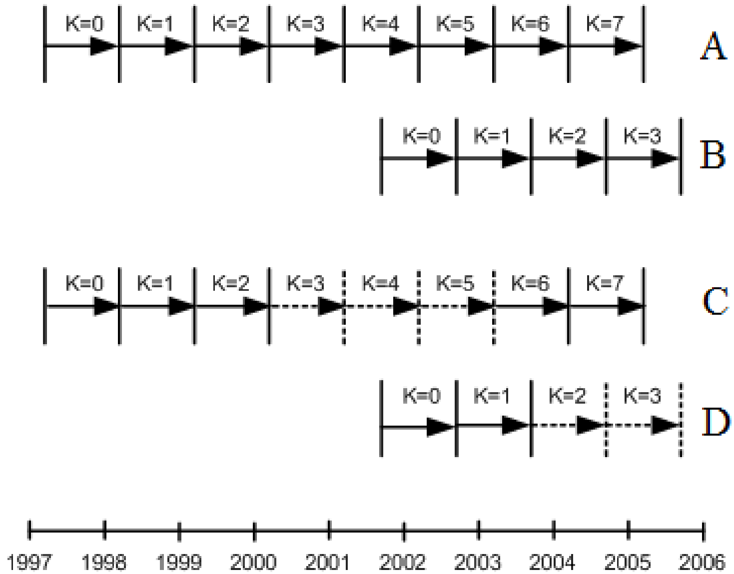

Figure 3.1: An illustration of the design of the data. Period k is defined as the kth year after the interview date. The two upper cases concern two individuals A and B. A is interviewed in POLS in January 1997 and his hospital use can therefore be observed for eight yearly periods, $k = 0, .., 7$. B is interviewed in June 2001, and his hospital use can be observed over four yearly periods $k = 0, ..3$. The two lower cases concern individuals C and D who's hospital use is censored during a part of the observation period.

for the POLS population in the years following the survey. For an individual from the 1997 survey, we can follow hospital use and mortality over a maximum of nine years (1997-2005). However, for an individual from the 2005 survey, we can follow hospital use and mortality over a maximum of only one year. We define a period k as the $k - 1$th year after the month an individual is interviewed in the POLS health survey. The POLS survey is organized in such a way that interview dates are equally spread over all months. Because we use yearly periods, only a small number of individuals can be followed over nine years (only the individuals interviewed in January 1997). Therefore, we restrict our analysis to a maximum period of eight years. The way in which a period is defined is illustrated in Figure 3.1: the upper line shows individual A who is interviewed in February 1997 and who's hospital use can therefore be followed over eight yearly periods. As shown, the periods k generally do not coincide with calendar years. The second line in Figure 3.1 shows individual B who is interviewed in October 2001 and can therefore be tracked over four periods.

The LMR records do not contain a unique personal identification key which would enable direct linkage to the POLS surveys. Instead, Statistics Netherlands provides a constructed identification key. This key is based on a linkage of records in the LMR to the Municipal Population Registration (GBA) by postal code, date of birth, gender and admission date. About 15 percent of the POLS population cannot be uniquely identified by this procedure. Because of removal to an area with another postal code or changing characteristics, identifiability can change over time. Individuals are only included in the estimation over the periods in which they are uniquely linkable. The procedure is illustrated by individuals C and D in the lower part of Figure 3.1. The two individuals are the same as for the lines on top, only they cannot be uniquely linked in all periods (indicated by the dotted lines).

Table 3.1 provides an overview of the population of the combined dataset for each period. The population is categorized according to age and health status for the four indicators of health that are use in our subsequent analysis (Section 3.3.4). Age groups below 50 are not included in the table, because not all indicators of health are available for those groups. The number of people in each category is reported as well as the percentage of uniquely linkable individuals (in brackets). The probability of being uniquely linkable seems to increase with age, while the probability is rather stable over periods and between health states.

3.3.2 Censoring bias

Because of the different interview dates and the linkage procedure a part of the data is censored: the hospital use of most individuals cannot be observed over the full evaluation period (eight years). If this censoring is not independent of hospital use, at least conditional on the x variables in the three part model, it may lead to biased estimates. It has often been argued that in modeling medical cost data this independence assumption does not hold (Lin, 2003; Başer et al., 2006). The argument is that individuals who survive during the whole evaluation period are at risk of being censored during a longer period of time than individuals who die during the evaluation period. Because hospital costs are known to be higher for deceased than for survivors (Zweifel et al., 1999), ignoring this difference may bias cost estimates upward.

The first cause of censoring, the different interview dates, does not lead to estimation bias. As illustrated by Figure 3.1, individuals are only included for the yearly time intervals that end before 2006. For example, if individual B would die in November 2005, his observation for $k = 4$ would not be included. Since censoring in this case is determined only by interview date, it is random and therefore does not influence the estimates. In contrast, the linkage procedure could lead to estimation bias: individuals who die during a period $t_k \leq t < t_{k+1}$ have a higher probability of being linked to the LMR than individuals who survive up to time t_{k+1}. The probability of unique linkage is known to depend on characteristics like age, income and ethnicity (De Bruin et al., 2003), but because the model includes socioeconomic background variables this is not a problem. However, it is not unlikely that the probability of linkage is also

Table 3.1: Overview of the population of the POLS health surveys, according to age, period and health state (1 = best, 3 = worst), for four health indicators. The numbers between brackets indicate the percentage of people which can be linked to the Dutch hospital register.

period		0			1			2			3			4			5			6			7	
health	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
perceived health status																								
50-60	1387	4279	2512	1187	3629	2135	983	3010	1775	820	2487	1487	657	1966	1210	498	1433	877	340	921	561	180	493	293
	(0.85)	(0.86)	(0.87)	(0.86)	(0.86)	(0.87)	(0.86)	(0.86)	(0.87)	(0.87)	(0.86)	(0.88)	(0.87)	(0.87)	(0.89)	(0.88)	(0.87)	(0.90)	(0.89)	(0.89)	(0.91)	(0.90)	(0.89)	(0.93)
60-70	908	3143	2079	788	2712	1792	648	2279	1508	523	1901	1242	421	1531	1026	310	1156	791	204	785	538	104	421	312
	(0.91)	(0.91)	(0.89)	(0.91)	(0.90)	(0.89)	(0.91)	(0.92)	(0.89)	(0.90)	(0.92)	(0.90)	(0.91)	(0.92)	(0.91)	(0.91)	(0.92)	(0.91)	(0.90)	(0.93)	(0.91)	(0.89)	(0.95)	(0.90)
70-80	418	1920	2036	364	1637	1717	303	1346	1444	241	1109	1222	199	870	957	151	660	722	101	446	481	49	229	273
	(0.92)	(0.92)	(0.91)	(0.92)	(0.92)	(0.91)	(0.91)	(0.92)	(0.92)	(0.92)	(0.92)	(0.92)	(0.90)	(0.93)	(0.93)	(0.90)	(0.94)	(0.94)	(0.92)	(0.94)	(0.95)	(0.89)	(0.96)	(0.95)
>80	119	614	735	99	528	613	78	436	525	64	352	447	53	279	353	38	207	258	34	134	170	20	74	85
	(0.96)	(0.94)	(0.96)	(0.96)	(0.95)	(0.96)	(0.96)	(0.96)	(0.97)	(0.98)	(0.98)	(0.97)	(0.96)	(0.99)	(0.98)	(0.97)	(0.97)	(1.00)	(0.97)	(0.98)	(1.00)	(0.91)	(0.97)	(1.00)
long-term impairments																								
50-60	3586	1989	1140	3029	1660	953	2470	1387	755	2041	1176	643	1599	944	521	1202	696	382	798	447	244	421	227	140
	(0.86)	(0.86)	(0.87)	(0.86)	(0.85)	(0.87)	(0.86)	(0.86)	(0.87)	(0.87)	(0.88)	(0.88)	(0.87)	(0.88)	(0.89)	(0.88)	(0.88)	(0.88)	(0.90)	(0.89)	(0.88)	(0.91)	(0.90)	(0.93)
60-70	2351	1715	961	2004	1469	827	1644	1235	688	1344	1038	579	1059	859	478	816	649	369	572	430	249	316	219	141
	(0.91)	(0.90)	(0.90)	(0.91)	(0.90)	(0.89)	(0.92)	(0.90)	(0.90)	(0.92)	(0.91)	(0.90)	(0.92)	(0.92)	(0.90)	(0.93)	(0.92)	(0.89)	(0.93)	(0.93)	(0.88)	(0.94)	(0.92)	(0.88)
70-80	926	1200	1108	780	1018	919	646	826	758	531	680	645	412	541	505	316	413	393	216	285	262	110	153	135
	(0.92)	(0.92)	(0.90)	(0.92)	(0.92)	(0.90)	(0.92)	(0.92)	(0.90)	(0.92)	(0.92)	(0.92)	(0.92)	(0.92)	(0.93)	(0.92)	(0.93)	(0.94)	(0.93)	(0.94)	(0.94)	(0.94)	(0.96)	(0.92)
>80	121	264	516	104	224	410	85	177	339	69	147	283	53	117	225	41	84	166	29	58	112	19	28	66
	(0.94)	(0.95)	(0.96)	(0.94)	(0.97)	(0.96)	(0.96)	(0.98)	(0.95)	(0.96)	(0.99)	(0.98)	(0.95)	(0.98)	(0.99)	(0.98)	(0.97)	(0.99)	(0.97)	(0.97)	(1.00)	(0.90)	(0.93)	(1.00)
ADL																								
50-60	3714	628	240	3145	526	204	2574	431	163	2134	348	131	1732	280	100	1292	193	77	847	127	50	454	79	28
	(0.87)	(0.87)	(0.89)	(0.87)	(0.86)	(0.88)	(0.87)	(0.87)	(0.90)	(0.88)	(0.89)	(0.90)	(0.89)	(0.91)	(0.88)	(0.89)	(0.91)	(0.90)	(0.91)	(0.92)	(0.91)	(0.92)	(0.93)	(0.90)
60-70	4608	1024	489	3972	901	411	3333	743	351	2755	616	289	2253	487	234	1719	353	181	1164	234	128	627	133	77
	(0.91)	(0.90)	(0.88)	(0.90)	(0.90)	(0.88)	(0.91)	(0.90)	(0.90)	(0.91)	(0.89)	(0.89)	(0.92)	(0.90)	(0.91)	(0.92)	(0.90)	(0.91)	(0.93)	(0.90)	(0.89)	(0.94)	(0.89)	(0.87)
70-80	2435	1095	835	2083	935	694	1734	772	583	1443	637	489	1147	499	377	874	370	286	607	226	193	308	129	113
	(0.92)	(0.91)	(0.90)	(0.92)	(0.91)	(0.90)	(0.92)	(0.92)	(0.91)	(0.92)	(0.93)	(0.92)	(0.92)	(0.93)	(0.93)	(0.93)	(0.93)	(0.93)	(0.94)	(0.94)	(0.95)	(0.95)	(0.95)	(0.94)
>80	480	428	545	411	358	460	335	305	391	283	250	325	220	197	265	160	143	197	115	86	135	65	44	69
	(0.96)	(0.94)	(0.95)	(0.97)	(0.94)	(0.96)	(0.97)	(0.96)	(0.96)	(0.99)	(0.97)	(0.97)	(0.99)	(0.97)	(0.98)	(0.99)	(0.97)	(0.99)	(0.97)	(1.00)	(1.00)	(0.94)	(1.00)	(1.00)
Comorbidity																								
50-60	3304	2007	1368	2789	1696	1112	2295	1387	875	1937	1153	696	1531	904	539	1165	667	379	770	421	249	400	233	142
	(0.85)	(0.87)	(0.87)	(0.85)	(0.87)	(0.87)	(0.85)	(0.88)	(0.88)	(0.86)	(0.88)	(0.88)	(0.86)	(0.89)	(0.89)	(0.87)	(0.89)	(0.90)	(0.88)	(0.90)	(0.89)	(0.89)	(0.91)	(0.93)
60-70	2174	1530	1247	1868	1301	1027	1552	1085	819	1292	870	666	1038	699	517	777	535	410	519	367	286	282	217	160
	(0.90)	(0.91)	(0.89)	(0.90)	(0.91)	(0.89)	(0.91)	(0.92)	(0.89)	(0.91)	(0.91)	(0.89)	(0.92)	(0.92)	(0.90)	(0.92)	(0.93)	(0.90)	(0.92)	(0.93)	(0.91)	(0.92)	(0.94)	(0.90)
70-80	1065	1006	1103	918	849	878	761	688	693	622	560	560	490	430	411	384	325	316	271	222	208	132	124	118
	(0.92)	(0.92)	(0.91)	(0.92)	(0.93)	(0.92)	(0.92)	(0.93)	(0.92)	(0.91)	(0.93)	(0.93)	(0.92)	(0.93)	(0.92)	(0.92)	(0.95)	(0.93)	(0.93)	(0.94)	(0.93)	(0.94)	(0.95)	(0.94)
>80	275	276	318	228	229	248	187	189	188	162	149	149	125	114	116	94	80	88	65	61	54	35	37	30
	(0.96)	(0.96)	(0.96)	(0.97)	(0.96)	(0.96)	(0.96)	(0.97)	(0.97)	(0.97)	(0.99)	(0.97)	(0.96)	(0.97)	(1.00)	(0.97)	(0.99)	(1.00)	(0.97)	(1.00)	(1.00)	(0.95)	(0.97)	(1.00)

dependent on survival probability. Therefore, we test whether individuals who die during period k have a higher probability of being uniquely linked than survivors.

3.3.3 Assigning costs

Costs per admission are not supplied in the dataset, but are calculated by using data from the Dutch Costs of Illness Study (Slobbe et al., 2006). In this so-called general cost of illness study, total health care expenditure are assigned to diseases and patient characteristics. For hospital expenditure a combined top-down and bottom-up approach is used. Total hospital expenditure is known from national health accounts and can be broken down to inpatient and ambulatory care respectively, using data from the Dutch hospital budget system. In this paper we focus on inpatient care including all clinical procedures and day cases, comprising 60% of total hospital expenditure. Costs per admission are split up into two parts: intervention costs and all other costs associated with hospital stay. Since all interventions are registered in the LMR in ICD-9 format, intervention costs per patient can be calculated using the detailed remuneration schemes of the Dutch hospital payment system. This scheme provides for each intervention all relevant doctor's fees and the hospital's reimbursement for associated costs of, among others, equipment, materials and personnel. All other costs of hospital stay, like nursing and accommodation costs, are calculated on a daily basis, using average per diem costs. Costs are aggregated per admission.

3.3.4 Indicators of health

We use four different measures of health status: self perceived health status, long term impairments, limitations in Activities of Daily Living (ADL), and comorbidity. For each measure we construct an indicator with three levels based on associated questions in POLS. The indicator for self-perceived health status is based on one question in which individuals are asked to describe their own health in terms of five answer categories. However, in 2001 the definition of the answer categories has been changed. This change causes a break in the trends for the lowest three categories. Therefore, we combine the lowest three categories into one new category which does not show a trend break (Botterweck et al., 2003). The classification of long-term impairments is based on parts of an OECD questionnaire included in the POLS survey. The questions and constructed indicators for each measure are reported in Table 3.2.

3.4 Results

The three part model for the relationship between health and costs of hospital use is estimated for each indicator of health separately. The same set of explanatory variables

Table 3.2: Indicators of health in POLS: questions, answers and elements of the constructed categories used.

Measure	Questions	Answers	Levels
Self perceived health	How would you describe your own health?	very good	1 very good
		good	2 good
		less than good	3 less than good
Long term impairments	Can you		
	follow a conversation in a group of 3 or more persons?	yes, without difficulty	1 yes, without difficulty
	have a conversation with one person?	with minor difficulty	2 at least one minor difficulty
	read the small print in the newspaper?	with major difficulty	3 at least one major difficulty
	recognize a face at a distance of four meters?	unable to do	
	carry an object of 5 kilograms for 10 meters?		
	bend down and pick up something from the floor?		
	walk 400 meters without resting?		
ADL Limitations	Can you		
	eat and drink?	yes, without difficulty	1 yes, without difficulty
	get up from a sitting position?	with minor difficulty	2 at least one minor difficulty
	get in- and out of bed?	with major difficulty	3 at least one major difficulty
	dres and undress?	only with aid	
	transfer to another room on the same floor?		
	climb up and down the stairs?		
	enter and leave the house?		
	transfer outdoors?		
	wash face and hands?		
	bath?		
Comorbidity	Occurrence in the last 12 months		1 no disease
	asthma		2 one disease
	diabetes		3 more than one disease
	rheumatism		
	migraine		
	high blood pressure		
	cancer		
	stroke		
	back disorder		
	heart disorder		
	intestines disorder		
	arthrosis		

is used for all indicators and for each part of the three part model. The relationship between sex, age and health is introduced as a threeway interaction effect, using dummies for each threeway category. The parameters of this threeway interactions are duration dependent. The other included covariates are a series of calendar year dummies and a series of dummy variables for highest attained education level. A dummy variable for ethnicity was dropped, due to a lack of significance. A logit model, including the same set of variables as the three part model and a dummy for dying, has been used to test whether linkage to the hospital register during a certain period depends on surviving that period. No significant effect of survival on linkage probability has been found. Therefore, we decide not to use correction weights in the three part models.

Results from the Box-Cox test for different specifications of the model indicate that the log-link provides the best fit to the data. To determine the functional form of the third part, the GLM model for conditional costs of hospital use, we perform the modified Park test. The test indicates a quadratic relationship between mean and variance, equivalent to the Gamma family, for all indicators of health. Assessments of fit based on AIC and BIC criteria and likelihood ratio tests show a better fit for the models with linear duration dependence than constant duration dependence. The results are less clear on the choice between linear and quadratic duration dependence. Especially in the first part of the model, a quadratic duration dependence seems to provide a somewhat better fit than linear dependence. To keep the models parsimonious and comparable, between parts and between indicators of health, we use linear duration dependence for all models. The regression results for each health indicator, including the values of the information criteria and the LR tests, are reported in Appendix 3.A Tables 3.4-3.7. In each table, the coefficients and p-values for all three parts of the model are shown. The threeway dummies have two coefficients: one for the time constant, or baseline effect, and one for the time varying effect. For age, we use ten-year groups from 50 onwards.

We use the estimated parameters in Tables 3.4-3.7 to make predictions of survival, probability of hospital use, conditional- and unconditional costs of hospital use. Separate predictions are made for each combination of sex, age and health, while keeping the other background variables at their baseline level (education level is low and evaluation year is 1997). Figures 3.2-3.5 show the predictions and bootstrapped 95% confidence intervals for self perceived health status. Figure 3.2 shows the survival up to period k, which is constructed by multiplying the survival probabilities for each period up to k as described in Equation (3.5). Survival is consistently lower for individuals in bad health compared to individuals with the same age and sex in good health. The graphs also show a negative correlation between age and survival, and lower survival for men than for women with the same age and health.

The predicted probability of hospital use in period k conditional on being alive at the start of period k is shown in Figure 3.3. The probability of hospital use in the first period increases with worsening health state. The initial probability of hospital use also show a correlation with age, but the sex differences are limited. Considering the time patterns, the differences in probability of hospital use seem to be rather constant over time for the age group 50-60 and 60-70. For the two oldest age groups, there is convergence in probability of hospital use over time. For men older than 80 and women older than 70, the probability of hospital use given initial bad perceived health declines over time, whereas the probability of hospital use given excellent health between 70-80 increases.

The costs of hospital use conditional of having any hospital use in period k, displayed in Figure 3.4, are higher for individuals with bad perceived health than individuals in good perceived health. For bad health in the young age groups, the conditional costs of hospital use show a sharp increase over time. At higher ages, the differences again show some convergence over time.

Multiplying survival, probability of use and conditional costs of hospital use as in Equation (3.4), yields the unconditional predictions of hospital use for each period k in Figure 3.5. Here, it appears that the levels of expected hospital use in the first period increase with age, but the relative differences between bad health and good health remain relatively stable. At lower ages the differences in expected hospital use are quite persistent over time. At higher ages, the expected hospital use for individuals in bad health decreases over time whereas the hospital use for individuals in good and excellent health remains stable or even increases. As a result, for the highest male age group the expected hospital use is higher for individuals in excellent health than individuals in bad health in six and seven years after measurement of health.

For the other three indicators, being long-term limitations, limitations in activities in daily living and comorbidity, we only show the unconditional predictions in Figures 3.6, 3.7 and 3.8. The same general patterns seem to occur for all indicators: For younger age groups, differences in costs between good and bad health are relatively stable over time. For older age groups, the expected costs of individuals in bad and in good health converge over time. In case of major long-term impairments, shown in Figure 3.6, this convergence is already visible for men between 60 and 70. In contrast, for women this convergence only occurs for the oldest age group. The costs of men between 50 and 60 with major ADL limitations (Figure 3.7) show an increasing time pattern, whereas the costs for women with the same age show a declining pattern. The high uncertainty surrounding the prediction for men could suggest an outlier effect. For the other age groups, the initial differences between no impairments and major impairments are larger for men than for women. The expected costs of individuals with major impairments in the two oldest age groups are lower than the costs of individuals without initial impairments, after six to seven years. The costs of hospital use for comorbidity, in Figure 3.8, again show the same converging pattern over time for the oldest age group.

The expected costs over all eight periods (cumulative costs) are shown in Figure 3.9. For the age groups 50-60 and 60-70, the cumulative costs rise with worsening

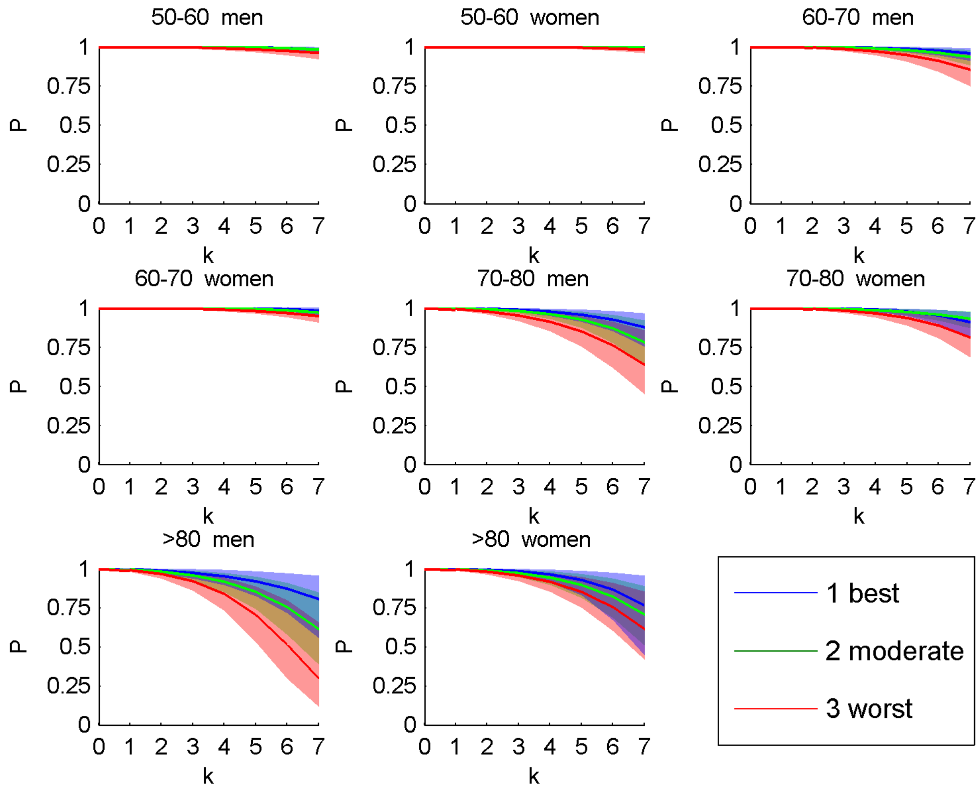

Figure 3.2: Part 1 for perceived health status: predicted probability of being alive in period p and bootstrapped 95% confidence intervals, .

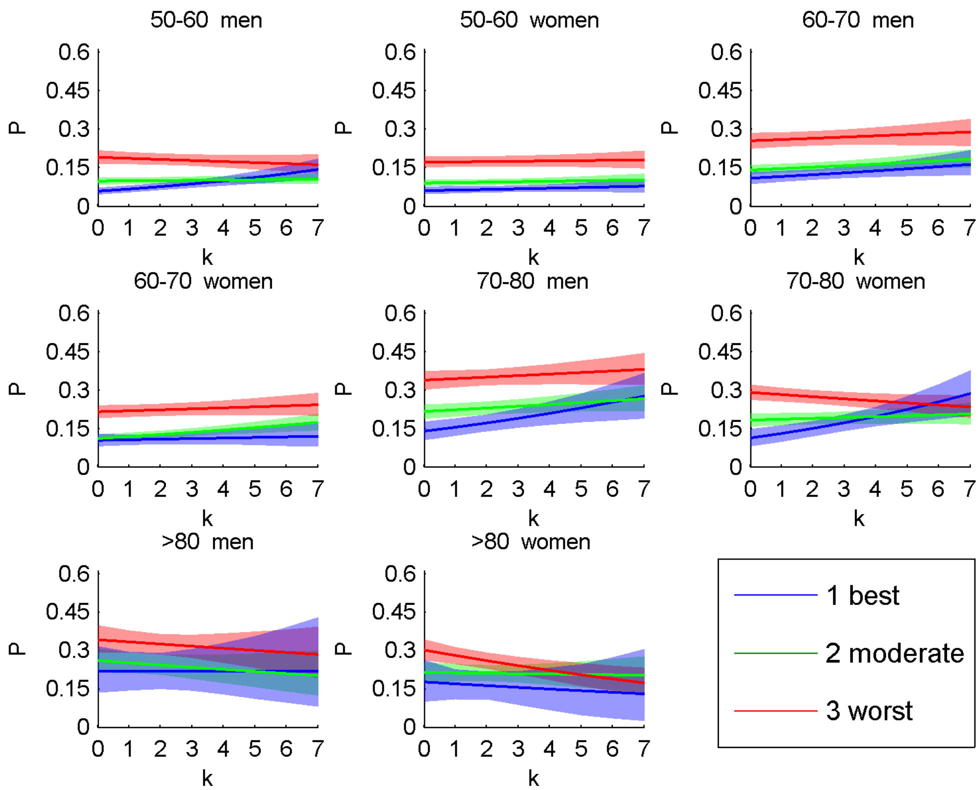

Figure 3.3: Part 2 for perceived health status: predicted probability of any hospital use in period p given alive in period p and bootstrapped 95% confidence intervals, by health state.

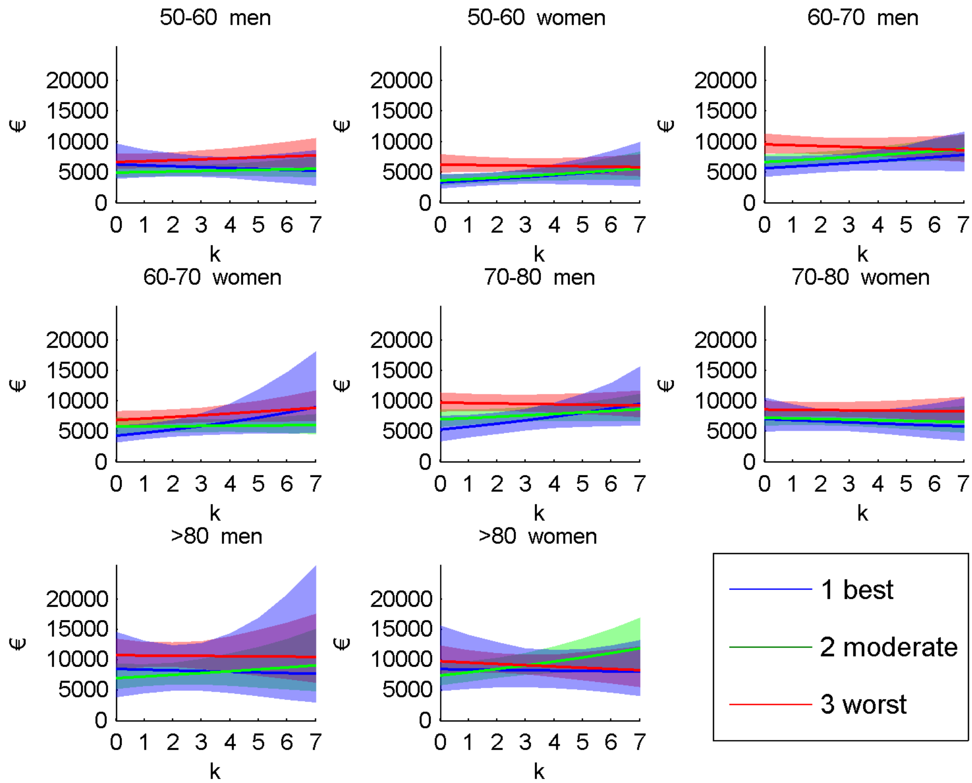

Figure 3.4: Part 3 for perceived health status: predicted costs (euro) of hospital use in period p given any hospital use in period p and bootstrapped 95% confidence interval, by health states.

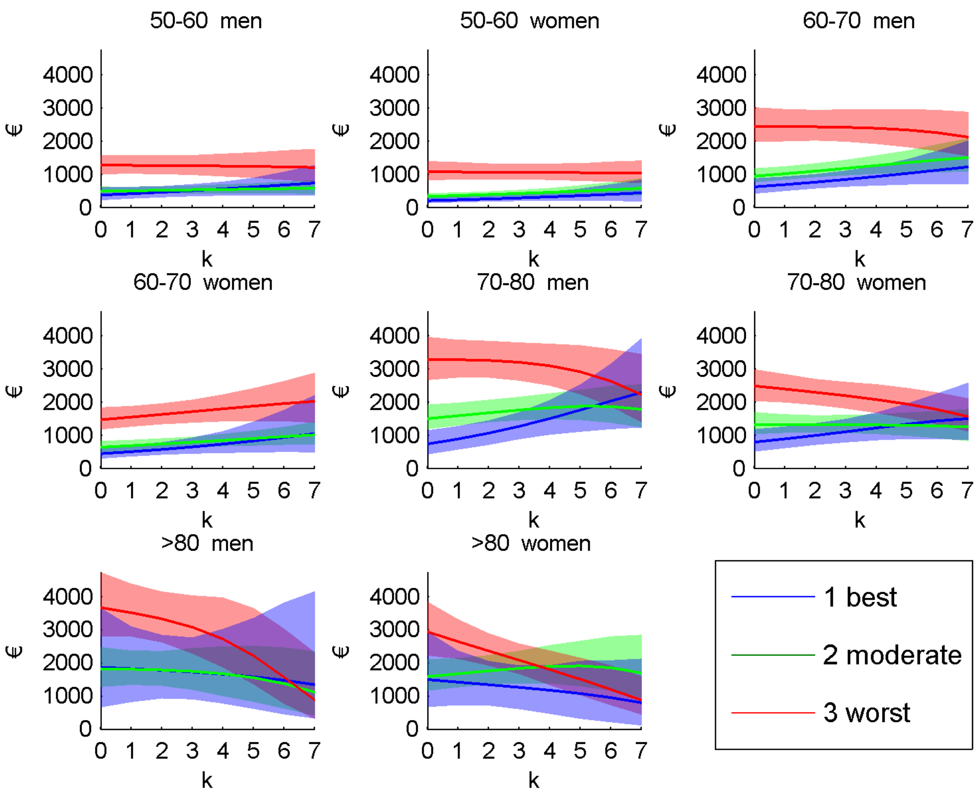

Figure 3.5: Total for perceived health status: predicted costs (euro) of hospital use in period p, by health state. Bootstrapped 95% confidence intervals.

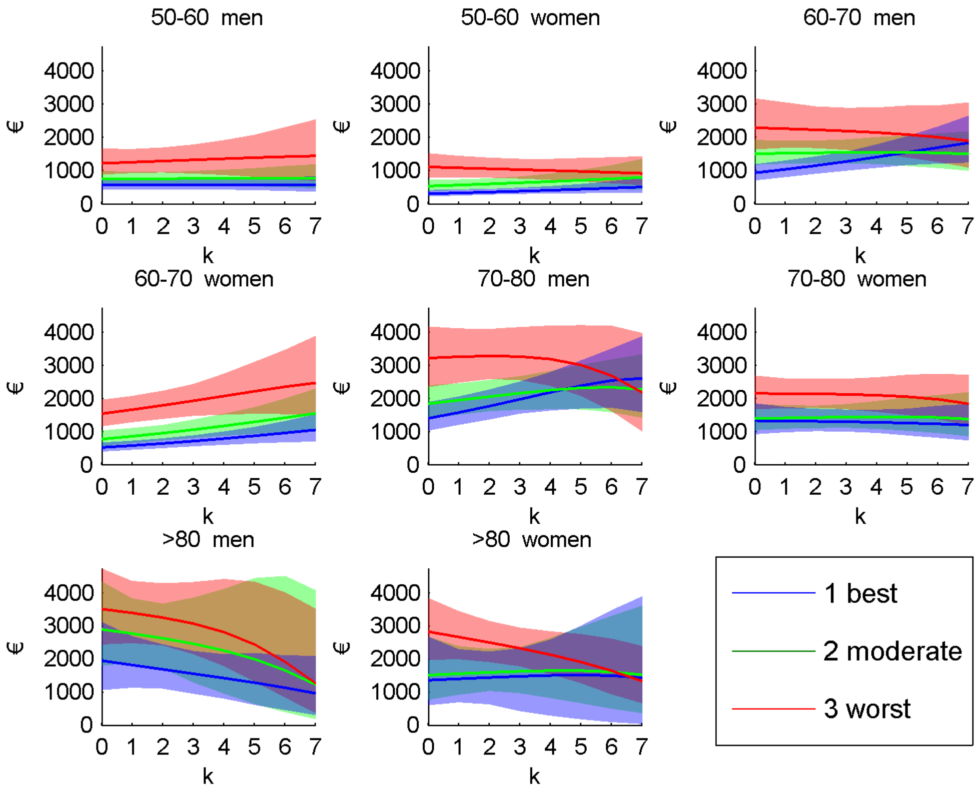

Figure 3.6: Predicted costs (euro) of hospital use, long-term impairments, by health state. Bootstrapped 95% confidence intervals.

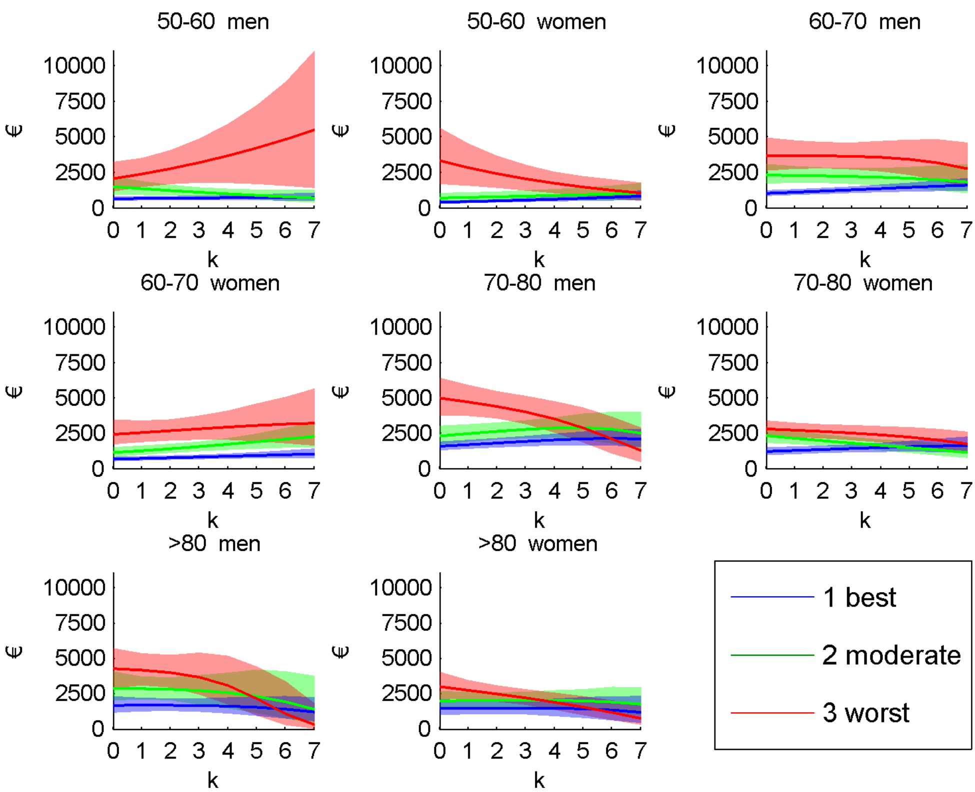

Figure 3.7: Predicted costs (euro) of hospital use, ADL limitations, by health state. Bootstrapped 95% confidence intervals.

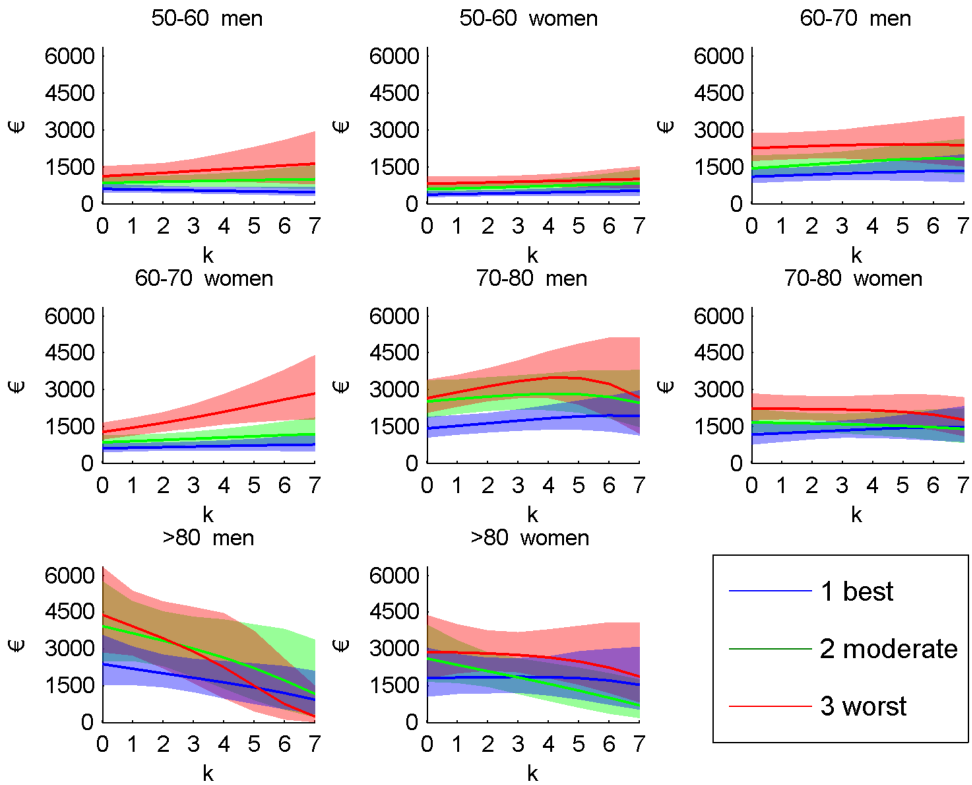

Figure 3.8: Predicted costs (euro) of hospital use, comorbidity, by health state. Bootstrapped 95% confidence intervals.

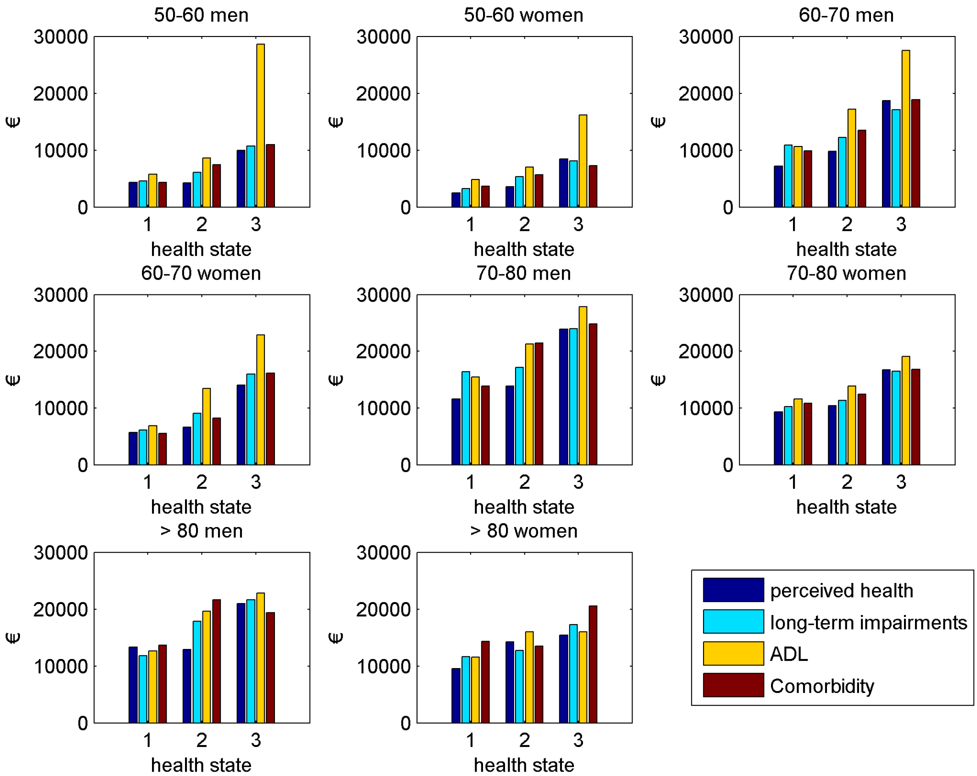

Figure 3.9: Cumulative costs (euro) of hospital use over eight periods by different levels of health (1,2,3) for different measures of health status. Perceived health (blue), long term impairments (mint), ADL (yellow) and comorbidity (red). The different health states are described in Table 3.2.

health for each indicator. For the older age groups, the cumulative costs for people in bad health are still higher than for people in good health, but the pattern is less strong. For instance, in the case of comorbidity the relative differences are much smaller at older ages compared to the differences at younger ages. The cumulative costs for men older than eighty with moderate perceived health are lower than the costs for men of the same age with excellent health. The cumulative costs for women in the highest age category are also higher with no comorbidity than with moderate comorbidity. Women older than eighty with severe ADL limitations have lower cumulative costs than women with only moderate ADL limitations.

Table 3.3 shows the difference in cumulative costs between excellent and bad health, for each indicator and age- and sex-group. Bootstrapped 5 % significance levels are also provided. The differences in cumulative costs increase with age for men in case of long-term impairments, and decrease for men in case of ADL. All the other groups first show an increase in cumulative costs between 50 and 70/80 and then a decline. In four cases of the oldest age group, the difference in cumulative costs is not significantly different from zero at a 5% significance level: self-perceived health and comorbidity for men, and long-term impairments and comorbidity for women. Table 3.3 also shows which part of the cost difference is due to increased intensity (where survival is kept at the level of good health), and the part which is due to the lower survival probability of individuals in bad health. The diminishing effect of survival on cost differences increases with age, and is larger for men than for women.

3.5 Discussion

In this paper, we have analyzed the longitudinal relationship between health status and costs of hospital use in the Netherlands. Initial health status has been related to costs of hospital use in the following eight years using a three part model, estimating survival, the probability of hospital use and costs of hospital use separately. We have estimated costs using four different indicators of health and several age groups. Our main finding is that for age groups up to 70, low health leads to higher costs of hospital use and the difference between bad and good health is generally persistent over an eight year period. For higher age groups, however, a different pattern arises: Mostly due to higher mortality, the expected costs of individuals in bad health show a decreasing pattern, resulting in lower expected costs after six to eight years compared to individuals in good health. This result is found for all four indicators of health.

The effect of health in the three part models is modeled with a linear time dependency. The regression results in Appendix 3.A Tables 3.4-3.7 show that not all time dependent parameters are significant (at a 5 % level). Because one of our goals is to explicitly describe the time dependency of initial health on hospital costs, we decided to keep the not significant time dependent parameters in the models. The most striking example of duration dependence is the effect of excellent perceived health on probability of hospital use, shown in Figure 3.3. For the ages 50 to 80, the probability of hospital use shows an increase over time for individuals in excellent health. There seems to be a postponement effect: in the long-run better health does not lead to lower hospital use, but merely to a postponement of hospital use to a later period in time.

The results on age effects are in line with what is expected: Older age leads to higher mortality, higher conditional probability of hospital use and higher conditional costs of hospital use. Considering the cumulative costs over eight years, the generally higher costs for ages 60 to 70 compared to ages 50 to 60 indicate that between ages 50 to 70 the effect of mortality on costs is relatively small. But after age 70, the cumulative costs are more or less constant, implying that the age effect on increasing costs is mitigated by the age effect on mortality. As shown by the split up of costs due

Table 3.3: Differences in cumulative costs (€), over the first eight years after measurement of health state, between worst health state and best health state. The total difference (total) is split up into a part due to difference in intensity, keeping survival at the good health level (const. surv), and the difference due to the lower survival for bad health (survival). Numbers in bold are not significantly different from zero (5% significance level, bootstrapped).

		men			women		
indicator	age	total	const. surv.	survival	total	const. surv.	survival
perc. health	50-60	5604	5699	95	5930	5969	39
	60-70	11537	12162	625	8290	8498	208
	70-80	12313	14521	2208	7430	7937	508
	> 80	**7693**	11623	3929	5875	6608	**733**
long-term imp.	50-60	6117	6178	**61**	4898	4921	**23**
	60-70	6180	6437	256	9865	10017	152
	70-80	7614	9591	1978	6274	6713	438
	> 80	9785	12214	2429	**5670**	**6571**	**902**
ADL	50-60	22922	23580	**657**	11319	11478	160
	60-70	16909	18936	2026	15972	16599	627
	70-80	12395	17027	4632	7444	8322	879
	> 80	10166	16785	6619	4454	5815	1361
comorbidity	50-60	6663	6750	**87**	3649	3661	**12**
	60-70	8965	9310	345	10577	10742	**165**
	70-80	10927	14276	3348	6025	6444	420
	> 80	**5761**	10047	4287	**6262**	**7112**	**849**

to difference in intensity and differences in survival, the lower survival probability of people in bad health has a large lowering influence on the costs difference with people in good health at higher ages. This effect is stronger for men than for women, due to the greater differences in survival between health states for men. Interestingly, the higher life expectancy of women compared to men does not lead to higher cumulative costs.

The general patterns are the same for the different indicators of health, but the results also show some relevant differences. At ages 50 to 70, the differences in cumulative costs between best and worst health state are considerably higher for ADL than for the other indicators, due to the high costs associated with major ADL impairments. Even at older ages, major ADL impairments are associated with higher costs than the worst health states of the other indicators. However, since major ADL impairments are also associated with higher mortality at older ages, the difference in cumulative costs between best and worst health state is much more similar to the other indicators. This result shows the importance of choice of health indicator and the interactive effect of health and age on health care costs as well as survival.

We have opted for the use of a marginal model framework instead of a random effects model, in which correlation between the different parts of the models is explicitly modeled, for example (Liu, 2009; Liu et al., 2010). The marginal model was chosen because of the interest in the population averaged effects. As noted by (Liu et al., 2010), random effects models can also be used to estimate population average effects by averaging over the distribution of the random effects. In case the individual effects indeed follow the distribution specified by the correlated random effects model, this model might yield more efficient population averaged estimates. However, in general the marginal model seems more robust to specification errors.

Although costs of hospital use are observed over all periods, health status is only observed at the beginning of the first period. As a result, the individual costs of hospital use cannot be directly related to changes in health status over time. The declining patterns of expected costs of low health at older ages seems to indicate that the expected hospital costs over remaining lifetime may well be lower for individuals in bad health than individuals in good health. Therefore, relating hospital costs directly to changes in health status over time and simulating costs over the remaining lifetime seem to be fruitful future extensions. At least, when duration dependence in transition probabilities is accurately dealt with.

This paper is limited to costs of hospital use. Hospital care is an important part of health care, but for other parts of care different results may be found. Especially relevant at old ages is institutional or long-term care, where substitution with hospital care may occur. The trade off, in terms of costs, between annual costs and life expectancy, will most likely also be present in other parts of the health care sector. However, the relative influence of these opposing components may be different from that in hospital care. For example, in a cross sectional study De Meijer et al. (2009)

find that after controlling for disability, age is still a significant determinant of long-term care. This might suggest that the influence of longer life expectancy is even larger in long-term care than in hospital care. However, to assess whether this is indeed the case, longitudinal research on the relationship between health status and long-term care costs is needed.

3.6 Conclusion

The ageing of the population will put pressure on health care expenditures. The improvement of health status is often seen as an instrument to contain the costs of health care. Therefore, insight into the longitudinal relationship between health and costs of healthcare use is necessary. In this paper we investigated the relationship between different indicators of health and costs of hospital use in the Netherlands over a period of eight years. We have found that for the relatively younger age groups, between 50 and 70, baseline good health is persistently associated with low expected costs of hospital use in comparison with bad health over an eight year period. At higher ages, the initial lowering effect of good health on costs seems to be counteracted over time by lower mortality.

Improvement of public health is an important policy goal in itself. However, this study suggests that health improvement of the elderly does not necessarily lead to containment of health care costs. Although specific health improvements can be cost effective, counting on general trends in health to lower long term costs of health care is too optimistic. Interaction between health and mortality, and possible postponement of costs, should be taken into account when making projections of future costs of health care.

3.7 Acknowledgements

We would like to acknowledge Statistics Netherlands and Prismant for providing the data. We kindly thank Dutch Hospital Data and the Federation of Medical Specialists for granting permission to use the LMR data.

3.A Regression tables

Table 3.4: Regression results of the three part model for perceived health status, coefficients and p-values. Part 1: logit model of the probability of being alive at the start of period k. Part 2: logit model for the probability of hospital use in period k conditional on being alive at the start of period k. Part 3: Gamma model for the costs of hospital use in period k conditional on going to the hospital in period k. Health: 1 excellent health, 2 good health, 3 less than good health. Likelihood Ratio tests: comparison between constant and linear duration dependence, and linear and quadratic duration dependence.

			Part 1		Part 2		Part 3	
			coef	p	coef	p	coef	p
age	sex	health						
t-indep.								
50-60	m	2	-0.48	0.48	0.55	0.00	-0.24	0.18
50-60	m	3	-2.04	0.00	1.32	0.00	0.06	0.74
50-60	w	1	-0.46	0.60	0.04	0.81	-0.63	0.01
50-60	w	2	1.38	0.11	0.46	0.00	-0.54	0.00
50-60	w	3	-1.14	0.10	1.19	0.00	-0.01	0.97
60-70	m	1	-1.37	0.07	0.67	0.00	-0.11	0.62
60-70	m	2	-1.53	0.02	0.96	0.00	0.06	0.75
60-70	m	3	-2.37	0.00	1.69	0.00	0.42	0.02
60-70	w	1	1.11	0.39	0.61	0.00	-0.38	0.11
60-70	w	2	-0.37	0.60	0.68	0.00	-0.09	0.64
60-70	w	3	-1.78	0.01	1.47	0.00	0.08	0.63
70-80	m	1	-2.10	0.01	0.94	0.00	-0.17	0.49
70-80	m	2	-2.37	0.00	1.47	0.00	0.10	0.57
70-80	m	3	-3.38	0.00	2.09	0.00	0.43	0.01
70-80	w	1	-0.96	0.28	0.70	0.00	0.11	0.70
70-80	w	2	-1.87	0.00	1.27	0.00	0.14	0.44
70-80	w	3	-2.30	0.00	1.87	0.00	0.31	0.07
> 80	m	1	-3.00	0.00	1.50	0.00	0.30	0.42
> 80	m	2	-3.15	0.00	1.72	0.00	0.11	0.63
> 80	m	3	-3.47	0.00	2.11	0.00	0.54	0.01
> 80	w	1	-2.13	0.02	1.23	0.00	0.30	0.41
> 80	w	2	-2.74	0.00	1.46	0.00	0.17	0.42
> 80	w	3	-3.17	0.00	1.92	0.00	0.44	0.02
t-depend.								
50-60	m	1	-0.55	0.00	0.14	0.00	-0.03	0.55
50-60	m	2	-0.47	0.00	0.01	0.49	0.02	0.52
50-60	m	3	-0.30	0.00	-0.03	0.14	0.02	0.39
50-60	w	1	-0.29	0.05	0.04	0.28	0.07	0.15
50-60	w	2	-0.63	0.00	0.02	0.24	0.06	0.02
50-60	w	3	-0.35	0.00	0.01	0.60	-0.01	0.68
60-70	m	1	-0.44	0.00	0.07	0.04	0.05	0.30
60-70	m	2	-0.49	0.00	0.04	0.01	0.04	0.08
60-70	m	3	-0.48	0.00	0.02	0.18	-0.01	0.54
60-70	w	1	-0.72	0.00	0.02	0.57	0.11	0.09
60-70	w	2	-0.55	0.00	0.08	0.00	0.01	0.81
60-70	w	3	-0.40	0.00	0.02	0.20	0.04	0.12
70-80	m	1	-0.50	0.00	0.12	0.00	0.08	0.14
70-80	m	2	-0.56	0.00	0.04	0.06	0.03	0.28
70-80	m	3	-0.49	0.00	0.03	0.21	-0.01	0.77
70-80	w	1	-0.64	0.00	0.16	0.00	-0.03	0.71
70-80	w	2	-0.43	0.00	0.02	0.29	-0.01	0.60
70-80	w	3	-0.54	0.00	-0.04	0.02	-0.01	0.83
> 80	m	1	-0.43	0.00	0.00	0.98	-0.01	0.90
> 80	m	2	-0.55	0.00	-0.05	0.28	0.04	0.57
> 80	m	3	-0.67	0.00	-0.04	0.38	0.00	0.95
> 80	w	1	-0.62	0.00	-0.05	0.57	-0.01	0.95
> 80	w	2	-0.56	0.00	-0.01	0.80	0.07	0.17
> 80	w	3	-0.54	0.00	-0.10	0.00	-0.02	0.59
1998					-0.08	0.25	0.16	0.10
1999			-0.96	0.01	-0.10	0.13	0.07	0.46
2000			-1.44	0.00	-0.05	0.41	0.01	0.92
2001			-1.52	0.00	-0.03	0.58	-0.10	0.24
2002			-1.64	0.00	0.06	0.33	-0.14	0.09
2003			-1.81	0.00	0.12	0.05	-0.14	0.09
2004			-1.85	0.00	0.21	0.00	-0.26	0.00
2005			-1.00	0.21	-0.03	0.83	-0.29	0.14
LS			0.29	0.00	0.01	0.70	-0.05	0.14
HS			0.22	0.00	-0.01	0.67	0.01	0.85
H			0.43	0.00	-0.07	0.02	-0.20	0.00
c			8.47	0.00	-2.76	0.00	8.75	0.00
No. of observations				92680		83010		14684
d.f.				58		59		59
Pseudo R^2				0.258		0.043		
Log Likelihood				-8830		-37076		-142511
AIC				17775		74270		285140
BIC				18323		74820		285588
LR constant v.s. linear				$X^2_{24}(2017)$		$X^2_{24}(102)$		$X^2_{24}(60)$
LR linear v.s. quadratic				$X^2_{24}(202)$		$X^2_{24}(23)$		$X^2_{24}(43)$

Table 3.5: Regression results of the three part model for long-term impairments, coefficients and p-values. Part 1: logit model of the probability of being alive at the start of period k. Part 2: logit model for the probability of hospital use in period k conditional on being alive at the start of period k. Part 3: Gamma model for the costs of hospital use in period k conditional on going to the hospital in period k. Health: 1 no difficulty, 2 at least one minor and no major difficulty, 3 at least one major difficulty. Likelihood Ratio tests: comparison between constant and linear duration dependence, and linear and quadratic duration dependence.

			part 1		part 2		part 3	
			coef	p	coef	p	coef	p
age	sex	health						
t-indep.								
50-60	m	2	-0.20	0.66	0.43	0.00	-0.11	0.40
50-60	m	3	-0.46	0.37	0.72	0.00	0.13	0.37
50-60	w	1	1.25	0.03	-0.11	0.20	-0.52	0.00
50-60	w	2	1.04	0.14	0.23	0.01	-0.27	0.03
50-60	w	3	0.48	0.42	0.68	0.00	0.06	0.63
60-70	m	1	-0.71	0.05	0.42	0.00	0.11	0.33
60-70	m	2	-0.70	0.07	0.75	0.00	0.31	0.01
60-70	m	3	-1.17	0.01	1.13	0.00	0.43	0.00
60-70	w	1	0.21	0.66	0.26	0.00	-0.33	0.01
60-70	w	2	0.67	0.23	0.39	0.00	-0.05	0.68
60-70	w	3	-0.11	0.82	0.94	0.00	0.18	0.17
70-80	m	1	-1.28	0.00	0.88	0.00	0.13	0.34
70-80	m	2	-1.29	0.00	1.10	0.00	0.24	0.05
70-80	m	3	-2.19	0.00	1.50	0.00	0.51	0.00
70-80	w	1	-0.70	0.17	0.59	0.00	0.32	0.05
70-80	w	2	-0.18	0.69	0.96	0.00	0.06	0.64
70-80	w	3	-0.95	0.01	1.20	0.00	0.31	0.01
> 80	m	1	-1.94	0.00	1.31	0.00	0.14	0.60
> 80	m	2	-1.64	0.00	1.53	0.00	0.38	0.05
> 80	m	3	-2.22	0.00	1.57	0.00	0.54	0.00
> 80	w	1	-1.01	0.26	0.90	0.00	0.09	0.79
> 80	w	2	-1.35	0.02	0.85	0.00	0.24	0.36
> 80	w	3	-2.18	0.00	1.26	0.00	0.55	0.00
t-depend.								
50-60	m	1	-0.36	0.00	0.02	0.35	-0.02	0.54
50-60	m	2	-0.41	0.00	-0.01	0.64	0.02	0.63
50-60	m	3	-0.41	0.00	-0.01	0.76	0.04	0.33
50-60	w	1	-0.51	0.00	0.03	0.17	0.05	0.10
50-60	w	2	-0.36	0.01	0.01	0.58	0.05	0.14
50-60	w	3	-0.48	0.00	0.02	0.54	-0.04	0.29
60-70	m	1	-0.46	0.00	0.06	0.00	0.06	0.02
60-70	m	2	-0.51	0.00	0.03	0.15	-0.01	0.64
60-70	m	3	-0.49	0.00	-0.02	0.54	0.00	0.93
60-70	w	1	-0.50	0.00	0.06	0.01	0.06	0.06
60-70	w	2	-0.58	0.00	0.08	0.00	0.04	0.17
60-70	w	3	-0.57	0.00	0.04	0.10	0.05	0.15
70-80	m	1	-0.57	0.00	0.08	0.00	0.06	0.11
70-80	m	2	-0.56	0.00	0.04	0.10	0.03	0.33
70-80	m	3	-0.59	0.00	0.05	0.10	-0.01	0.69
70-80	w	1	-0.41	0.00	0.08	0.01	-0.07	0.09
70-80	w	2	-0.64	0.00	-0.03	0.22	0.04	0.29
70-80	w	3	-0.58	0.00	-0.03	0.25	0.02	0.51
> 80	m	1	-0.49	0.00	-0.01	0.84	-0.06	0.54
> 80	m	2	-0.67	0.00	-0.14	0.02	0.06	0.47
> 80	m	3	-0.67	0.00	-0.01	0.89	-0.02	0.78
> 80	w	1	-0.59	0.00	-0.05	0.59	0.07	0.47
> 80	w	2	-0.56	0.00	-0.07	0.32	0.08	0.38
> 80	w	3	-0.53	0.00	-0.05	0.18	-0.02	0.72
1998					-0.07	0.41	0.17	0.10
1999			-1.29	0.02	-0.08	0.26	0.08	0.42
2000			-1.68	0.00	-0.03	0.64	-0.01	0.92
2001			-1.75	0.00	-0.04	0.58	-0.17	0.08
2002			-1.75	0.00	0.06	0.37	-0.15	0.12
2003			-1.92	0.00	0.12	0.08	-0.19	0.04
2004			-1.92	0.00	0.21	0.00	-0.30	0.00
2005			-1.55	0.08	0.03	0.87	-0.23	0.27
LS			0.27	0.00	-0.05	0.09	-0.02	0.57
HS			0.21	0.00	-0.06	0.05	0.00	0.95
H			0.47	0.00	-0.14	0.00	-0.19	0.00
c			7.67	0.00	-2.23	0.00	8.69	0.00
No. of observations				72433		65129		11192
d.f.				58		59		59
Pseudo R^2				0.246		0.034		
Log Likelihood				-6060		-28876		-108069
AIC				12236		57870		216256
BIC				12770		58406		216688
LR constant v.s. linear				$X^2_{24}(1462)$		$X^2_{24}(67)$		$X^2_{24}(68)$
LR linear v.s. quadratic				$X^2_{24}(132)$		$X^2_{24}(43)$		$X^2_{24}(29)$

Table 3.6: Regression results of the three part model for ADL limitations, coefficients and p-values. Part 1: logit model of the probability of being alive at the start of period k. Part 2: logit model for the probability of hospital use in period k conditional on being alive at the start of period k. Part 3: Gamma model for the costs of hospital use in period k conditional on going to the hospital in period k. Health: 1 no difficulty, 2 at least one minor and no major difficulty, 3 at least one major difficulty. Likelihood Ratio tests: comparison between constant and linear duration dependence, and linear and quadratic duration dependence.

			part 1		part 2		part 3	
			coef	p	coef	p	coef	p
age	sex	health						
t-indep.								
50-60	m	2	-0.44	0.00	0.57	0.00	0.34	0.05
50-60	m	3	-0.44	0.00	1.07	0.00	0.26	0.27
50-60	w	1	-0.26	0.10	-0.17	0.03	-0.33	0.00
50-60	w	2	-0.50	0.00	0.30	0.01	-0.20	0.25
50-60	w	3	-0.19	0.48	1.09	0.00	0.72	0.00
60-70	m	1	-0.20	0.13	0.29	0.00	0.20	0.04
60-70	m	2	-0.48	0.00	0.93	0.00	0.48	0.00
60-70	m	3	-0.49	0.00	1.52	0.00	0.53	0.00
60-70	w	1	-0.55	0.00	0.11	0.14	-0.07	0.51
60-70	w	2	-0.53	0.00	0.55	0.00	0.08	0.54
60-70	w	3	-0.44	0.00	1.07	0.00	0.42	0.00
70-80	m	1	-0.38	0.00	0.80	0.00	0.20	0.04
70-80	m	2	-0.51	0.00	1.15	0.00	0.32	0.01
70-80	m	3	-0.53	0.00	1.67	0.00	0.75	0.00
70-80	w	1	-0.61	0.00	0.53	0.00	0.16	0.14
70-80	w	2	-0.52	0.00	1.03	0.00	0.41	0.00
70-80	w	3	-0.52	0.00	1.26	0.00	0.43	0.00
> 80	m	1	-0.52	0.00	0.92	0.00	0.18	0.29
> 80	m	2	-0.50	0.00	1.35	0.00	0.41	0.02
> 80	m	3	-0.59	0.00	1.48	0.00	0.71	0.00
> 80	w	1	-0.84	0.00	0.73	0.00	0.18	0.29
> 80	w	2	-0.62	0.00	0.88	0.00	0.38	0.02
> 80	w	3	-0.47	0.00	1.23	0.00	0.53	0.00
t-depend.								
50-60	m	1	-0.60	0.00	0.03	0.10	0.00	0.99
50-60	m	2	-0.43	0.46	-0.01	0.78	-0.09	0.09
50-60	m	3	-1.70	0.01	0.04	0.53	0.12	0.11
50-60	w	1	1.25	0.02	0.03	0.09	0.08	0.00
50-60	w	2	0.81	0.46	0.05	0.14	0.02	0.75
50-60	w	3	-1.41	0.02	-0.02	0.70	-0.15	0.01
60-70	m	1	-0.52	0.09	0.06	0.00	0.03	0.13
60-70	m	2	-1.37	0.00	0.02	0.46	-0.02	0.53
60-70	m	3	-1.70	0.00	-0.02	0.58	0.02	0.59
60-70	w	1	0.56	0.14	0.05	0.00	0.02	0.30
60-70	w	2	-0.30	0.51	0.07	0.01	0.05	0.10
60-70	w	3	-1.39	0.00	0.03	0.36	0.03	0.39
70-80	m	1	-1.46	0.00	0.05	0.01	0.04	0.09
70-80	m	2	-2.05	0.00	0.06	0.07	0.04	0.31
70-80	m	3	-2.55	0.00	0.05	0.22	-0.07	0.09
70-80	w	1	-0.61	0.07	0.05	0.01	0.01	0.57
70-80	w	2	-0.95	0.01	-0.04	0.07	-0.05	0.11
70-80	w	3	-1.62	0.00	-0.04	0.10	0.00	0.93
> 80	m	1	-2.15	0.00	-0.01	0.79	0.02	0.71
> 80	m	2	-2.22	0.00	-0.05	0.32	0.04	0.58
> 80	m	3	-2.26	0.00	-0.05	0.49	0.02	0.83
> 80	w	1	-1.17	0.01	-0.03	0.54	0.04	0.51
> 80	w	2	-1.79	0.00	-0.01	0.76	0.03	0.61
> 80	w	3	-2.23	0.00	-0.11	0.00	0.00	0.93
1998					-0.07	0.38	0.14	0.14
1999			-0.93	0.02	-0.12	0.09	0.09	0.36
2000			-1.40	0.00	-0.05	0.43	0.01	0.91
2001			-1.44	0.00	-0.04	0.50	-0.12	0.19
2002			-1.53	0.00	0.05	0.45	-0.14	0.09
2003			-1.71	0.00	0.09	0.16	-0.16	0.07
2004			-1.76	0.00	0.18	0.01	-0.27	0.00
2005			-0.99	0.21	0.04	0.81	-0.31	0.12
LS			0.27	0.00	0.01	0.80	-0.07	0.04
HS			0.16	0.01	-0.02	0.52	0.00	0.95
H			0.41	0.00	-0.08	0.01	-0.20	0.00
c			7.38	0.00	-2.06	0.00	8.68	0.00
No. of observations				74871		67459		12884
d.f.				58		59		59
Pseudo R^2				0.255		0.035		
Log Likelihood				-8161		-31753		-125602
AIC				16438		63624		251324
BIC				16973		64162		251959
LR constant v.s. linear				$X^2_{24}(2028)$		$X^2_{24}(80)$		$X^2_{24}(84)$
LR linear v.s. quadratic				$X^2_{24}(173)$		$X^2_{24}(26)$		$X^2_{24}(32)$

Table 3.7: Regression results of the three part model for comorbidity, coefficients and p-values. Part 1: logit model of the probability of being alive at the start of period k. Part 2: logit model for the probability of hospital use in period k conditional on being alive at the start of period k. Part 3: Gamma model for the costs of hospital use in period k conditional on going to the hospital in period k. Health: 1 no chronic disease, 2 at least one chronic disease, 3 more than one chronic disease. Likelihood Ratio tests: comparison between constant and linear duration dependence, and linear and quadratic duration dependence

			Part 1		Part 2		Part 3	
			coef	p	coef	p	coef	p
age	sex	health						
t-indep.								
50-60	m	2	-0.32	0.47	0.45	0.00	-0.06	0.64
50-60	m	3	-0.52	0.31	0.72	0.00	-0.01	0.93
50-60	w	1	1.18	0.04	-0.14	0.12	-0.34	0.01
50-60	w	2	1.57	0.04	0.29	0.00	-0.27	0.04
50-60	w	3	0.44	0.47	0.59	0.00	-0.22	0.09
60-70	m	1	-0.69	0.07	0.43	0.00	0.22	0.07
60-70	m	2	-0.59	0.15	0.68	0.00	0.27	0.03
60-70	m	3	-1.67	0.00	1.24	0.00	0.29	0.02
60-70	w	1	-0.11	0.82	0.15	0.11	-0.13	0.34
60-70	w	2	0.65	0.27	0.41	0.00	-0.02	0.87
60-70	w	3	-0.08	0.86	0.91	0.00	-0.03	0.81
70-80	m	1	-1.30	0.00	0.87	0.00	0.11	0.43
70-80	m	2	-1.71	0.00	1.16	0.00	0.46	0.00
70-80	m	3	-2.15	0.00	1.57	0.00	0.22	0.10
70-80	w	1	-0.64	0.17	0.44	0.00	0.27	0.09
70-80	w	2	-1.09	0.01	1.01	0.00	0.16	0.26
70-80	w	3	-0.48	0.25	1.25	0.00	0.27	0.03
> 80	m	1	-1.29	0.02	1.23	0.00	0.35	0.10
> 80	m	2	-2.28	0.00	1.71	0.00	0.52	0.01
> 80	m	3	-2.40	0.00	1.70	0.00	0.64	0.01
> 80	w	1	-1.11	0.06	0.96	0.00	0.29	0.23
> 80	w	2	-2.32	0.00	1.16	0.00	0.50	0.01
> 80	w	3	-1.92	0.00	1.33	0.00	0.47	0.01
t-depend.								
50-60	m	1	-0.37	0.00	0.02	0.44	-0.05	0.09
50-60	m	2	-0.41	0.00	-0.01	0.79	0.03	0.29
50-60	m	3	-0.40	0.00	-0.02	0.45	0.08	0.06
50-60	w	1	-0.51	0.00	0.02	0.37	0.03	0.27
50-60	w	2	-0.57	0.00	0.01	0.61	0.04	0.24
50-60	w	3	-0.41	0.00	0.03	0.15	0.01	0.86
60-70	m	1	-0.46	0.00	0.04	0.07	0.01	0.74
60-70	m	2	-0.58	0.00	0.05	0.02	0.01	0.63
60-70	m	3	-0.36	0.00	0.01	0.60	0.02	0.61
60-70	w	1	-0.46	0.00	0.02	0.32	0.02	0.61
60-70	w	2	-0.59	0.00	0.05	0.03	0.01	0.77
60-70	w	3	-0.56	0.00	0.08	0.00	0.06	0.03
70-80	m	1	-0.53	0.00	0.03	0.31	0.05	0.16
70-80	m	2	-0.54	0.00	0.08	0.00	-0.01	0.77
70-80	m	3	-0.59	0.00	0.05	0.12	0.07	0.07
70-80	w	1	-0.52	0.00	0.07	0.02	-0.01	0.77
70-80	w	2	-0.44	0.00	-0.03	0.31	0.01	0.75
70-80	w	3	-0.68	0.00	0.00	1.00	0.00	0.99
> 80	m	1	-0.64	0.00	-0.04	0.51	-0.05	0.49
> 80	m	2	-0.59	0.00	-0.04	0.52	-0.04	0.56
> 80	m	3	-0.79	0.00	-0.06	0.46	-0.06	0.60
> 80	w	1	-0.61	0.00	-0.03	0.55	0.04	0.57
> 80	w	2	-0.55	0.00	-0.07	0.26	-0.04	0.55
> 80	w	3	-0.55	0.00	-0.04	0.42	0.03	0.68
1998					-0.09	0.29	0.16	0.15
1999			-0.93	0.06	-0.09	0.22	0.09	0.37
2000			-1.41	0.00	-0.04	0.61	-0.01	0.95
2001			-1.53	0.00	-0.05	0.52	-0.13	0.19
2002			-1.49	0.00	0.03	0.63	-0.16	0.09
2003			-1.67	0.00	0.10	0.18	-0.19	0.05
2004			-1.68	0.00	0.19	0.01	-0.27	0.01
2005			-1.24	0.14	0.02	0.92	-0.24	0.25
LS			0.33	0.00	-0.06	0.03	-0.05	0.20
HS			0.31	0.00	-0.09	0.00	-0.04	0.36
H			0.55	0.00	-0.20	0.00	-0.24	0.00
c			7.41	0.00	-2.21	0.00	8.73	0.00
No. of observations				70262		63175		10737
d.f.				58		59		59
Pseudo R^2				0.245		0.039		
Log Likelihood				-5804		-27675		-103748
AIC				11725		55468		207614
BIC				12256		56002		208043
LR constant v.s. linear				$X^2_{24}(1445)$		$X^2_{24}(52)$		$X^2_{24}(53)$
LR linear v.s. quadratic				$X^2_{24}(132)$		$X^2_{24}(27)$		$X^2_{24}(25)$

Chapter 4

Modeling the relationship between health and health care expenditures using a latent Markov model

Abstract

We investigate the dynamic relationship between several dimensions of health and health care expenditures for older individuals. Health data from the Longitudinal Aging Survey Amsterdam is combined with data on hospital and long term care use. We estimate a latent variable based jointly on observed health indicators and expenditures. Annual transition probabilities between states of the latent variable are estimated using a Markov model. States associated with good current health and low annual health care expenditures are not associated with lower cumulative health care expenditures over remaining lifetime. We conclude that, although the direct health care cost saving effect is limited, the considerable gain in healthy lifeyears can make investing in the improvement of health of the older population worthwhile.

Based on
Wouterse, B., Huisman, M., Meijboom, B.R., Deeg, D.J.H., & Polder, J.J. (2013). Modeling the relationship between health and health care expenditures using a latent Markov model. *Journal of Health Economics*, 32(2), 423-439.

4.1 Introduction

The expected budgetary consequences of the aging of the Western populations have made the relationship between health and health care expenditures an important topic for policy as well as research. Age is strongly associated with health care expenditures and this association is to a large extent related to health and disability. Together with relatively high post World War 2 fertility rates, increasing longevity is the main cause of the growth of the older population. When trends in health do not coincide with this trend in life expectancy, the consequences of longevity gains for health care expenditures are different from those predicted by models based only on age or proximity to death (Zweifel et al., 1999). In the most positive scenario, it has been suggested that increases in health of the older population can offset some of the expected expenditure growth. However, instead of decreasing expenditures, health gains might merely postpone expenditures to a later period in life. Therefore, models are needed that, firstly, relate expenditures to different aspects of health and that, secondly, can capture the dynamics between health and expenditures over remaining lifetime.

Health comprises a large number of interrelated dimensions, with time trends that are not necessarily converging (Mackenbach et al., 2008; Parker and Thorslund, 2007; Lafortune and Balestat, 2007; Christensen et al., 2009). These dimensions include, amongst other things, the presence or absence of diseases, cognitive functioning, physical functioning, and self-perception of health. Another important related aspect is the effect of health on functioning, or disability. Especially in the older population, health is a very heterogeneous concept (Lafortune et al., 2009). Thus, the choice of a single health indicator has a large influence on estimated relationships between health and covariates like income and smoking (Frijters and Ulker, 2008). The same is true for utilization of health care, which not only depends on physical health but also on other dimensions such as emotional and mental aspects (Portrait et al., 2000). The relevant dimensions of health can differ between sectors. For instance, utilization of acute care is strongly related to the presence of diseases whereas use of long-term care is more related to disability (Koopmanschap et al., 2010)

The second aspect regards dynamics in individual health over time. A number of studies have shown that, although better initial health is associated with lower current health care spending, expenditures are not lower over total remaining lifetime due to longer life expectancy and postponement of expenditures (Laditka, 1998; Lubitz et al., 2003; Lubitz, 2005; Goldman et al., 2005). Wouterse et al. (2011) have found that choice of health indicator is also relevant in this longitudinal context. A common way to analyze time dynamics in health is to apply a discrete transition model, estimating transitions between health states over fixed periods of time. In order to obtain efficient parameter estimates the number of different health states should not be too large. Given the relevance of including a diverse set of health indicators, a method is needed that can incorporate different dimensions of health into a parsimonious model with a limited number of states.

We develop such a model using latent class and Markov techniques. The model has two elements: the estimation of a summarized measure of health and its relationship with health care expenditures, and the modeling of dynamics in this relationship. The first element requires the summarization of a large number of health indicators into a smaller set. For this purpose, we use Latent Class Analysis (LCA). LCA assumes that the values of a set of observed outcome variables depend on a latent (unobserved) variable with a finite number of discrete states (Collins and Lanza, 2010). An advantage of LCA is that the latent variable itself is assumed to be discrete. This means that the different values of the latent variable can often be given a meaningful interpretation, and that transitions between latent health states can be estimated. LCA has been applied in a number of studies to model specific aspects of health and disability (Bandeen-Roche et al., 1997, 2006; Moran et al., 2004), and is used by Lafortune et al. (2009) to model different dimensions of health for older individuals. In health care expenditure modeling, latent class techniques have been used in two distinct ways: either to create summarized measures of health based solely on health indicators, or to estimate use groups based solely on health care expenditures.

To create summarized health measures Manton et al. (2007) apply the Grade of Membership (GoM) technique, closely related to latent class analysis, to predict future health care expenditures on the basis of trends in disability. Portrait et al. (2000) and McNamee (2004) use GoM to estimate the use of long-term care services by older persons based on a large set of health variables. The use of LCA to define use groups based on expenditures has been applied quite extensively (e.g. Bago d'Uva (2005, 2006); Bago d'Uva and Jones (2009); Deb and Trivedi (2002)). The idea behind this application of LCA is that the distribution of health care expenditures is a mixture of expenditure distributions for a finite number of use groups. Individual membership of a use group is not observed, but has to be inferred based on the level of expenditures itself. Although groups are defined solely on expenditures, the groups are often hypothesized to be based on underlying health status. For instance, Deb and Trivedi (2002) use an ex-post analysis to show that membership of a latent class is indeed associated with different values of health indicators. They argue that the use of latent class models may be a potentially powerful measure of health status based on health care utilization and demographic characteristics, rather than on clinical measures. In this paper, we combine the two approaches and base the latent variable jointly on observed health indicators as well as expenditures. This way, different dimensions of health can be related to expenditures through the latent variable, and the resulting classes have a direct interpretation in terms of health as well as expenditures.

For the second element of the model, the dynamics in health and expenditures over time, we can take advantage of the fact that the latent variable is discrete. This means that transitions between health states can be modeled using a Markov framework (Van de Pol and Langeheine, 1990; Reboussin et al., 1999; Paas et al., 2007).

Latent Transition Analysis is for instance used to estimate transition probabilities between latent health states over time (Lafortune et al., 2009). However, in most latent class models for health care expenditures, transition probabilities between latent classes are not estimated. Even when panel data is used, the probability of belonging to a particular latent class is assumed constant (e.g. Bago d'Uva (2005)). The limited use of health indicators in finite mixture expenditure models and the absence of transition models might be partially due to data limitations. Data that contains both detailed health information as well as extensive cost information is scarce. Also, health panel surveys often have waves longer than one year, so that interpolation techniques have to be applied to obtain estimates of annual transition probabilities (Laditka and Wolf, 1998; Lièvre and Brouard, 2003; Craig and Sendi, 2002). Here, the suggested combination of expenditures and health information to form the latent variable can have an additional advantage. By linking health panel surveys to external data, for example insurance files, a dataset can be created that contains both extensive health information as well as expenditure data. For the years in which no health information is available, cost information can be used to make inferences about the latent states. Studies by Laditka and Wolf (2006) and Molla and Lubitz (2008) show that estimates of interpolated transition probabilities indeed improve when additional (retrospective) information about health in unobserved years is included.

In this paper, we estimate a Latent Markov model to describe the relationship between dimensions of health and health care expenditures. We aim to make two contributions to current literature. First, we combine Dutch longitudinal health survey data with register data on health care use and base the estimation of the latent health state on observed health indicators and expenditures jointly. Health information is based on the Longitudinal Aging Study Amsterdam (LASA), which covers a broad range of health dimensions: subjective as well as objective, cognitive as well as physical aspects of health. With the resulting model, we try to find how different dimensions of health are related to health care expenditures. Second, we analyze dynamics in health and expenditures by using the Markov framework. By estimating an annual transition model we are able to show whether states associated with good health outcomes and low expenditures on an annual basis, are also associated with better health and lower expenditures over total remaining lifetime. We extend earlier research on this topic by using a compound indicator of health instead of single indicators. The dependence of the latent variable on expenditures as well as health enables the estimation of annual transition probabilities between states using a health survey with non annual time intervals between waves.

4.2 Methods

The Latent Markov model involves two main elements: First, the definition of the latent variable that determines the distribution of the observed health indicators and the distribution of the expenditures. And second, the modeling of annual transitions between the latent health states over time. After a discussion of these two elements, we introduce an Expectation Maximization algorithm to estimate the model. Finally, we discuss implementation of the model when annual observations of the health indicators are not available.

4.2.1 Latent class model

Suppose that for each individual i at time t a vector of health indicators $y_{i,t} = [y^1_{i,t}, ..., y^J_{i,t}]$ is observed. Each element $y^j_{i,t}$ of $y_{i,t}$ is a discrete variable that can take on values $k = 1, .., K_j$. A vector of health care expenditures $c_{i,t}$ and a vector of covariates $x_{i,t}$ are also observed. We assume that the probability distributions of the health indicators as well as the distribution of the health care expenditures depend on an underlying discrete variable $\eta_{i,t}$ with M classes. In case of a health indicator variable, this assumptions means that the probability that $y^j_{i,t}$ takes on value k depends on $\eta_{i,t}$. More precisely, the unconditional probability distribution of $y^j_{i,t}$ is a mixture of the conditional probabilities $P(y^j_{i,t} = k|\eta_{i,t} = m)$ for each state m of the latent variable. Or,

$$P(y^j_{i,t} = k|\pi^1_{i,t}, .., \pi^M_{i,t}) = \sum_{m=1}^{M} \pi^m_{i,t} P(y^j_{i,t} = k|\eta_{i,t} = m), \tag{4.1}$$

where $\pi^m_{i,t} = P(\eta_{i,t} = m)$ is the mixture probability. We do not include covariates in the mixture models for the health indicators. As a result, the interpretation of the latent variable in terms of health is the same irrespective of age, education level, or other variables.

The probability distribution of the expenditures is also a finite mixture. Since expenditures are continuous instead of discrete, the unconditional probability distribution is a mixture of continuous probability density functions:

$$f(c_{i,t}|x_{i,t}; \pi^1_{i,t}, .., \pi^M_{i,t}) = \sum_{m=1}^{M} \pi^m_{i,t} f_m(c_{i,t}|x_{i,t}), \tag{4.2}$$

where $f_m(c_{i,t}|x_{i,t})$ is the density function of $c_{i,t}$ given $\eta_{i,t} = m$. In contrast to the probability functions for the health indicators, the conditional distribution functions of the expenditures also depend on the values of the covariates in $x_{i,t}$. In line with the local independence assumption commonly used in latent class analysis, we assume that the outcome variables are independently distributed conditional on the latent variable $\eta_{i,t}$. Then, the joint probability density function of $y_{i,t}$ and $c_{i,t}$ can be written as

$$g(c_{i,t}, y_{i,t}|x_{i,t}; \pi^1_{i,t}, .., \pi^M_{i,t}) = \sum_{m=1}^{M} \pi^m_{i,t} g_m(c_{i,t}, y_{i,t}|x_{i,t}), \tag{4.3}$$

with

$$g_m(c_{i,t}, y_{i,t}|x_{i,t}) = f_m(c_{i,t}|x_{i,t}) \prod_{j=1}^{J} P(y^j_{i,t}|\eta_{i,t} = m). \tag{4.4}$$

Since we include health indicators as well as health care expenditures as outcomes, in our case, the local independence assumption also implies that all variation in health care expenditures related to the health indicators is to be captured by the latent variable. To better understand the relationship between the latent variable and health care expenditures we can think of the expenditure model in terms of interaction effects: as a different specification of the expenditure model is estimated for each state of the latent variable, the finite mixture model can actually be seen as an expenditure model where all covariates are allowed to interact with the latent variable. The effect of an explanatory variable in $x_{i,t}$ therefore differs for each state of the latent variable. Because the latent variable determines the relationship between the health indicators and health care expenditures, all covariates in fact interact with health. If education level, for instance, would be included in the expenditure model, its effect on health care expenditures is allowed to differ between individuals in good and in poor health.

In addition to states related to individuals who are alive, and thus have both observed health indicators as well as health care expenditures, we also include a state related to death. When period of dying is known, as is the case in our data, we can define an additional death state. Probability of death is 1 in this state and 0 in all others. Reversely, probability of the death state is 0 when health indicators and expenditures are observed. We will define death to be 1 in period t if an individual has deceased before the beginning of period t, and 0 otherwise.

The joint probability density function is a finite mixture of both discrete variables (the health indicators) and a continuous variable (health care expenditures). Latent class analysis based on mixed outcome variables has for example been applied by Lin et al. (2000), who model prostate-specific antigen and time to onset of prostate cancer. Entink et al. (2011) jointly analyze trajectories in cognitive functioning and survival. In health economics, latent class analysis is mostly used for one of two purposes: either to model the correlation between a set of discrete health indicators, or to define use groups based solely on expenditures. The use of latent class analysis is most attractive if the states of the latent variable have a natural interpretation (Deb and Trivedi, 2002). In both types of applications, this interpretation is most often in terms of (unobserved) health. For instance, latent class analysis is used to combine a large set of health indicators into a much smaller number of states, pertaining to different health domains. For example, Cutler and Landrum (2012) combine 19 measures of disability into three broad categories. In an expenditure based finite mixture model, it seems intuitive to interpret the latent states as pertaining to better or worse unobserved health depending on the level of expenditures associated with that state. Statistically speaking, however, a finite mixture model may just be a flexible way to model the data. In some cases, states of the latent variable just relate to specific aspects of the data, such as outliers, without a clear interpretation. Therefore, the interpretation of the latent states should be supported both by a priori reasoning and by meaningful a posteriori differences (Deb and Trivedi, 2002).

For finite mixtures based solely on expenditures, a way to examine the interpretation of the latent variable, is to estimate the relationship between class membership probabilities and health indicators ex-post. In our case, the definition of the latent variable is based on expenditure as well as observed health indicators. This means that we can analyze the relationship between the latent variable and health directly, without having to estimate this relationship ex post. The a posteriori interpretability can be examined by looking at the relationships between the loadings of the health indicators, and the level of health care expenditure in each latent states. For instance, we would expect a priori that a latent state associated with high probabilities of poor health is also associated with high health care expenditures. Also, we would expect that when a latent state is associated with high probabilities of good health for some indicators, and low probabilities for others, the state can be interpreted as being related to a particular health domain.

4.2.2 Functional forms of the models

For the functional forms of the conditional probabilities $P(y_{i,t}^j = k|\eta_{i,t} = m)$ we use a multinomial logit specification:

$$P(y_{i,t}^j = k|\eta_{i,t} = m; \gamma_j^m) = \frac{\exp(\gamma_{j,k}^m)}{\sum_{l=1}^{K_j} \exp(\gamma_{j,l}^m)}, \tag{4.5}$$

for $k = 1, .., K_j$. A multinomial logit model has to be specified for all J observed health indicators. To allow a unique identification of the models, $\gamma_{j,1}^m$ is set to 1 for all J models. As discussed before, $P(y_{i,t}^j = k|\eta_{i,t} = m)$ does not depend on $x_{i,t}$.

The density function of the expenditures, $f_m(c_{i,t}|x_{i,t})$, is specified as a two-part model (Duan et al., 1983). In this specification, the probability of using any health care is modeled separately from the conditional expectation of the expenditures. The two-part model is often applied to analyze health care utilization because of its ability to deal with the large number of excess zeros (individuals that do not use health care in a particular year). Latent class, or finite mixture models, can be applied as an alternative for the two-part model (Deb and Trivedi, 2002), but the two methods can also be combined (Bago d'Uva, 2006). By applying a different two-part model for each latent state, we assume that conditional on the value of the latent state, health care expenditures are determined by a two-stage decision process: the decision to use health care, and the amount of health care that is utilized.

For the first part of the model, the probability of hospital use, we use the logit specification:

$$P(c_{i,t} > 0|\eta_{i,t} = m; x_{i,t}; \beta_{1,m}) = \frac{\exp(x'_{i,t}\beta_{1,m})}{1 + \exp(x'_{i,t}\beta_{1,m})}. \tag{4.6}$$

For the second part we use a Generalized Linear Model (GLM). The GLM relates the conditional expectation of expenditures to a linear combination of the covariates through the function $h()$ (Manning and Mullahy, 2001):

$$\mathrm{E}(c_{i,t}|\eta_{i,t} = m; c_{i,t} > 0; x_{i,t}; \beta_{2,m}) = h_m(x'_{i,t}\beta_{2,m}). \tag{4.7}$$

GLM requires the choice of $h()$ and the functional form of the variance. The choice of $h()$ can be formulated as the choice for the appropriate link function between $\mathrm{E}(c_{i,t})$ and $x'_{i,t}\beta_{2,m}$. The link function is the inverse of h, such that $h^{-1}\{\mathrm{E}(c_{i,t}|\eta_{i,t} = m; c_{i,t} > 0; x_{i,t}; \beta_{2,m})\} = x'_{i,t}\beta_{2,m}$. We determine the appropriate link function using Box-Cox tests. We limit the choice of variance functions to the class of power-proportional variance functions that specify the variance to be equal to the v-th power of the expected value, or:

$$Var(\mathrm{E}(c_{i,t})) = \mathrm{E}(c_{i,t})^v, \tag{4.8}$$

where v is an integer. We use the modified Park test (Manning and Mullahy, 2001) to determine the value of v.

Most applications of the two-part model are based on cross sectional data and assume that the probability of use is independent of the conditional expectation of expenditures. However, there is a growing literature of two-part models with correlated random effects (e.g. Van Ourti (2004) and Liu et al. (2010)). In the latent class framework, the two parts of the expenditure model are assumed to be independent conditional on the state of the latent variable. However, since both the probability of use and the expectation of the expenditures depend on the value of $\eta_{i,t}$, both parts are correlated unconditional on the latent class (Bago d'Uva, 2006).

4.2.3 Markov transition model

Now that we have established the relationship between the latent variable $\eta_{i,t}$ and the observed indicator of health and health care expenditures in t, we can turn to how this latent health variable changes over time. For this purpose we define a Latent Transition first-order Markov model with annual transition between states. The Markov assumption entails that the probability of a transition in latent state between the current time period and the next time period only depends on the current state. In other words,

$$P(\eta_{i,t} = m|\eta_{i,t-1}, .., \eta_{i,0}; x_{i,t}) = P(\eta_{i,t} = m|\eta_{i,t-1}; x_{i,t}).$$

The transitions are modeled by specifying a separate multinomial logit for $P(\eta_{i,t} = m|\eta_{i,t-1} = l)$ for each state l of the latent variable:

$$P(\eta_{i,t} = m|\eta_{i,t-1} = l; x_{i,t}; \Lambda_l) = \frac{\exp(x'_{i,t}\lambda_{l,m})}{\sum_{j=1}^{M}\exp(x'_{i,t}\lambda_{l,j})}. \tag{4.9}$$

In these models we do allow the x variables to have an effect on the transition probabilities.

4.2.4 The full Latent Markov model

The full latent Markov model consists of two components: a structural component, modeling individual changes in the latent variable over time, and a measurement component defining the relationship between the value of the latent variable and the observed health indicators and health care expenditures (Paas et al., 2007). The structural component consists of the transition probabilities defined by Equation (4.9) and the initial latent state probability. The latter can be defined as $P(\eta_{i,0} = m_0)$, the probability that an individual is in latent state m at the first measurement. We do not include covariates for this probability, so that it is equivalent to the proportion of all respondents in state m at the first measurement.

Let $c_i = [c_{i,1}, .., c_{i,T}]$ be a vector containing the expenditures of individual i in periods $t = 1, .., T$, and $Y_i = [y_{i,1}, .., y_{i,T}]$ be a matrix containing the observed health indicators in these periods. To simplify notation, let θ be a vector containing all parameters in β, γ, and Λ. Now, assume that individual i has the following particular combination of latent states over time: $\eta_{i,0} = m_0$, .., $\eta_{i,T} = m_T$. The likelihood of observing this sequence of states, and observing c_i ad Y_i is $P(c_i, Y_i, m_{i,0}, .., m_{i,T}|X_i, \theta)$. This probability is given by multiplication of the two components of the model: First, the probability of observing this particular sequence of health states. This is defined by $P(\eta_{i,0} = m_0)$ and the transition probabilities defined by Equation (4.9):

$$P(\eta_{i,0} = m_0|\theta)\prod_{t=1}^{T} P(\eta_{i,t} = m_t|\eta_{i,t-1} = m_{t-1}; x_{i,t}; \theta).$$

Second, the probability of observing a particular combination of $c_{i,t}$ and $y_{i,t}$ given $\eta_{i,t} = m_t$, defined by Equation (4.3), over all periods:

$$\prod_{t=0}^{T} g_{m_t}(c_{i,t}, y_{i,t}|x_{i,t}; \theta).$$

In the actual data, the latent variable is not observed. Therefore, we need $P(c_i, Y_i|X_i, \theta)$, the marginal probability of observing c_i and Y_i, unconditional on the values of the latent variable. This probability is obtained by summing over all possible combinations of the latent variable over time (Paas et al., 2007). Combining the structural and the measurement component, we get:

$$\begin{aligned} &P(c_i, Y_i|X_i, \theta) = \\ &\quad \sum_{m_0=1}^{M} \sum_{m_1=1}^{M} \cdots \sum_{m_T=1}^{M} \{P(\eta_{i,0} = m_0|\theta) \prod_{t=1}^{T} P(\eta_{i,t} = m_t|\eta_{i,t-1} = m_{t-1}; x_{i,t}; \theta) \\ &\quad \times \prod_{t=0}^{T} g_{m_t}(c_{i,t}, y_{i,t}|x_{i,t}; \theta)\}. \end{aligned} \tag{4.10}$$

4.2.5 Estimation

Estimation is performed by maximizing the log-likelihood over all individuals,

$$L = \sum_{i=1}^{N} \log(P(c_i, Y_i|X_i, \theta)).$$

For this purpose, we use the Expectation Maximization (EM) algorithm (Dempster et al., 1977; Van de Pol and Langeheine, 1990; Paas et al., 2007). EM is an iterative optimization procedure that can be used in the presence of latent or incomplete data. After an initial guess of the parameters θ', the algorithm iterates between an estimation step and a maximization step until convergence is reached. In the E-step, the unobserved membership probabilities of the latent class are updated based on the latest estimate of θ. In the M-step, the parameters are estimated by maximizing the log-likelihood given the updated membership probabilities. The advantage of EM is that the M-step can be performed using standard estimation methods.

As an illustration, we write the contribution of i to the expected log-likelihood as an explicit function of the posterior membership probabilities (written in bold):

$$\begin{aligned} &\mathrm{E}(\log(L_i)) = \\ &\quad \sum_{m_0=1}^{M} \{\log[P(\eta_{i,0} = m_0; \theta)]\mathbf{P}(\boldsymbol{\eta}_{\mathbf{i,0}} = \mathbf{m_0}|\mathbf{c_i}, \mathbf{Y_i}; \mathbf{X_i}; \boldsymbol{\theta})\} + \\ &\quad \sum_{t=1}^{T} \sum_{m_{t-1}=1}^{M} \sum_{m_t=1}^{M} \{\log[P(\eta_{i,t} = m_t|\eta_{i,t-1} = m_{t-1}; x_{i,t}; \theta)] \\ &\quad \times \mathbf{P}(\boldsymbol{\eta}_{\mathbf{i,t}} = \mathbf{m_{i,t}}, \boldsymbol{\eta}_{\mathbf{i,t-1}} = \mathbf{m_{i,t-1}}|\mathbf{c_i}, \mathbf{Y_i}, \mathbf{X_i}; \boldsymbol{\theta})\} + \\ &\quad \sum_{t=0}^{T} \sum_{m_t=1}^{M} \{\log[g_{m_t}(c_{i,t}, y_{i,t}|\theta)]\mathbf{P}(\boldsymbol{\eta}_{\mathbf{i,t}} = \mathbf{m_t}|\mathbf{c_i}, \mathbf{Y_i}; \mathbf{X_i}; \boldsymbol{\theta})\}. \end{aligned} \tag{4.11}$$

In the E-step the posterior membership probabilities are updated. Direct estimation of the posterior probabilities would require the evaluation of all possible sequences of the latent variable over time. Since the number of sequences increases exponentially with T, we instead use the forward-backward algorithm to estimate the posterior probabilities (Baum et al., 1970; Fearnhead and Meligkotsidou, 2004). This recursive scheme, described in detail by Paas et al. (2007), reduces computing time considerably. In the M-step the log-likelihood of the different elements of the model can be maximized separately, since conditionally on the posterior probabilities the different elements of the model are independent. Maximization can be performed using standard software to estimate weighted multinomial models for the conditional probabilities of the observed variables and the transition probabilities, and weighted GLM models for the expenditures. The estimation weights are the membership probabilities from the E-step. Estimates of the standard errors are obtained using the method of Louis (1982).

4.2.6 Estimating the LMM with partially observed outcome variables

Thus far, we have assumed that in each period t, health care expenditures $c_{i,t}$ and observed health indicators $y_{i,t}$ are both available. Unfortunately, time periods between waves in many longitudinal health surveys are longer than one year. To estimate annual transitions between health states based solely on non-annual survey data, interpolation techniques would be required. Methods, such as embedded Markov chains (Laditka and Wolf, 1998; Lièvre and Brouard, 2003; Charitos et al., 2008), have been developed to interpolate between non-annual observation of a single (observed) health indicator. Estimation of the annual transition probabilities can be based on the fact that the transition probabilities for n years are combinations of consecutive annual transition probabilities, and given by the n-th power of the annual transition matrix. However, the performance of interpolation methods is not always satisfactory especially when the time between observations is long. Moreover, estimation performance seems to improve when retrospective health data is included (Laditka and Wolf, 2006; Molla and Lubitz, 2008).

In our model, the latent variable is not solely based on health indicators, but also on health care expenditures. Often, expenditures are not obtained directly from the health survey, but from a register (for example insurance data) that is linked to the survey. This means that in the years between two survey waves, expenditures, in contrast to observed health indicators, are known. Provided that the time between waves does not depend on the relationship between health indicators and expenditures, a relatively easy extension can be applied to the Latent Markov Model to make use of the expenditure information in the years between waves. For the periods in which $y_{i,t}$ is not observed, we replace $g_{m_t}(c_{i,t}, y_{i,t}|x_{i,t};\theta)$ by $f_{m_t}(c_{i,t}|x_{i,t};\theta)$ in Equation (4.10). In other words, when health indicators are not available in period t, expenditures in t are still taken into account in defining the latent variable. This procedure does not imply that the value of $\eta_{i,t}$ is wholly determined by $c_{i,t}$. As can be seen in Equation

(4.10), through the Latent Markov model, the value of $\eta_{i,t}$ also depends on observed indicators and expenditures in all other periods. This is an advantage of the estimation method, in which the state probabilities and transition probabilities are estimated jointly.

4.3 Data

We apply the Latent Markov model to Dutch data on health and hospital expenditures over the period 1995-2007. Health indicators are obtained from the Longitudinal Aging Study Amsterdam (LASA) and hospital use is based on register data. As an extension, we also estimate long term care expenditures associated with each state of the latent variable based on another register available for the years 2004-2007. The different datasets are combined through linkage to the Dutch Municipal Register (GBA) which contains basic information on everyone enlisted in a Dutch municipality. We first describe the different datasets and then turn to the linkage procedure.

4.3.1 LASA

LASA is an ongoing longitudinal study on predictors and consequences of changes in well-being and autonomy in the older populations (Huisman et al., 2011). The study follows a representative sample of adults ≥ 55 in the Netherlands over a long period of time. Data has been collected on a broad number of health dimensions. The LASA sample consists of two cohorts. The first cohort started in 1992. In 2002, a new cohort was introduced, containing younger birth years. Table 4.1 provides an overview of the consecutive waves. Waves A to E only include the old sample, the wave A/B only include the new cohort and in wave F the two cohorts are combined. Of special interest to our research is the time interval between consecutive observations of the same individual. The design of the study is such that interviews for successive waves are conducted over a 13 months time period and the interval between two consecutive interviews for the same individual is approximately three years. For the older cohort, the time period between wave E and F is about four years. Date of death is obtained from the administrative GBA data. The last time interval for individuals who have died, is therefore determined by the date of the last LASA interview before death and date of death.

Health indicators

Seven indicators of health and disability are used, covering physical as well as mental aspects of health. Table 4.2 provides an overview. Perceived health is measured by an indicator in which the respondent is asked to rate his own health on a five point scale ranging from excellent to poor. Physical functioning is measured by a self-reported

Table 4.1: Composition of the LASA sample (number of respondents) with respect to year of birth

Birthyear	Wave A	Wave B	Wave C	Wave D	Wave E	Wave F
	1992	1992-1993	1995-1996	1998-1999	2001-2002	2005-2006
1903-1907	689	-	-	-	-	-
1908-1912	774	580	384	233	133	42
1913-1917	712	575	431	318	215	109
1918-1922	589	472	384	313	242	160
1923-1927	593	492	441	386	335	278
1928-1932	580	512	463	416	385	330
1933-1937	557	476	442	410	381	338
Total	4494	3107	2545	2076	1691	1257
		Wave A/B				Wave F2
		2002-2003				2005-2006
1938-1942		508				459
1943-1947		494				449
Total		1002				908

indicator as well as an objective indicator. The first indicator consists of three items, each pertaining to a mobility activity in daily life: walking up and down a 15-step staircase without stopping, using private or public transportation, and to cut one's own toenails. The indicator is a total score, ranging between 1 (no limitations) and 4 (limitations for all three activities). The second indicator is a performance test, measuring the time it takes for the respondent to put on and take off a cardigan. Respondents are assigned a score between 1 and 4, depending on the quartile their times falls into. Respondents who are not able to perform the test are assigned the score 5. Limitations in daily activities are self-reported. Respondents are asked whether health problems limit their daily activities. The three answer categories are "no", "slightly", and "severely". The presence of chronic diseases is also self-reported. The indicator has a four point scale, ranging between no chronic disease and more than two chronic diseases. The mental aspect of health included in the study are depressive symptoms and cognitive impairments. For depressive symptoms the Center for Epidemiological Studies Depression Scale (CES-D) is used. The CES-D scale is a widely used self-reported measure of depression. The score ranges between 0 to 60. Respondents scoring more than 16 are indicated as having clinically relevant symptoms of depression. Cognitive impairments are measured by the Mini Mental States Examination (MMSE). Respondent are placed on a scale of cognitive functioning between 0 and 30, where a lower score indicates worse functioning. We use the commonly accepted cut-off point of 24.

Table 4.2: Health indicators in the LASA survey

Indicator	Description	Categories
Chronic diseases		No disease One Two More than two
Upper body performance	Time putting on-off cardigan	first quartile second quartile third quartile fourth quartile cannot
Functional limitations	Climb staircase Cut toenails Use own or public transportation	No limitations 1 limitation 2 limitations 3 limitations
Activity Limitations	Health problems limit daily activities	No Slightly Severely
Self-perceived health		Excellent Good Fair Sometime good/bad Poor
Depressive symptoms	CES-D scale (0-60) Cut-off at 16	No Yes
Cognitive impairments	MMSE (0-30) Cut off at 24	Unimpaired Impaired

4.3.2 Dutch Hospital Discharge Register

The Dutch Hospital Discharge Register (LMR) is a register of hospital admissions. All university and general hospitals and most specialized hospitals participate in the LMR. Therefore, the dataset provides a nearly complete coverage of hospital inpatient treatments in the Netherlands. All clinical and day admissions are registered based on a uniform registration system. The data include admission and discharge dates, diagnosis information on ICD-9 level, and extensive treatment information (including about 10,000 medical procedures). Costs per admission are not supplied in the LMR, but costs on a 2003 level can be calculated using data from the Dutch Costs of Illness Study (Slobbe et al., 2006; Wouterse et al., 2011). In this study, total health care expenditures are assigned to diseases and patient characteristics. For hospital expenditure a combined top-down and bottom-up approach is used. Total hospital expenditure is known from national health accounts and can be broken down to inpatient and ambulatory care respectively, using data from the Dutch hospital budget system. In this paper we focus on inpatient care including all clinical procedures and day cases, comprising 60% of total hospital expenditure. Costs per admission are split up into two parts: intervention costs and all other costs associated with hospital stay. Since all interventions are registered in the LMR, intervention costs per patient can be calculated using the detailed remuneration schemes of the Dutch hospital payment system. This scheme provides for each intervention all relevant doctor's fees and the hospital's reimbursement for associated costs of, among others, equipment, materials and personnel. All other costs of hospital stay, like nursing and accommodation costs, are calculated on a daily basis, using average per diem costs. Costs are aggregated per admission. The LMR data is available for the years 1995-2007.

4.3.3 Long term care data

A register for long term care use in the Netherlands is only available starting in 2004. This means that for the largest part of our sample, no LTC data is available. Since time between waves of the health survey is only available once every three years, for most respondents we observe health indicators and LTC expenditures in the same period only once. Therefore, we do not include LTC expenditures in the definition of the latent variable. However, given the importance of LTC for health care expenditures of the elderly, we do want to investigate how the latent states defined by the joint model of hospital expenditures and health indicators relate to LTC expenditures. Therefore, we estimate LTC expenditures ex post. After the estimation of the Latent Markov model, the LTC expenditures associated with each latent state are estimated with a weighted two-part model. The weights are the posterior class-membership probabilities resulting from the joint model of hospital costs and health. This ex-post post analysis can also provide some additional information to interpret the latent variable.

The payment of most long term care services in the Netherlands is covered by the Exceptional Medical Expenses Act (AWBZ). The Register of the Administrative Office Exceptional Medical Expenses (CAK) contains records on all use of long term care services in the Netherlands covered by the AWBZ. We use this register for the years 2004-2007 to obtain costs of institutional long term care. Just like the LMR, the CAK register does not provide direct information on costs. Again we apply costs from the Cost of Illness Study.

4.3.4 Linkage procedure

The LMR and CAK register are both available as part of the Health Statistics Database (HSB) of Statistics Netherlands. This database is a large collection of separately collected surveys and registers on a wide number of topics for the Dutch population. Observations form the different datasets can be linked on an individual level through a unique personal identification number assigned to each Dutch citizen. This number is available in the Municipal Population Registration (GBA). Besides this identification code, the GBA contains basic information like date of birth, registered partners, and postal code for everyone enlisted in a Dutch municipality. In the CAK register the personal identification code is also provided and linkage to the GBA is straightforward. In LASA and LMR the identification code is not recorded. Instead the identification code has to be obtained by linking the data to the GBA on the basis of other identifying variables. These variables are postal code, date of birth, gender, and in the case of LMR admission date. About 93 percent of all LASA respondents can be linked to the GBA. Since, unlike LASA, the LMR does also not have an internal identification code, identifiability can change over time. Statistics Netherlands provides a dataset indicating whether or not an individual can be uniquely identified based on his characteristics in a particular year for the whole population in the GBA. Of the identified LASA respondents more than 90 percent can be uniquely identified in the LMR. The resulting number of observations per year and the number of observations with observed health (either in LASA or deceased) are shown in Table 4.3.

There are three possible reasons why a LASA respondent cannot be included in the dataset or drops out. First, LASA respondents cannot be uniquely identified during the whole study period. Second, respondents whose hospital use in the LMR cannot be identified. Respondents whose hospital use can only be identified during a part of the study period, are only included in the years that their hospital use is observed. The probability of unique linkage depends on socioeconomic characteristics like age and income (De Bruin et al., 2003). Since our model includes socioeconomic background variables this is not a problem. Third, individuals drop out of LASA if they are not willing or able to participate in following waves of the study. This reason for drop out could be related to health. Previous research has found that neither contact frequency nor respondent burden related refusal was selective with respect to socio-demographic characteristics and physical and mental health indicators in LASA (Deeg et al., 2002).

Table 4.3: Number of observations in the linked dataset per year: total and with observed health

Year	No. Obs	With health
1995	3414	547
1996	3437	1626
1997*	3313	117
1998	3192	660
1999	3081	1351
2000*	2967	99
2001	2873	617
2002	2762	1493
2003	2634	500
2004*	2533	99
2005	2428	630
2006	2336	1346
2007*	2228	117

*Years without a wave of the LASA study. Observations with known health states in these years are individuals who died in that particular year.

Moreover, as discussed in Section 4.2.6 hospital expenditures of individuals that do not participate in all waves of the LASA study can still be included in the sample. Therefore,we only have to assume that participation in LASA does not depend on the relationship between health and expenditures.

4.4 Results

4.4.1 Model selection

The specification of the model involves three main choices: the selection of relevant covariates, the choice of family and link function for the GLM in the second part of the expenditure models, and the number of latent states. The selection of covariates is determined by including demographic and socioeconomic variables that are significant in different specifications of the model. The included variables are sex, $partnerstatus$, age, age^2, age^3, $education\ level$ and calendar year dummies. Although LASA includes an income variable, income level was missing for about 18 percent of the cases. We therefore opted not to include income. Since the Dutch health care system is highly accessible, we do not expect the omission of income will result in serious bias. Box-Cox tests for different specifications of the model indicate that the log-link function, $h^{-1}\{\mathrm{E}(c_{i,t}|c_{i,t} > 0)\} = \log\{\mathrm{E}(c_{i,t}|c_{i,t} > 0)\}$, provides the best fit to the data. The modified Park test indicates a quadratic relationship between mean and variance (Gamma family) in all specifications of the models.

The choice of the number of latent states is based on an assessment of model fit as well as interpretability of the states in terms of health. To assess the fit, Table 4.4 shows the values of the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) for different numbers of states. Both criterions try to weigh model fit and number of parameters (lower values of BIC or AIC are preferred). The relationships between the health indicators and the states of the latent variable are determined by Equation (6.5). Figure 4.1 shows the expected value of each health indicator given the value of the latent variable for different specifications of the model. For comparability, the expected values are scaled to lie between 0 and 1. The 2 and 3 states specifications show clear differences between the states in terms of difference in health for all indicators. When we consider the loadings in the 3 state model in Figure 4.1 we can see that for each indicator, state 1 corresponds to the best health outcomes and state 3 to the worst (with the exception of the presence of chronic diseases, which are slightly higher for state 2). More specifically, the difference between states 1 and 2 lies mostly in a higher presence of chronic diseases, worse functioning, more limitations and worse perceived health. The difference between states 2 and 3 lies in even worse functioning and more limitations and also the presence of depressive symptoms and cognitive impairments.

The differences in the 4 states specifications are more ambiguous: state 3 scores

Table 4.4: Model fit for different specifications of the model

No. states	No. obs	LL	AIC	BIC
2	37198	-138190	276663	277865
3	37198	-136440	273347	275333
4	37198	-135360	271398	274287

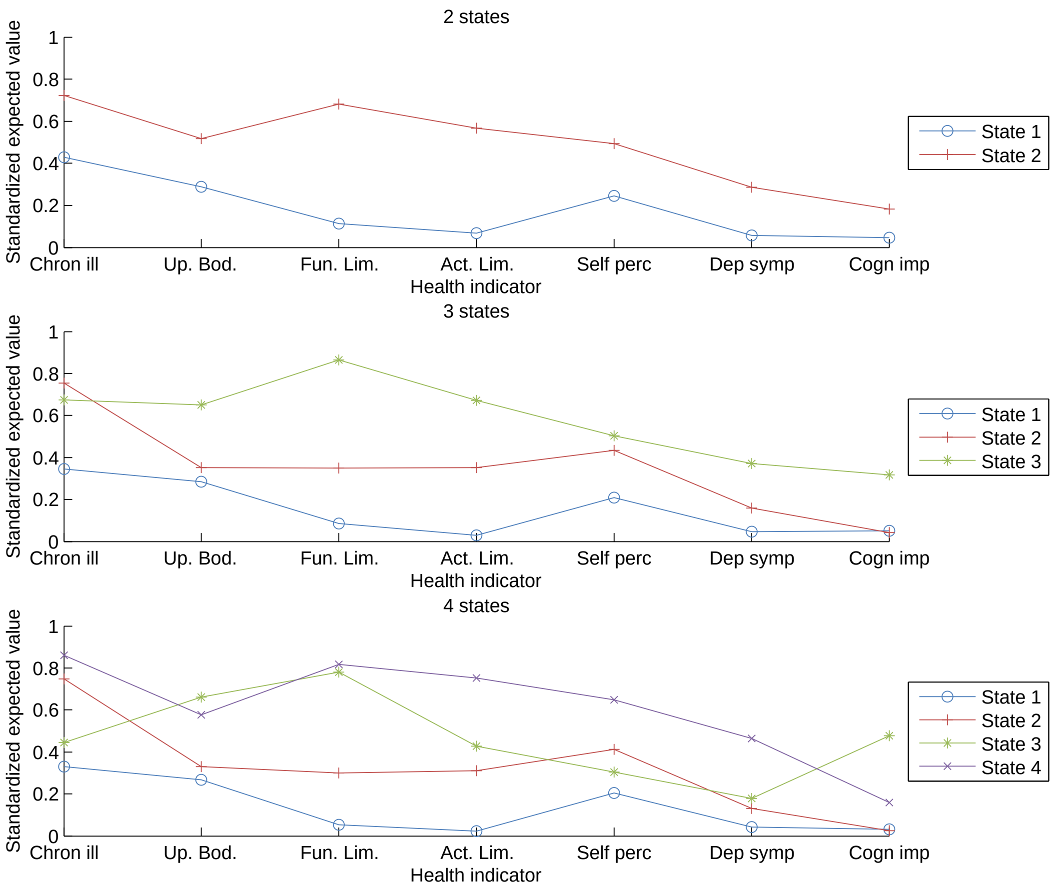

Figure 4.1: Standardized loadings of the health indicators for specification of the model with 2,3 or 4 latent states.

is associated with poorest upper body performance and cognitive impairments, while state 4 is associated with poorest outcomes for the other indicators. Also state 2 is associated with a higher presence of chronic diseases than state 3. To decide between the 3 state and 4 state specification we have compared both models in terms of lifetime patterns in health and expenditures between the 3 state and 4. In the 4 state specification one of the states has very high exit probabilities, leading to a similar lifetime pattern of health and expenditures as one of the other three states. Since the 3 state specification also offers a more straightforward interpretation in terms of health indicator loadings and the addition of a fourth state leads to a relatively small increase in model fit, we concentrate the further discussion of the results on the model with three states.

4.4.2 Expenditure models

The regression results of two-part models for hospital expenditures for the 3 state specification are reported in 4.A Table 4.6. Although the sign and significance of the coefficients can be directly interpreted, it is difficult to interpret the influence of the covariates on hospital expenditures based solely on the coefficients. Therefore, we plot the two elements of the two-part model (the probability of use and the conditional expectation of expenditures) and the resulting unconditional expectation of expenditures against age in the left side of Figure 4.2. Except age, all other variables are kept at their baseline value: sex = man, partner = no, calendar year = 2004, and education level = "secondary or intermediate college level". The probability of hospital use (part 1) is relatively constant with age conditional on the value of the latent variable, and slightly decreasing with high ages. Given a particular age, the probability is highest for state 3. The total unconditional hospital expenditures first show an increasing pattern with age, and then a decreasing pattern. Again, expenditures are highest for state 3. The right part of Figure 4.2 also shows the age patterns of the three part models for LTC expenditures. The underlying regression results are in 4.A Table 4.7. In contrast to hospital use, the probability of LTC use is increasing with age. Again, probability of use and expected unconditional expenditures are highest for state 3. The probability of LTC use for state 1 is higher than for state 2 at the highest ages.

4.4.3 Transitions between health states

The regression results of the multinomial logit models for the transition probabilities are shown in Appendix 4.A Table 4.8. To give some insight in the resulting dynamics between the states of the latent variable, we calculate the probabilities of being in particular state over time given an initial value of the latent variable. We start with a 65 year old in state $\eta_{i,t} = m$. Given his or her initial state and the transition probabilities from the multinomial logit model, we can calculate the probability that the individual will be in a particular state m at age 66. Given the probabilities of being in a particular

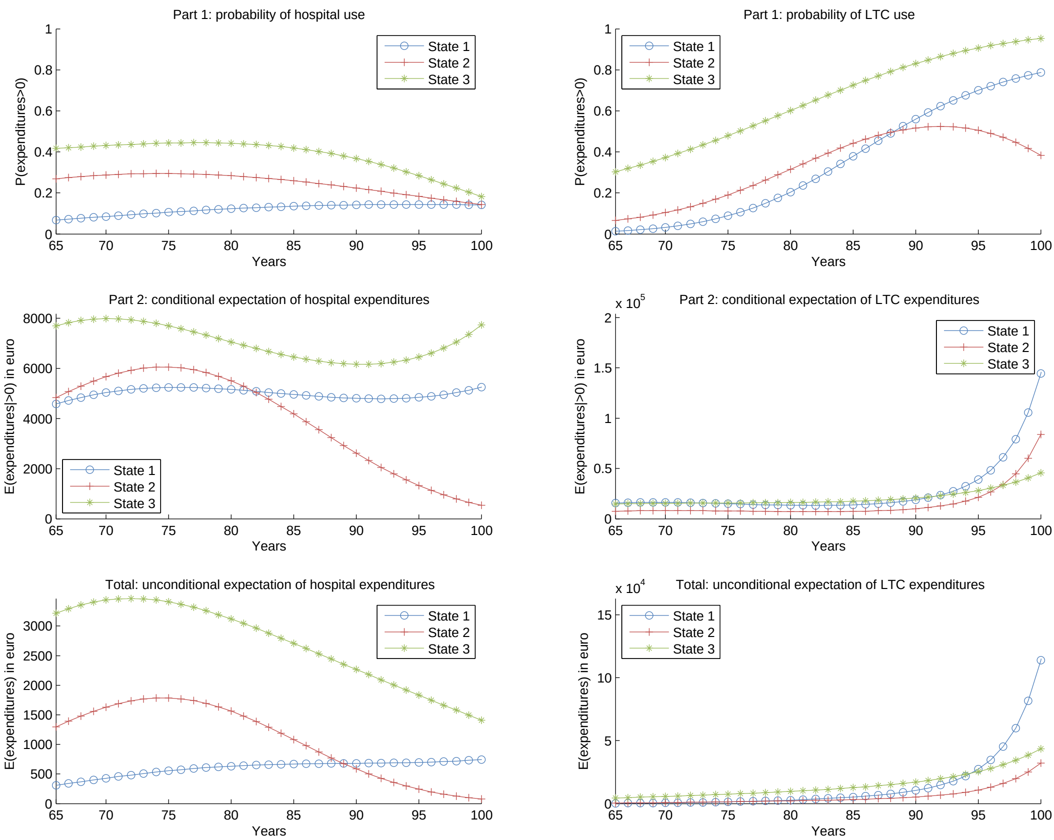

Figure 4.2: Two part models for hospital (left) and LTC (right) expenditures: probability of use, conditional expectation of expenditures and unconditional expectation of expenditures for each state of the latent variable. Men, year = 2004, partner = no, education level = "secondary or intermediate college level".

state at 66, we can again use the transition probabilities to calculate probabilities of being in a state at 67. We repeat this procedure up to age 100. Figure 4.3 shows the resulting probabilities that a 65 year old in initial state $\eta_{i,t} = m$ will be in a particular state $\eta_{i,t+x} = m$ at age $65 + x$. Results for men are on the left and women on the right. For both men and women, the remaining expected lifetime (time not spent in state "deceased") is highest for the state associated with the best health (state 1) and lowest for the initial state associated with the poorest health (3). Given a particular initial state, women have a higher remaining life expectancy, but these additional life years seem to be mostly spent in state 3. For instance, for initial state 1, the time spent in state 1 seems to be almost equal for men and women, whereas the time spent in state 3 is clearly longer for women.

4.4.4 Health and expenditures during remaining lifetime

The health paths from Figure 4.3 can be combined with the two-part expenditure models to calculate expected expenditures during remaining lifetime. Figure 4.4 shows the expected hospital expenditure per health state over remaining lifetime given initial health m at age 65. For individuals in state 1 at 65, the age at which hospital expenditures are expected to reach their highest value is 78. For individuals in state 2 this is 73, and for individuals in state 3 this is 65. As the initial latent state at 65 is associated with better health outcomes, a larger part of expected hospital expenditures shifts to older ages. Comparing the lifetime patterns between men and women with the same initial state, it appears that men have slightly higher expected expenditures at earlier ages, but total expected health care spending is higher for women than for men. Figure 4.5 also shows expected expenditures, but now LTC expenditures are also included. As can be seen, the majority of lifetime LTC expenditures occur in state 3. Also, the inclusion of LTC expenditures shift the distribution of lifetime spending over ages to the right. LTC expenditures during remaining lifetime are considerably higher for women than for men for all initial states

Table 4.5 shows total remaining life years and expenditures in a particular state given initial state m at different ages. For all ages and for both men and women, total remaining life years are highest for initial state 1. Moreover, individuals in state 1 spend more remaining life years in state 1 and less remaining life years in states associated with poorer health than individuals in initial state 2 or 3. For instance men at 65 with initial state 1 spend 10.5 remaining years in state 1 and 3.7 years in state 3, whereas men of the same age with initial state 3 are expected to spend 0.1 years in state 1 and 7.1 years in state 3. For all initial ages, total spending over remaining lifetime are higher for women than for men. This difference is mostly due to higher LTC expenditures. Generally, hospital expenditures over remaining lifetime are lowest when initial health is 1 for all initial ages, whereas LTC expenditures are highest when initial health is 1. For example, women in state 1 at age 75 on average

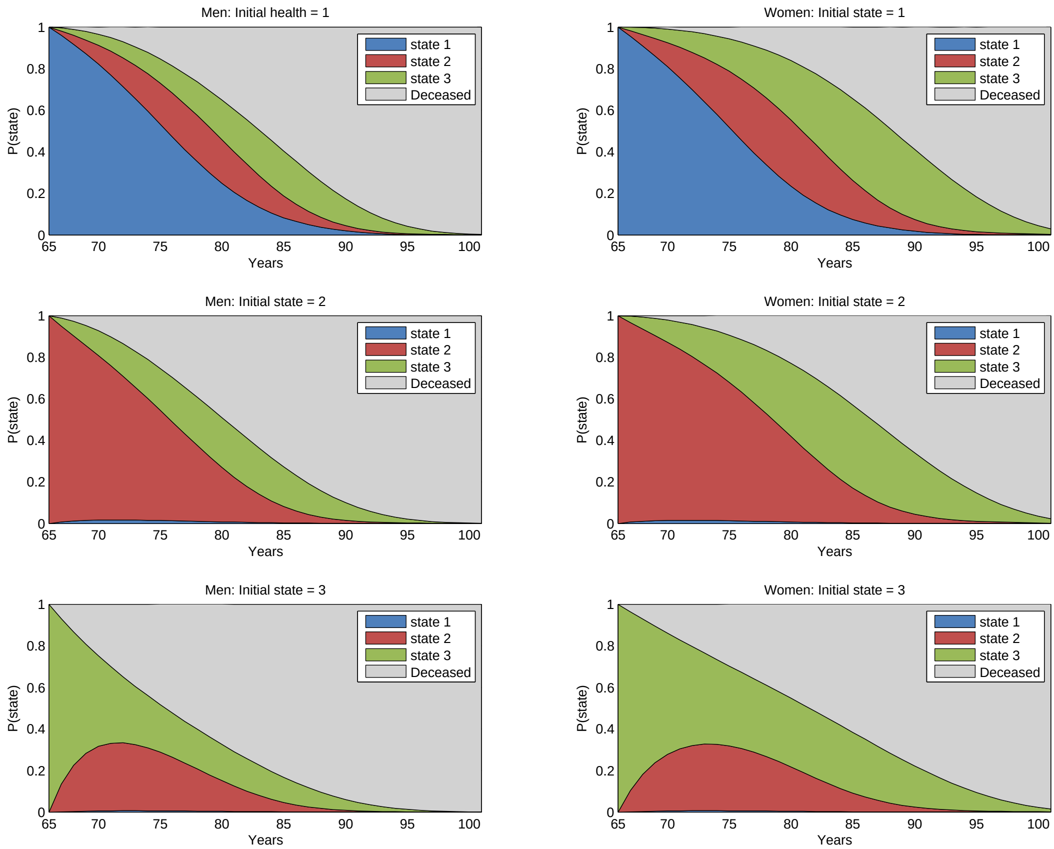

Figure 4.3: Yearly probabilities of being in a state calculated up to age 100 for individuals in a particular initial state at age 65. For each subsequent age, the probability of being in states 1-3 or death can be read. Year = 2004, partner = no, education level = "secondary or intermediate college level"

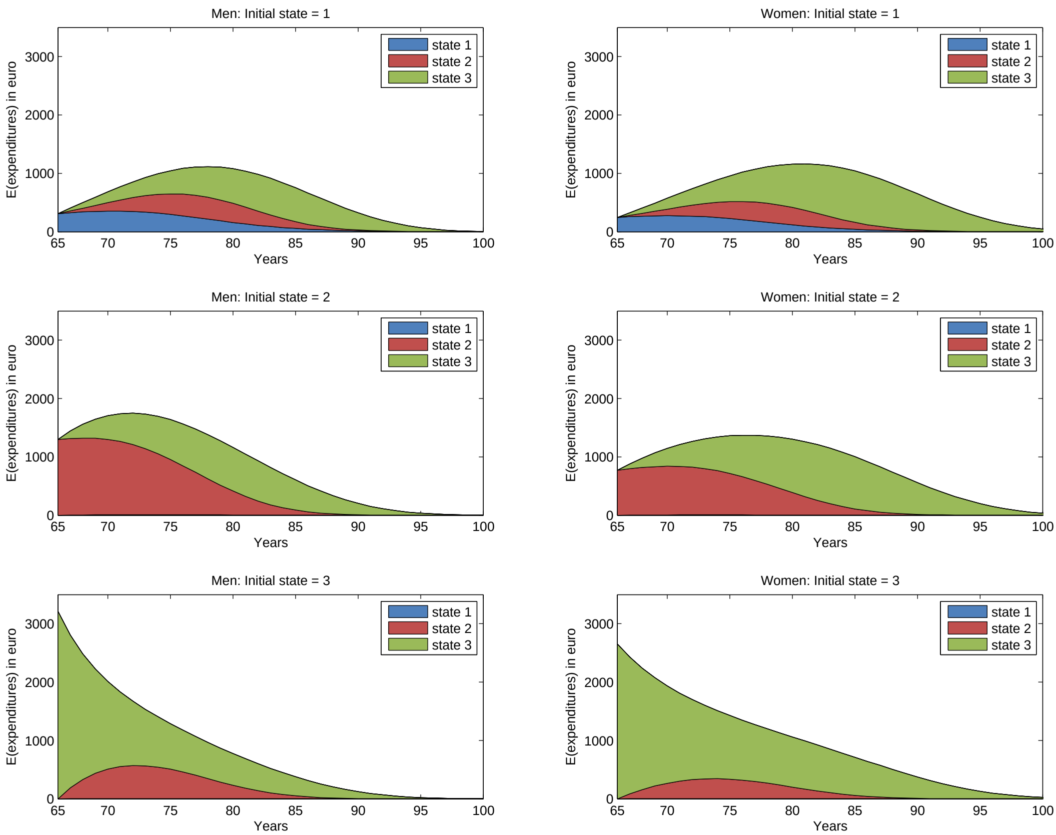

Figure 4.4: Expected hospital expenditures for individuals in a particular initial state at age 65. For each subsequent age, the expected expenditures spent in states 1-3 can be read. Year = 2004, partner = no, education level = "secondary or intermediate college level"

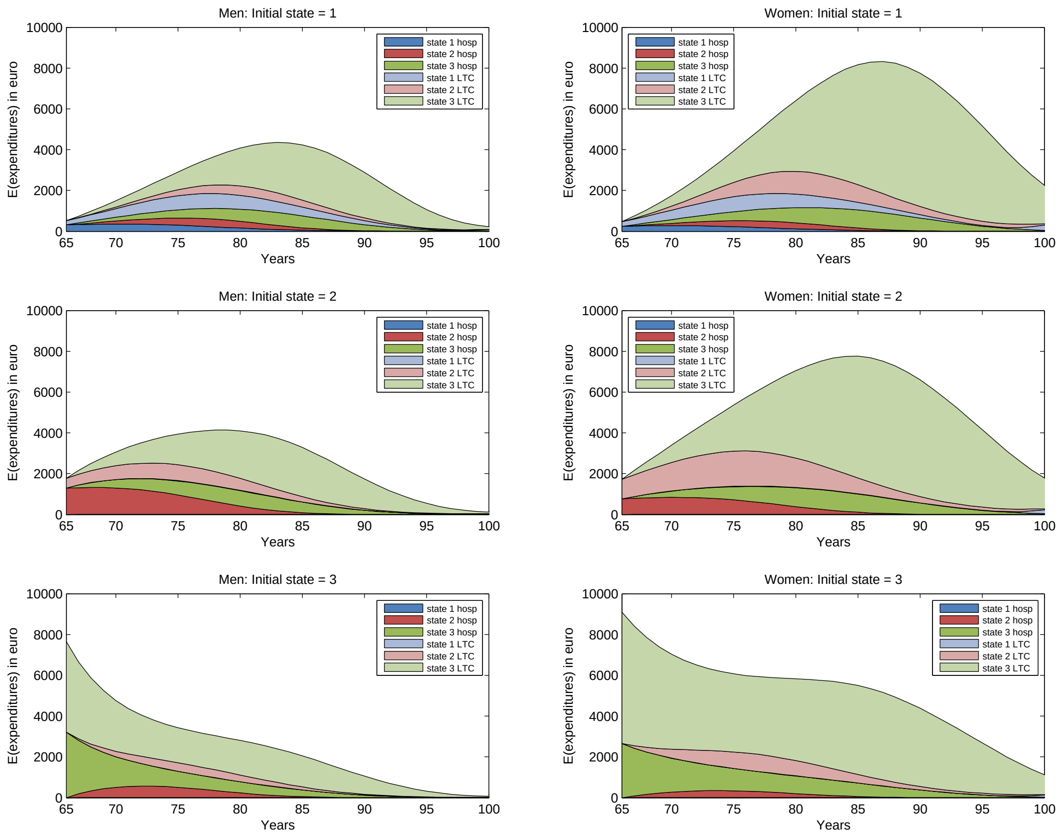

Figure 4.5: Expected hospital and LTC expenditures for individuals in a particular initial state at age 65. For each subsequent age, the expected expenditures spent in states 1-3 can be read. Year = 2004, partner = no, education level = "secondary or intermediate college level"

have a total of approximately 183,000 euros of lifetime expenditures, of which 17,000 are hospital expenditures and 166,000 euros LTC expenditures. Women of the same age in state 3, on average have 22,000 euros hospital expenditures and 136,000 euros LTC expenditures, with a total of 158,000 euros. With the exception of men at 65, lifetime total spending is higher for individuals in initial state 1 than for individuals in initial state 3.

4.5 Discussion

In this paper we have modeled the longitudinal relationship between dimensions of health and health care expenditures using a Latent Markov model. We have aimed to make two main contributions. First, we have defined latent use groups based on health indicators and expenditures jointly. This joint modeling allows us to define groups with a meaningful interpretation, both in terms of health as well as health care costs. Second, by analyzing dynamics in health and expenditures over time in a Latent Markov framework we can investigate whether initial differences in health and expenditures also lead to differences in expenditures during remaining lifetime.

The analysis in this paper shows the potential of Latent Markov modeling as a parsimonious method to capture dynamics in large sets of health indicators. In our application of this model, we have based the definition of the latent variable on health information as well as health care expenditures. Given the often used interpretation of expenditure-based finite mixture models in terms of health, this approach seems worthwhile. Also, it avoids the need for interpolation in years where no health information is available. Interpretation of the latent variable in terms of health should be done with care. The estimated relationship between health indicators and expenditures could be partly due to specific properties of the data. However, the relationships between the latent states, health loadings and hospital expenditures suggest that the latent state indeed relates to health. The modeling framework can be adjusted to accommodate analysis based solely on health, by excluding the expenditure distribution from the likelihood function. The expenditure distribution for each class can then be estimated ex-post. Such analysis seems worthwhile especially when health indicators are observed in each time period. Based on suggestions by the reviewers, we have estimated such interpolated model based solely on health. Results showed similar health loadings. There were differences in estimated transition probabilities. Ex-post estimation of hospital expenditures also showed different results, mainly small differentiation in expected expenditures between state 2 and 3 at younger ages. Differences in the expenditure function between the joint model and the interpolation model seemed to be mostly influenced by observations in periods where no health survey data was available. These results seem to suggest that, at least in our analysis, including expenditure data leads to a better identification of individual's health states during years in which no health indicator data is available.

Table 4.5: Expected remaining life years and expected health care expenditures over remaining lifetime per state for initial states of the latent variable at several ages. Year = 2004, partner = no, education level = "secondary or intermediate college level"

65		men				women			
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 1$	Years	17.4	10.5	3.2	3.7	22.3	10.3	4.8	7.2
	Hosp	20407	4992	4776	10640	23838	3830	4190	15819
	LTC	65057	13071	6768	45218	160772	19153	17675	123943
	Total	85465	18063	11544	55858	184610	22983	21865	139762
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 2$	Years	14.9	0.2	10.4	4.3	20.8	0.2	12.8	7.8
	Hosp	29411	113	16314	12984	29588	88	11797	17703
	LTC	58149	517	12901	44731	159516	5477	31087	122952
	Total	87560	630	29215	57715	189104	5565	42884	140654
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 3$	Years	11.2	0.1	4.0	7.1	16.2	0.1	4.6	11.5
	Hosp	29305	44	6517	22744	33572	40	4325	29207
	LTC	58200	244	6045	51911	150790	3324	13419	134048
	Total	87505	288	12562	74655	184363	3364	17743	163255

75		men				women			
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 1$	Years	11.1	5.7	2.0	3.4	14.9	5.6	3.0	6.3
	Hosp	14705	3554	2491	8661	17375	2743	2167	12465
	LTC	73031	17852	6048	49132	165509	25650	14808	125050
	Total	87736	21406	8538	57792	182884	28394	16975	137515
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 2$	Years	9.5	0.0	5.5	4.0	13.7	0.0	6.8	6.8
	Hosp	19455	9	8476	10970	20183	15	6002	14165
	LTC	64512	349	12377	51787	159138	7045	26276	125817
	Total	83968	359	20853	62756	179321	7060	32278	139982
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 3$	Years	6.0	0.0	0.5	5.5	9.6	0.0	0.5	9.0
	Hosp	17584	7	667	16909	21919	9	419	21492
	LTC	57189	102	1280	55807	136215	2797	2464	130954
	Total	74773	109	1948	72716	158134	2805	2883	152446

85		men				women			
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 1$	Years	6.8	3.6	0.5	2.7	9.2	3.6	0.8	4.8
	Hosp	8511	2408	305	5798	9903	1910	259	7733
	LTC	91247	31462	3143	56642	177805	44145	7278	126382
	Total	99758	33870	3448	62440	187708	46056	7537	134115
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 2$	Years	6.6	0.0	3.3	3.3	9.1	0.1	4.0	5.0
	Hosp	9681	21	2532	7128	9934	38	1695	8201
	LTC	81658	2489	15258	63911	179115	21605	28270	129241
	Total	91339	2510	17790	71039	189049	21643	29965	137442
		Total	$\eta = 1$	$\eta = 2$	$\eta = 3$	Total	$\eta = 1$	$\eta = 2$	$\eta = 3$
int. state $\eta = 3$	Years	4.0	0.0	0.0	4.0	6.3	0.0	0.0	6.3
	Hosp	9498	2	10	9487	11509	4	6	11499
	LTC	63779	96	95	63587	137052	5759	168	131125
	Total	73277	98	105	73074	148561	5764	174	142623

The loadings of the health variables on the latent variable show the relevance of the inclusion of several dimensions of health: whereas the difference between states 1 and 2 lies for an important part in a higher presence of chronic diseases, the difference between states 2 and 3 does not lie in a larger presence of chronic diseases, but in a larger disabling effect of these diseases as well as the presence of cognitive impairments. Also, although state 3 is clearly associated with worse outcomes on a number of health dimensions than state 2, perceived health is almost the same. Therefore, an analysis based for instance only on perceived health would overlook a relevant aspect of health and functioning.

The latent variable also seems to relate to hospital expenditures in a meaningful way. State 1 corresponds to the smallest probability of hospital use, and state 3 to the highest probability. The result that, conditional on (latent) health, the influence of age on probability of hospital use is small is in line with other findings on the role of age after controlling for time to death (TTD) (Zweifel et al., 1999) or more direct measures of morbidity (Dormont et al., 2006). The decreasing probability of hospital use for the oldest ages may be the result of substitution with LTC; something which seems to be confirmed by the results on LTC expenditures. Although unlike hospital expenditures, LTC expenditures were not included in defining the latent variable, the states seem to relate quite well to different levels of LTC expenditures. This finding provides some additional evidence that the latent variable not just relates to combinations of health indicators that fit hospital expenditures well, but that its interpretation is useful beyond the hospital context. State 3 is associated with the highest LTC expenditures. This association is related to the poor scores on functioning and cognitive impairments (De Meijer et al., 2011; Forma et al., 2011). In contrast to hospital expenditures, LTC expenditures rise with age even conditional on health. This relationship is also found in other studies (De Meijer et al., 2011; Weaver et al., 2009). Particulary relevant in this respect are variables related to frailty which might have additional explanatory power for LTC expenditures at higher ages. Since frailty related variables are included in recent waves of the LASA study, including frailty in a latent class analysis is a promising lead for further research.

Individuals who currently are in state 1, associated with best current health outcomes and lowest current expenditures, generally do not have lower expenditures over remaining lifetime than individuals of the same age currently in state 2 or 3. However, individuals in state 1 are expected to live longer and spend more years in better health. The same trade off between lower current expenditures and higher future expenditures due to longer life has also been found by Lubitz et al. (2003) for Medicare. They show that at 70 years, differences in functional limitations or self reported health do not lead to large differences in cumulative expenditures over remaining lifetime. Compared to Lubitz et al. (2003), our approach is novel in three respects. First, we have used a multidimensional concept of health instead of a single indicators. Second, we have reported differences in lifetime expenditures for a range of different initial ages

(65, 75, 85). Third, we differentiate between hospital expenditures and LTC expenditures. Results differ by age. At 65 differences are relatively small: men currently in state 1 have slightly lower expected total expenditures over remaining lifetime than men currently in state 3, while women currently in state 1 have slightly higher remaining lifetime total expenditures than those in state 3. For older ages, state 1 is always associated with highest total expenditures over remaining lifetime, and the differences are more pronounced. This result might be due to the fact that, at older ages, health differences are more indicative for differences in survival. Results also differ by type of care. Individuals currently in state 1 have lower expected hospital expenditures over remaining lifetime, but higher expected LTC expenditures than individuals of the same age currently in state 3. Again, it is important to note that lifetime results might differ when LTC expenditures are jointly estimated with the latent health class. Findings by Lubitz et al. (2003) for individuals who are already institutionalized in the initial year suggest that when a health state is very strongly related to use of institutional use, lifetime expenditures may be higher than for individuals in good health.

We consider differences in expenditure patterns between hospital and LTC expenditures. Based on our results for these two types of medical care it seems worthwhile to include other types, like drugs and medical devices, in future research. Given the considerable part of health care expenditures spent in poor health with many limitations, even for individuals with initial good health, it is very relevant to explore whether costs can be saved by introducing devices and drugs that can lower the disabling effect of chronic diseases. More generally, our model could be extended by including substitution mechanisms between types of care more explicitly.

We have used the Latent Markov model to analyze dynamics in health and expenditures on an individual level. The model could also be used to simulate the effects of longevity gains on aggregate expenditures under different health scenarios. Although the implementation of such an exercise is beyond the scope of this paper, the individual results do provide insights relevant for the debate on aging, time to death (TTD), and health care expenditure growth. We have not included proximity to death as an explanatory variable in the expenditure models for two reasons. First, since death is also an outcome of the Markov model, interpretation of the effect of proximity to death would be difficult. Second, we consider TTD to be proxy of health rather than an additional explanatory variable next to health. De Meijer et al. (2011), for instance, found that TTD has no significant effect on LTC use once disability is controlled for. Differences in longevity seem to be related to a postponement of expenditures to later ages rather than to an increase in expenditures. The main point of TTD analysis is that the effect of longevity gains on health care expenditures is limited, since health care use is related to proximity to death rather than to age. Gains in longevity therefore only shift expenditures to later ages. To some extent, our analysis seems to confirm this finding: At least at 65, individuals in state 1 have the longest life expectancy, but their health care expenditures are almost the same as for individuals in state 2 or 3, with smaller life expectancy. However, for LTC we find that state 1 is associated with longest life expectancy, but also highest expenditures. Also, longevity gains might not only be the result of better health, but also of a decrease of the probability of dying *given* a certain health state (in terms of the Markov model, this would imply changing transition probabilities). In such cases, the effect of longevity depends very much on the specific changes in underlying health. For instance, there is evidence that time spent with one or more chronic diseases is increasing, while time spent with severe disability remains more or less constant (Martin et al., 2010). A modeling approach such as ours is more flexible to cope with such scenarios than TTD models.

4.6 Conclusion

In order to analyze the consequences of aging on health care spending, insight is needed in the dynamic relationship between dimensions of health and expenditures. In this paper, we have combined health information based on a diverse set of indicators with expenditures in a Latent Markov model. We have compared expenditures over remaining lifetime between individuals with good current health and low current expenditures, and individuals of the same age with poor current health and high current expenditures. We have found that for the first group, expenditures tend to be postponed to later ages. As a results of this postponement effect, although expected hospital expenditures over remaining lifetime are still somewhat lower, expected LTC expenditures are considerably higher for the first group compared to the second. Although we have not considered the effects of specific health interventions, the results suggest that expectations of costs saving effects due to improvement of health of the older population should not be too high. However, the group associated with best current health is also associated with the highest life expectancy and the longest time spent in good health. This finding provides a motivation for investing in the improvement of health of the older population for its own sake.

4.7 Acknowledgements

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4.A Regression tables

Table 4.6: Two-part models for hospital expenditures for each state η. Part1: probability of use. Part 2: conditional expectation of expenditures.

$\eta = 1$

	Part 1 coef	std	p-val		Part 2 coef	std	p-val
$\Delta(woman)$	-0.10739	0.06327	0.090	$\Delta(woman)$	-0.13825	0.06949	0.047
$\Delta(partner)$	0.35813	0.07820	0.000	$\Delta(partner)$	-0.23136	0.08648	0.007
age	0.44835	0.41070	0.275	age	0.87074	0.46197	0.059
age^2	-0.00412	0.00581	0.478	age^2	-0.01062	0.00651	0.103
age^3	0.00001	0.00003	0.650	age^3	0.00004	0.00003	0.157
$education$	0.00099	0.02873	0.973	$education$	-0.00640	0.03128	0.838
$\Delta(1996)$	0.16168	0.13593	0.234	$\Delta(1996)$	0.18562	0.14635	0.205
$\Delta(1997)$	-0.07879	0.14480	0.586	$\Delta(1997)$	0.17995	0.15629	0.250
$\Delta(1998)$	-0.07538	0.14650	0.607	$\Delta(1998)$	-0.05407	0.15827	0.733
$\Delta(1999)$	0.11202	0.14237	0.431	$\Delta(1999)$	-0.37060	0.15326	0.016
$\Delta(2000)$	0.04348	0.14595	0.766	$\Delta(2000)$	0.00409	0.15693	0.979
$\Delta(2001)$	0.22466	0.14176	0.113	$\Delta(2001)$	-0.55017	0.15157	0.000
$\Delta(2002)$	0.21499	0.14369	0.135	$\Delta(2002)$	-0.14421	0.15461	0.351
$\Delta(2003)$	-0.05314	0.15495	0.732	$\Delta(2003)$	-0.10886	0.16708	0.515
$\Delta(2004)$	0.19145	0.14846	0.197	$\Delta(2004)$	-0.22915	0.15866	0.149
$\Delta(2005)$	0.32462	0.14629	0.026	$\Delta(2005)$	-0.39397	0.15562	0.011
$\Delta(2006)$	0.26544	0.15089	0.079	$\Delta(2006)$	-0.55476	0.16132	0.001
$\Delta(2007)$	0.30718	0.15172	0.043	$\Delta(2007)$	-0.44707	0.16772	0.008
c	-17.92428	9.57307	0.061	c	-14.79131	10.81151	0.171
No. of obs	15176			No. of obs	1273		
LR $\chi^2(18)$	340			Deviance	1344		
Pseudo R^2	0.04			LL	-11727		
LL	-4204						

$\eta = 2$

	Part 1 coef	std	p-val		Part 2 coef	std	p-val
$\Delta(woman)$	-0.31679	0.05130	0.000	$\Delta(woman)$	-0.28128	0.05051	0.000
$\Delta(partner)$	-0.02586	0.05819	0.657	$\Delta(partner)$	-0.11672	0.05728	0.042
age	0.46461	0.32006	0.147	age	0.12754	0.32997	0.699
age^2	-0.00460	0.00456	0.314	age^2	0.00149	0.00470	0.752
age^3	0.00001	0.00002	0.546	age^3	-0.00002	0.00002	0.334
$education$	-0.02063	0.02382	0.386	$education$	0.01823	0.02331	0.434
$\Delta(1996)$	0.01373	0.12181	0.910	$\Delta(1996)$	-0.36847	0.12003	0.002
$\Delta(1997)$	0.00396	0.12279	0.974	$\Delta(1997)$	-0.65030	0.12063	0.000
$\Delta(1998)$	0.07160	0.12212	0.558	$\Delta(1998)$	-0.41020	0.11936	0.001
$\Delta(1999)$	-0.00985	0.12448	0.937	$\Delta(1999)$	-0.74416	0.12216	0.000
$\Delta(2000)$	0.05811	0.12402	0.639	$\Delta(2000)$	-0.73644	0.12118	0.000
$\Delta(2001)$	0.15261	0.12293	0.214	$\Delta(2001)$	-0.82766	0.11961	0.000
$\Delta(2002)$	0.25071	0.12214	0.040	$\Delta(2002)$	-0.56911	0.11827	0.000
$\Delta(2003)$	0.17503	0.12424	0.159	$\Delta(2003)$	-0.96318	0.12043	0.000
$\Delta(2004)$	0.31145	0.12285	0.011	$\Delta(2004)$	-0.69845	0.11872	0.000
$\Delta(2005)$	0.30949	0.12378	0.012	$\Delta(2005)$	-1.16837	0.11913	0.000
$\Delta(2006)$	0.31310	0.12511	0.012	$\Delta(2006)$	-0.72276	0.12003	0.000
$\Delta(2007)$	0.40467	0.12545	0.001	$\Delta(2007)$	-1.11864	0.11961	0.000
c	-15.62190	7.40157	0.035	c	0.42694	7.65320	0.956
No. of obs	11067			No. of obs	2147		
LR $\chi^2(18)$	182			Deviance	2214		
Pseudo R^2	0.02			LL	-19849		
LL	-5353						

$\eta = 3$

	Part 1 coef	std	p-val		Part 2 coef	std	p-val
$\Delta(woman)$	-0.34639	0.04651	0.000	$\Delta(woman)$	0.02503	0.04290	0.560
$\Delta(partner)$	-0.14506	0.04790	0.002	$\Delta(partner)$	0.06705	0.04423	0.130
age	-0.62599	0.21985	0.004	age	1.14819	0.20938	0.000
age^2	0.00961	0.00304	0.002	age^2	-0.01472	0.00290	0.000
age^3	-0.00005	0.00001	0.000	age^3	0.00006	0.00001	0.000
$education$	0.06135	0.02170	0.005	$education$	0.03361	0.02024	0.097
$\Delta(1996)$	-0.23773	0.10385	0.022	$\Delta(1996)$	0.02253	0.09293	0.808
$\Delta(1997)$	-0.15666	0.10390	0.132	$\Delta(1997)$	-0.01891	0.09207	0.837
$\Delta(1998)$	-0.10988	0.10505	0.296	$\Delta(1998)$	-0.19357	0.09270	0.037
$\Delta(1999)$	-0.42982	0.10896	0.000	$\Delta(1999)$	-0.05629	0.09950	0.572
$\Delta(2000)$	-0.49641	0.11053	0.000	$\Delta(2000)$	-0.18876	0.10141	0.063
$\Delta(2001)$	-0.30566	0.10977	0.005	$\Delta(2001)$	-0.32741	0.09900	0.001
$\Delta(2002)$	-0.35985	0.11213	0.001	$\Delta(2002)$	-0.22441	0.10209	0.028
$\Delta(2003)$	-0.20239	0.11137	0.069	$\Delta(2003)$	-0.40107	0.09950	0.000
$\Delta(2004)$	-0.21516	0.11193	0.055	$\Delta(2004)$	-0.55998	0.10054	0.000
$\Delta(2005)$	-0.01435	0.11096	0.897	$\Delta(2005)$	-0.40706	0.09715	0.000
$\Delta(2006)$	-0.08692	0.11162	0.436	$\Delta(2006)$	-0.44029	0.09799	0.000
$\Delta(2007)$	-0.10016	0.11307	0.376	$\Delta(2007)$	-0.75159	0.10045	0.000
c	13.06051	5.21487	0.012	c	-19.98399	4.96089	0.000
No. of obs	9655			No. of obs	3295		
LR $\chi^2(18)$	183			Deviance	4051		
Pseudo R^2	0.01			LL	-33440		
LL	-6106						

Part 1 is a logit model and part 2 is a GLM with Gamma family and log-link.
$\Delta(woman) = 1$ indicates woman. $\Delta(partner) = 1$ indicates partner = yes. $\Delta(year) = 1$ indicates calendar year. Education level: 1 = primary school only, 2 = lower vocational training, 3 = secondary or intermediate college level, 4 = higher vocational training and academic level.

Table 4.7: Two-part models for LTC expenditures for each state η. Part1: probability of use. Part 2: conditional expectation of expenditures.

$\eta = 1$

	Part 1 coef	std	p-val		Part 2 coef	std	p-val
$\Delta(woman)$	0.30728	0.19362	0.113	$\Delta(woman)$	-0.19937	0.31086	0.521
$\Delta(partner)$	-0.80922	0.19071	0.000	$\Delta(partner)$	0.08605	0.31082	0.782
age	0.25350	2.13353	0.905	age	3.25314	4.28664	0.448
age^2	0.00136	0.02735	0.960	age^2	-0.04399	0.05394	0.415
age^3	-0.00002	0.00012	0.896	age^3	0.00020	0.00022	0.382
$education$	-0.17914	0.08617	0.038	$education$	-0.05716	0.14547	0.694
$\Delta(2005)$	-0.37094	0.25423	0.145	$\Delta(2005)$	0.15317	0.40260	0.704
$\Delta(2006)$	-0.15648	0.28085	0.533	$\Delta(2006)$	-0.27054	0.40676	0.506
$\Delta(2007)$	0.01571	0.24807	0.950	$\Delta(2007)$	-0.17080	0.40226	0.671
c	-22.03588	55.09822	0.689	c	-69.86051	112.90883	0.536
No. of obs	3482			No. of obs	166		
LR $\chi^2(9)$	445			Deviance	423		
Pseudo R^2	0.33			LL	-1749		
LL	-445						

$\eta = 2$

	Part 1 coef	std	p-val		Part 2 coef	std	p-val
$\Delta(woman)$	0.75059	0.13178	0.000	$\Delta(woman)$	0.00839	0.25647	0.033
$\Delta(partner)$	-0.95554	0.11803	0.000	$\Delta(partner)$	0.18292	0.22055	0.829
age	-2.11989	1.25935	0.092	age	3.66685	3.09322	1.185
age^2	0.03108	0.01651	0.060	age^2	-0.04900	0.03980	-1.231
age^3	-0.00014	0.00007	0.047	age^3	0.00022	0.00017	1.279
$education$	-0.21671	0.05659	0.000	$education$	-0.28134	0.10629	-2.647
$\Delta(2005)$	-0.18449	0.15783	0.242	$\Delta(2005)$	-0.07204	0.29390	-0.245
$\Delta(2006)$	-0.11958	0.15749	0.448	$\Delta(2006)$	-0.17648	0.29301	-0.602
$\Delta(2007)$	-0.15221	0.16038	0.343	$\Delta(2007)$	0.06421	0.30340	0.212
c	43.33755	31.80659	0.173	c	-81.45841	79.64913	-1.023
No. of obs	2911			No. of obs	468		
LR $\chi^2(9)$	540			Deviance	988		
Pseudo R^2	0.21			LL	-4694		
LL	-1014						

$\eta = 3$

	Part 1 coef	std	p-val		Part 2 coef	std	p-val
$\Delta(woman)$	0.49043	0.09395	0.000	$\Delta(woman)$	0.05617	0.08071	0.486
$\Delta(partner)$	-0.72990	0.09655	0.000	$\Delta(partner)$	-0.18335	0.07403	0.013
age	-0.04700	0.91688	0.959	age	0.94647	0.98131	0.335
age^2	0.00072	0.01185	0.952	age^2	-0.01284	0.01216	0.291
age^3	0.00000	0.00005	0.968	age^3	0.00006	0.00005	0.243
$education$	-0.03966	0.04417	0.369	$education$	0.00226	0.03669	0.951
$\Delta(2005)$	-0.07972	0.12530	0.525	$\Delta(2005)$	0.05317	0.10191	0.602
$\Delta(2006)$	0.03310	0.12509	0.791	$\Delta(2006)$	0.01234	0.10140	0.903
$\Delta(2007)$	-0.23811	0.12548	0.058	$\Delta(2007)$	-0.00831	0.10535	0.937
c	-1.29519	23.44913	0.956	c	-13.68949	26.20010	0.601
No. of obs	2731			No. of obs	1601		
LR $\chi^2(9)$	670			Deviance	2853		
Pseudo R^2	0.18			LL	-17344		
LL	-1518						

Part 1 is a logit model and part 2 is a GLM with Gamma family and log-link.
$\Delta(woman) = 1$ indicates woman. $\Delta(partner) = 1$ indicates partner = yes. $\Delta(year) = 1$ indicates calendar year. Education level: 1 = primary school only, 2 = lower vocational training, 3 = secondary or intermediate college level, 4 = higher vocational training and academic level.

Table 4.8: Mulitinomial logit models for transition probabilities for each initial state η_t

$\mathrm{P}(\eta_{t+1} = m \mid \eta_t = 1)$	coef	std	p-val
State 2			
$\Delta(woman)$	0.25701	0.08776	0.003
$\Delta(partner)$	-0.03533	0.09809	0.719
age	-7.34944	0.51263	0.000
age^2	0.10555	0.00755	0.000
age^3	-0.00050	0.00004	0.000
$education$	-0.11147	0.03973	0.005
c	164.21650	11.43044	0.000
State 3			
$\Delta(woman)$	0.11739	0.10219	0.251
$\Delta(partner)$	0.02432	0.10888	0.823
age	0.86506	0.67598	0.201
age^2	-0.01222	0.00917	0.183
age^3	0.00006	0.00004	0.119
$education$	-0.20648	0.04570	0.000
c	-25.90880	16.43368	0.115
Deceased			
$\Delta(woman)$	-1.65952	0.33435	0.000
$\Delta(partner)$	-0.67923	0.26637	0.011
age	5.71689	3.51860	0.104
age^2	-0.06901	0.04571	0.131
age^3	0.00028	0.00020	0.155
$education$	0.04632	0.11330	0.683
c	-162.47210	89.80407	0.070
No. of obs	14342		
LR $\chi^2(18)$	1258		
Pseudo R^2	0.12		
LL	-4610		

$\mathrm{P}(\eta_{t+1} = m \mid \eta_t = 2)$	coef	std	p-val
State 2			
$\Delta(woman)$	0.14351	0.12806	0.262
$\Delta(partner)$	-0.11457	0.18240	0.530
age	-4.84856	0.86304	0.000
age^2	0.08119	0.01284	0.000
age^3	-0.00042	0.00006	0.000
$education$	-0.27622	0.06199	0.000
c	93.73756	18.89013	0.000
State 3			
$\Delta(woman)$	-0.11799	0.14530	0.417
$\Delta(partner)$	-0.08912	0.19712	0.651
age	-9.04735	0.91744	0.000
age^2	0.13848	0.01357	0.000
age^3	-0.00068	0.00006	0.000
$education$	-0.42910	0.06961	0.000
c	191.03150	20.23380	0.000
Deceased			
$\Delta(woman)$	-1.32497	0.36178	0.000
$\Delta(partner)$	-1.40153	0.37916	0.000
age	-1.70921	4.90363	0.727
age^2	0.04753	0.06578	0.470
age^3	-0.00031	0.00029	0.291
$education$	-0.75177	0.17924	0.000
c	-2.91039	121.29660	0.981
No. of obs	10336		
LR $\chi^2(18)$	1627		
Pseudo R^2	0.17		
LL	-4117		

$\mathrm{P}(\eta_{t+1} = m \mid \eta_t = 3)$	coef	std	p-val
State 2			
$\Delta(woman)$	-0.33537	0.27549	0.223
$\Delta(partner)$	-3.29534	0.81552	0.000
age	-8.09561	1.62830	0.000
age^2	0.11359	0.02262	0.000
age^3	-0.00053	0.00010	0.000
$education$	-0.07649	0.12955	0.555
c	197.75430	38.88650	0.000
State 3			
$\Delta(woman)$	0.01341	0.25319	0.958
$\Delta(partner)$	-3.20413	0.80420	0.000
age	-6.36933	1.37715	0.000
age^2	0.08662	0.01835	0.000
age^3	-0.00039	0.00008	0.000
$education$	-0.22006	0.11920	0.065
c	160.80850	34.02988	0.000
Deceased			
$\Delta(woman)$	-0.72877	0.26033	0.005
$\Delta(partner)$	-3.20026	0.80632	0.000
age	-4.04368	1.48236	0.006
age^2	0.05778	0.01961	0.003
age^3	-0.00026	0.00009	0.002
$education$	-0.21355	0.12242	0.081
c	95.73741	36.93164	0.010
No. of obs	8953		
LR $\chi^2(18)$	1484		
Pseudo R^2	0.14		
LL	-4671		

$\Delta(woman) = 1$ indicates woman. $\Delta(partner) = 1$ indicates partner = yes. Education level: 1 = primary school only, 2 = lower vocational training, 3 = secondary or intermediate college level, 4 = higher vocational training and academic level.

Chapter 5

The effect of trends in health and longevity on health care expenditures in the older population. A scenario analysis.

Abstract

The effect of population aging on health care expenditure growth depends on the relationship between health and life expectancy. This relationship is complex. Trends in different aspects of health diverge, and empirical evidence is often not decisive. However, most health care expenditure studies rely on strong implicit assumptions on the relationship between longevity and health, or use only a single dimension of health. We implement a simulation study based on a latent Markov model that includes different dimensions of health. Using two values of future remaining life expectancy at 65, we analyze different health scenarios based on common hypotheses on the relationship between longevity and health: expansion of morbidity, compression of morbidity, and dynamic equilibrium. We use the scenarios to predict health care expenditure growth in the Netherlands between 2010 and 2050. Hospital expenditures are predicted to decline after 2040, whereas home care and institutional long-term care will continue to rise at least up to 2050. We find considerable differences in expenditure growth rates between scenarios with the same life expectancy in 2050 but different trends in health. Compression of morbidity generally leads to the lowest expenditure growth. The effect of additional life expectancy gains *within* the same health scenario is relatively small for hospital care, but considerable for long-term care. There seems

to be room for health improvement policies to contain expenditure growth, although potential effects should not be exaggerated. When associated with improvement in underlying health, additional growth in life expectancy has only a limited effect on expenditure growth.

Based on
Wouterse, B., Huisman, M., Meijboom, B.R., Deeg, D.J.H., & Polder, J.J. (2012). The effect of changing trends in health and longevity on health care expenditures in the older population. A scenario analysis. *Submitted*

5.1 Introduction

Trends in health do not necessarily coincide with the trend in life expectancy. For instance, most Western countries have been experiencing considerable longevity gains over the past decades (Oeppen and Vaupel, 2002), whereas the number of years spent with chronic diseases have been increasing (Crimmins and Beltrán-Sánchez, 2010), and those spent with disability have been declining or stable (Martin et al., 2010). In the epidemiological literature, three hypotheses about the relationship between rising life expectancy and health are generally used (Robine et al., 2009). First, the extension of morbidity hypothesis, in which life expectancy gains are paired with an increase in the number of lifeyears spent in poor health (Gruenberg, 1977; Kramer, 1980). Second, the compression of morbidity hypothesis, where the number of lifeyears spent in poor health decreases (Fries, 1980). Third, the dynamic equilibrium hypothesis, where a trade off between increasing survival and prevalence of chronic diseases results in a constant number of years spent in poor health (Manton, 1982). These scenarios of longevity and health influence the consequences of population aging on health care expenditure growth. For instance, life expectancy gains resulting from increasing survival of individuals in poor health can be expected to have a different effect on health care expenditure growth than life expectancy gains caused by improvements in population health. Out of the large number of aging studies, there are only a few that directly consider underlying health scenarios. For example, recent long-term projections of health care spending in Europe include several different scenarios of changes in the age profile of health care spending related to changes in population health, but health itself is not modeled or simulated (European Commission, 2012). In other cases, health care projections are based on only a single health measure.

A substantial part of aging research focuses on the relationship between proximity to death and health care expenditures (Zweifel et al., 1999; Payne et al., 2007). The main finding of this literature is that the positive association between age and health care expenditures is for a large part due to the relationship between mortality and health care expenditures, and not to age itself. This finding implies that longevity gains postpone health care expenditures rather than increase them. In these studies, proximity to death functions as a proxy for morbidity. In contrast, a number of other studies investigate the consequences of aging on health care expenditures using a more direct measure of health. An often used indicator is disability, especially for studies concerning long-term care. Laditka (2001), Manton et al. (2007), and Stearns et al. (2007) include disability trends in their predictions of health care use and expenditures in the U.S.. For the Netherlands, De Meijer et al. (2012) analyze the consequences of projected trends in disability for long-term care (LTC) use. They conclude that longevity gains, paired with a compression of severe disability, do not lead to large increases in LTC spending. Goldman et al. (2005) use a more diverse set of health variables to make projections of health care expenditures in the U.S.. Their model includes lifestyle risk factors, a set of chronic diseases, and disability measures. They only find small differences in expenditure growth between optimistic and pessimistic health scenarios. This result can mostly be attributed to the fact that in their analysis improvements in health also imply a decrease in mortality (Lubitz et al., 2003; Lubitz, 2005). As a result, initial savings are compensated by health care expenditures at older ages.

Both time to death studies and studies using a direct health measure assume a particular relationship between health and longevity. However, this relationship remains implicit. For example, time to death studies assume that a rise in life expectancy does not change the relationship between proximity to death and health care expenditures. They thus adhere to a compression, or at least postponement, of morbidity scenario. When health trends do not follow the trend in life expectancy, this assumption does not hold. Other studies that include more detailed health information often focus on a single dimension of health. Even Goldman et al. (2005) include only a limited number of chronic diseases and disability states. Brouwers et al. (2011) who make predictions of health care expenditures in Sweden using scenarios based on the three common morbidity hypotheses, do not seem to differentiate their scenarios between health dimensions. When trends in dimensions of health diverge, the use of a single health indicator, describing just one health dimension is not sufficient. This point is especially relevant when different health dimensions relate to different types of care. Empirical research shows that the relationship between further increasing life expectancy and trends in health is surrounded by a great amount of uncertainty (Martin et al., 2010; Christensen et al., 2009). This uncertainty warrants a scenario analysis in which the consequences of the different morbidity hypotheses for health care expenditures are compared.

In this paper, we use a simulation model to analyze different health scenarios. The model is based on a latent health variable that incorporates a large set of health indicators, including chronic diseases, self-perception of health, cognitive functioning, and disability. In contrast to other studies, we consider different health scenarios resulting in the same increase in life expectancy. Our approach shows how the effect of increasing life expectancy on health care expenditure growth is driven by the uncertain relationship between longevity and health. We base our scenarios on the three general hypotheses on this relationship. Although we relate the scenarios to empirical evidence on trends in health, our main aim is not to provide the most accurate forecast of health care expenditure growth. Instead, we use the scenarios to gain insight into the health dynamics that drive the effect of aging on expenditure growth. We apply the model to health care expenditure projections in the Netherlands between 2010 and 2050. We focus on expenditures in hospital care, home care and institutional LTC.

5.2 Trends in health

In most Western countries, life expectancy has increased by about 30 years during the last century (Christensen et al., 2009). Although no consensus exists whether this rise will continue at the same pace in the long run, almost all projections foresee a further increase of life expectancy in the coming decades. Oeppen and Vaupel (2002) even argue that the maximum value life expectancy will continue to rise linearly by 3 months per year. In the Netherlands, (female) life expectancy seemed to stagnate at the end of the 20th century, but has been rising steadily since 2001. In 2010, life expectancy at birth was 78.8 for men and 82.7 for women. Janssen and Kunst (2010) predict an almost linear increase, resulting in a life expectancy at birth of 83.8 for men and 88.1 for women by 2050. Their forecast for remaining life expectancy at 65 is 21.1 years for men and 24.6 years for women, compared to 16.7 respectively 20.1 years in 2006.

The consequences of longevity gains for health care expenditures depend on the relationship between longevity and health and disability. The three most common hypotheses about this relationship have been formulated in the 1980s (Robine et al., 2009). First, Gruenberg (1977) and Kramer (1980) posed that medical progress would mostly lead to an increasing survival of people in poor health, but not to a change in the age specific onset of (chronic) diseases. As a result, the number of years spent in poor health would expand. Instead, Fries (1980) expected that medical progress would be mostly aimed at improvements in health, and would thus postpone the age specific onset of diseases. Therefore, he expected a compression of the number of years spent in poor health. Finally, Manton (1982) proposed a dynamic equilibrium between increases in survival and the progress of chronic diseases, resulting in a constant proportion of life spent in poor health. In this hypothesis, the prevalence of chronic diseases increases but the severity decreases. Time spent with severe disability therefore remains the same, whereas time spent with mild disability might increase.

The relationship between health and longevity depends on the dimension of health under consideration. Here, we discuss evidence on trends in chronic diseases, disability, and lifestyle. Prevalence of chronic diseases seems to be rising in most countries (Christensen et al., 2009; Crimmins and Beltrán-Sánchez, 2010; Robine and Michel, 2004). As a result, the expected number of lifeyears spent with one or more chronic diseases is growing. Although findings diverge per country, rising trends in the prevalence of heart disease, arthritis, cancer and cardiovascular diseases have generally been found. Results are mixed for hypertension and stroke (Christensen et al., 2009). This dual trend in life expectancy and chronic diseases might partly be the result of improved medical treatments of some fatal conditions that do not change the age-specific onset of those conditions. Other explanations are improved diagnosis and changes in lifestyle, such as obesity and smoking. In the Netherlands, a decline in life expectancy without chronic diseases from 53 to 48 years for men and 52 to 43 years for women between 1983 and 2007 has been observed (Van der Lucht and Polder, 2010; Hoeymans et al., 2012).

Evidence on trends in functioning and disability is mixed, sometimes even between different studies in the same country. In the U.S., a number of studies have found improvements in functioning and a decline of disability in the 1980s and 1990s (Martin et al., 2010). There is some debate whether this trend will continue into the future. Some researchers argue that the trend is mainly due to improved medical treatment, and will therefore continue (Manton et al., 2007), while others argue that based on lifestyle and disability in younger age cohorts, an eventual rise in disability can be expected (Lakdawalla et al., 2003). In a study of twelve OECD countries, Lafortune and Balestat (2007) find that only five countries, including the Netherlands, show a decline in severe disability. Robine and Michel (2004) report evidence for several countries that the expected number of years spent with severe disability is declining or stable, while the number of years spent with moderate disability is increasing. This trend is also observed for the Netherlands by Puts et al. (2008) and Van Gool et al. (2011). It seems that severe disability is strongly related to the end of life, whereas mild disability is not (Guralnik et al., 1991; Chen et al., 2007; Klijs et al., 2011), implying that an extension of life expectancy increases lifeyears spent with mild disability, but years spent with severe disability remain stable.

Lifestyle differences between cohorts do not all point in the same direction. Obesity rates in the U.S. have been increasing for successively born cohorts. Also in the U.S., an increase in disability among the younger population has been observed. However, trends in smoking behavior are optimistic (Martin et al., 2010). An important positive influence on the health of the future older population is the rise in education level (Robine and Michel, 2004; Martin et al., 2010). In the Netherlands, an increase in the prevalence of obesity and a slight decline in smoking, especially for men, have also been observed (Van der Lucht and Polder, 2010). Visser et al. (2005) find higher prevalence of obesity, higher alcohol consumption and lower physical activity of 55-64 year olds in 2002-2003 compared to 1992-1993 in the Netherlands.

Whereas the trend, or at least the direction, in life expectancy is relatively clear, the trends in specific dimensions of health are more diverse and uncertain. There is strong evidence for a further increase in life expectancy. It is likely that this is paired with an increase in the prevalence of chronic diseases. Also there is some evidence for an increase in mild disability and a declining or stable trend in severe disabilities. Findings on the effects of lifestyle differences between younger cohorts and the current older population are not conclusive. To account for the uncertainty in health trends, we base our simulation study on all three hypotheses, and use a broad indicator of health that allows for different interactions between health dimensions.

5.3 Data

To analyze the consequences of different health scenarios on health care expenditure growth we use a simulation model developed by Wouterse et al. (2012). This model can be used to analyze dynamics in the relationship between different health dimensions and health care expenditures. The model has been estimated using a combined dataset of longitudinal health survey data and registry data on health care use.

5.3.1 Health survey data

The Longitudinal Ageing Study Amsterdam (LASA) is an ongoing longitudinal study on predictors and consequences of changes in well-being and autonomy in the older population (Huisman et al., 2011). The study follows a representative sample of adults ≥ 55 in the Netherlands over a long period of time. Data has been collected on a broad number of health dimensions. Respondents are interviewed every three years. The LASA sample consists of two cohorts. The first cohort started in 1992 with almost 4500 respondents born between 1903 and 1937. In 2002, a new cohort was added. This cohort consists of 1000 respondent born between 1938 and 1947. For our analysis, we use the four waves between 1995 and 2006.

Seven indicators of health and disability are used in the model, covering physical as well as mental aspects of health. Table 5.1 provides an overview. Self-perceived health is measures on a five point scale. Physical functioning is measured by a self-reported indicator as well as an objective indicator. The first indicator consists of three items, each pertaining to a mobility activity in daily life. The indicator is a total score, ranging between 1 (no limitations) and 4 (limitations for all activities) (Kriegsman et al., 1997). The second indicator is a performance test, measuring the time it takes for the respondent to put on and take off a cardigan. Limitations in daily activities are measured with the Global Activity Limitation Indicator (GALI) (Van Oyen et al., 2006). The presence of chronic diseases is also self-reported. The mental aspects of health included in the study are depressive symptoms and cognitive impairments. For depressive symptoms the Center for Epidemiological Studies Depression Scale (CES-D) is used (Radloff, 1977). Cognitive impairments are measured by the Mini Mental States Examination (MMSE) (Folstein et al., 1976).

5.3.2 Data on health care use

We use registry data on hospital use and LTC use. Both these datasets are included in the Health Statistics Database (HSB) of Statistics Netherlands. This database is a large collection of separately collected surveys and registers on a wide number of topics for the Dutch population. Observations from the different datasets can be linked on an individual level through a unique personal identification number assigned to each Dutch citizen. With the use of the personal identification number it is possible to

Table 5.1: Health indicators in the LASA survey

Indicator	Description	Categories
Chronic diseases		No disease One Two More than two
Upper body performance	Time putting on-off cardigan	first quartile second quartile third quartile fourth quartile cannot
Functional limitations	Climb staircase Cut toenails Use own or public transportation	No limitations 1 limitation 2 limitations 3 limitations
Activity Limitations	Health problems limit daily activities	No Slightly Severely
Self-perceived health		Excellent Good Fair Sometime good/bad Poor
Depressive symptoms	CES-D scale (0-60) Cut-off at 16	No Yes
Cognitive impairments	MMSE (0-30) Cut off at 24	Unimpaired Impaired

link the LASA survey to this database on an individual level (Wouterse et al., 2012). The Dutch Hospital Discharge Register (LMR) is a register of hospital admissions. All university and general hospitals and most specialized hospitals participate in the LMR. Therefore, the dataset provides a nearly complete coverage of hospital inpatient treatments in the Netherlands. All clinical and day admissions are registered based on a uniform registration system. The data include admission and discharge dates, diagnosis information on ICD-9 level, and extensive treatment information (including about 10,000 medical procedures). For each admission, costs on a 2003 level can be calculated using data from the Dutch Costs of Illness Study (Slobbe et al., 2006; Wouterse et al., 2011). The LMR data is available for the years 1995-2007.

The payment of most long-term care services in the Netherlands is covered by the Exceptional Medical Expenses Act (AWBZ). The Register of the Administrative Office Exceptional Medical Expenses (CAK) contains records on all use of long-term care services in the Netherlands covered by the AWBZ. Data on the years 2004-2007 have been used to obtain costs of institutional long-term care. Based on the use data, costs are assigned using the Dutch Cost of Illness Study.

5.4 Methods

5.4.1 Simulation model

The simulation model is based on a latent Markov framework. The relationship between the separate health indicators and expenditures is modeled through an unobserved (latent) discrete variable. Individuals switch between health states annually, according to the Markov assumption that transition probabilities only depend on current latent health. The state of the latent variable determines the probability distributions of the separate health indicators as well as of health care expenditures. For each health indicator, the probability of being in a particular health state is specified as a finite mixture of the conditional multinomial probabilities for each state of the latent variable. For each value of the latent variable, the relationship with health care expenditures and other explanatory variables is also estimated separately. Health care expenditures, for hospital care, home care, and institutional LTC, are estimated in two stages. First, the probability of any health care use in a particular year is estimated. Second, the expected costs of health care use in a particular year, conditional on using health care in that year are estimated. For the first part of the model, a logit specification is used, and for the second part, a general linear model (GLM) with log-link and Gamma family. Covariates sex, $partnerstatus$, age, age^2, age^3, $education\ level$, and calendar year dummies are used in both parts of the model. The relationship between health indicators as well as hospital expenditures with the latent variable is estimated jointly. Because of the limited number of available years, the relationship between home care and institutional LTC expenditures with the latent variable are

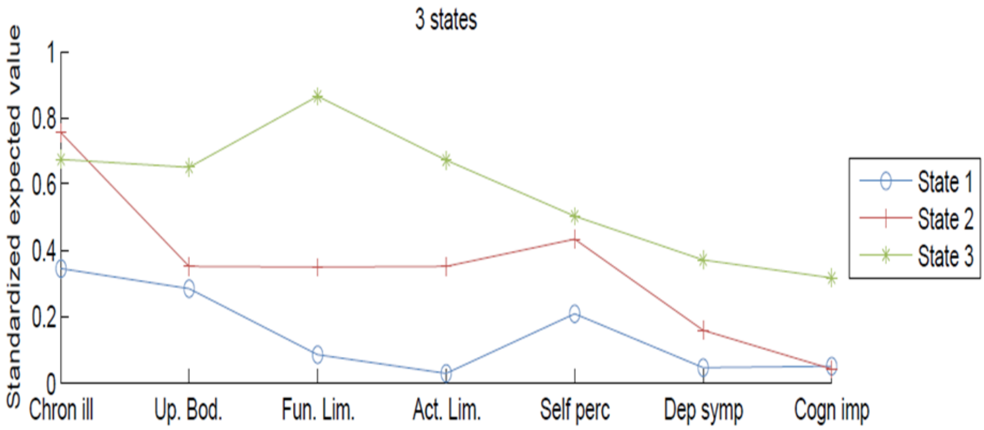

Figure 5.1: Standardized loadings of the health indicators for specification of the model with 3 latent states.

estimated ex-post.

Annual transition probabilities between the states of the latent variable are jointly modeled with the observed health indicators and expenditure distributions. The transition probabilities are modeled using multinomial logit models with the same covariates as the expenditure models, with the exception of the calendar year dummies. Details of the model specification and estimation results are discussed by Wouterse et al. (2012).

The number of discrete health states can be selected based on model fit. We use four states: three health states and death. An advantage of the use of a discrete instead of a continuous health variable is that the different states of the latent variable can be related to different combinations of health dimensions in a meaningful way. Figure 5.1 shows how the latent health states are related to the observed health indicators. For ease of comparison, the outcomes for each indicator are standardized to lie between 0 (best outcome) and 1 (worst outcome). The figure shows the standardized expected value of each indicator for each state of the latent variable. State 1 is related to good health for all indicators. State 2 is related to moderate health: a high probability of having chronic diseases and only a moderate probability of having disability. State 3 is poor health: high probability of disability and cognitive impairments.

As an example, Table 5.2 shows how the latent states are related to health care expenditures for a 70 year old woman, with all other variables set at their reference level. The table shows the probability of health care use as well as the unconditional expectation of health care use, for hospital care, home care, and institutional LTC separately. The latent states show a clear relationship with expenditures: probability of use and expected costs increase with worsening health state. The table also shows

Table 5.2: Health care expenditures and transition matrix for each state of the latent variable, for a 70 year old woman.

	Expenditures			
	$\eta_t = 1$	$\eta_t = 2$	$\eta_t = 3$	
P(hosp)	0.081	0.230	0.351	
E(hosp)	360	1,009	2,874	
P(home)	0.036	0.203	0.380	
E(home)	59	1,041	3,145	
P(LTC)	0.012	0.034	0.099	
E(LTC)	672	967	3,673	
	Transition matrix			
	$P(\eta_{t+1} = 1)$	$P(\eta_{t+1} = 2)$	$P(\eta_{t+1} = 3)$	$P(deceased)$
$\eta_t = 1$	0.924	0.047	0.026	0.003
$\eta_t = 2$	0.001	0.947	0.047	0.006
$\eta_t = 3$	0.001	0.059	0.882	0.058
deceased	0	0	0	1

the transition matrix. This matrix relates the current health state, η_t to the probability of being in health state m next year, $t + 1$.

We use the model to make predictions of health care expenditures on a population level for the period 2010-250. We start with the Dutch older population between 65 and 95 in base year 2010. The initial distribution over the health states of this population is based on the age- and sex-specific distribution of health states in the LASA sample. Based on the transition probabilities from the model, the future health and expenditure distribution for the initial cohort can be obtained. Each year, a new cohort of 65-year olds is added. The size of this new cohort is obtained from population projections of Statistics Netherlands (Poelman et al., 2010). The health distribution of these new 65-year olds is based on the health scenario that we implement.

5.4.2 Scenarios

We fix remaining life expectancy at 65 in 2050 at two values, one based on predictions by (Janssen and Kunst, 2010), and one based on more optimistic expectations. The inclusion of two different life expectancy values enables us to assess the influence of additional longevity given a particular health scenario. Also, past forecasts of life expectancy have generally been too pessimistic (Christensen et al., 2009; Oeppen and Vaupel, 2002). For both life expectancy values, we consider different scenarios of changes in underlying health that can lead to those levels of life expectancy. This way, we can assess the effect of changes in life expectancy growth as well as the influence of health on health care expenditure growth. The health scenarios are implemented by gradually changing selected parameters in the simulation model in accordance to the desired remaining life expectancy in 2050. We first describe the scenarios, and then turn to the implementation in the simulation model.

We use three different scenarios, based on the morbidity hypotheses described in Section 5.2. In the first scenario, we let the life expectancy gain be the result of an overall decrease in mortality rates. This scenario is in accordance with the expansion of morbidity hypothesis. Changes in lifestyle do not lead to an improvement in age specific health, and medical technology is mostly applied to decrease mortality for individuals in poor health without changing the age specific onset of diseases. We implement this scenario by decreasing the probability of dying in each health state by the same proportion. This implementation corresponds to the idea of a decrease in the lethality of diseases. Since the poorest health states are associated with the highest probability of dying, there is more room for mortality decreasing technology in these states. It can be expected that this scenario leads to an increase in the number of years spent in poor health.

The second scenario relates to the compression of morbidity hypothesis. Prevention and changes in lifestyle result in better population health. As a result, life expectancy gains are paired with longer remaining lifetime spent in good health. We implement this scenario by increasing the probabilities of remaining in state 1, or 2, compared to worse health outcomes. In the third scenario, we adhere to the dynamic equilibrium hypothesis: lifeyears years spent with one or more chronic diseases increase, whereas the number of lifeyears spent with severe disability remains constant. The third scenario is implemented by increasing the time spent in state 2.

5.4.3 Implementation

We choose two values for remaining life expectancy in 2050: the predicted values of 21.1 for men and 24.6 for women, and the more optimistic values of 24.1 for men and 27.6 for women. There are two ways in which health changes can be implemented in the simulation model: First, we can change the proportion of people in a particular health state (initial health profile), for new cohorts of 65 year-olds. Such a change can be seen as a consequence of health changes that materialize at younger ages, before 65. Second, we can change the transition probabilities between health states in the model. These changes are related to effects of trends in health that materialize after 65. The implementation of each scenario starts with the desired remaining life expectancy in 2050. For each health scenario, the relevant model parameters are selected. The required total change in the parameters needed to reach the desired life expectancy is numerically determined. Changes in the parameter values are then gradually applied up to 2050 using annual growth rates.

For the first scenario, expansion of morbidity, we keep the initial health profile at 65 at its 2010 level. The scenario can thus be modeled by only changing the transition probabilities. For the other two scenarios, we model health changes either solely trough changes in the transition probabilities, or by a combination of changes in the initial health profile and changes in the transition probabilities. We end up with eight scenarios: a modest and extreme life expectancy version for each scenario, and for the compression and dynamic equilibrium scenarios an additional version of the modest life expectancy scenario, where only transition probabilities are changed. Additionally, we include a baseline scenario in which the initial health profile and transition probabilities are kept at their 2010 values. Table 5.3 shows which parameters are changed in each scenario.

In the modest life expectancy version of scenario 1, the probability of dying is decreased annually by 1.31 % for men and 1.11 % for women. The annual absolute increase in the probability of remaining in the same state is equal to the absolute decrease in the probability of dying. For example, if the current probability of dying for men in state 2 would be 0.10, then next year's probability of dying in state 2 would be $0.10 - 0.10 * 0.0131 = 0.0987$. The probability of staying in state 2 would then be increased by 0.0013. Scenario $1++$ is the more extreme life expectancy version of scenario 1.

In scenario 2 (compression of morbidity), the probabilities of going from state 1 to state 2, 3, and death, and from state 2 to 3 or death are decreased. The decrease is compensated by an equivalent increase in the probability of remaining in state 1, respectively state 2. In scenario $2+$, we model the compression of morbidity by a combination of increasing initial health at 65 and a decrease in probabilities of going from state 1 and 2 to worse health states. We let the proportion of individuals in state 1 at 65 gradually go to 100 % in 2050. The proportions of 65 year-olds in states 2 and 3 are decreased equivalently. Remaining annual decrease in transition probabilities needed for a life expectancy of 21.1/24.6 by 2050 can then be numerically determined. Scenario $2++$ is the extreme version of scenario $2+$.

In scenario 3 (dynamic equilibrium), the remaining lifetime spent in state 2 is prolonged, while the time spent in state 3 is kept constant. We implement this scenario by decreasing the probabilities of going from state 1 and 2 to states 3 and 4 in favor of going to or remaining in state 2. To be able to set both the remaining lifetime as well as the time spent in state 3, we also decrease the probability of dying in state 3 with a separate growth rate. In scenario $3+$, we let the initial proportion of 65 year-olds in state 2 increase to 45 % in 2050. Scenario $3++$ is the extreme version.

5.5 Results

We discuss the effects of the different scenarios from three perspectives. First, we take an individual perspective, and consider the differences in remaining life expectancy

Table 5.3: Health scenarios. Annual changes (%) in transition probabilities and health profile at 65.

	State at $t+1$			
State at t	state 1	state 2	state 3	Dead
1 Expansion of morbidity				
state 1	+			- 1.31/-1.11
state 2		+		- 1.31/-1.11
state 3			+	- 1.31/-1.11
1++ Expansion of morbidity				
state 1	+			- 2.24/-2.38
state 2		+		- 2.24/-2.38
state 3			+	- 2.24/-2.38
2 Compression of morbidity. Transition				
state 1	+	- 1.99/-2.12	- 1.99/-2.12	- 1.99/-2.12
state 2		+	- 1.99/-2.12	- 1.99/-2.12
state 3				
2++ Compression of morbidity. Transition and initial				
state 1	+	- 1.47/-1.4	- 1.47/-1.4	- 1.47/-1.4
state 2		+	- 1.47/-1.4	- 1.47/-1.4
state 3				
Health at 65	+1.03/+1.32	-	-	
2++ Compression of morbidity. Transition and initial				
state 1	+	- 2.72/-3.35	- 2.72/-3.35	- 2.72/-3.35
state 2		+	- 2.72/-3.35	- 2.72/-3.35
state 3				
Health at 65	+1.03/+1.32	-	-	
3 Dynamic equilibrium. Transition				
state 1		+	- 2.02/-1.51	- 2.02/-1.51
state 2		+	- 2.02/-1.51	- 2.02/-1.51
state 3			+	- 0.48/-0.88
3+ Dynamic equilibrium. Transition and initial				
state 1		+	-2.1/-1.51	-2.1/-1.51
state 2		+	-2.1/-1.51	-2.1/-1.51
state 3			+	-0.5/-0.89
Health at 65	-	+1.26/+0.91	-	
3++ Dynamic equilibrium. Transition and initial				
state 1		+	- 3.36/-2.63	- 3.36/-2.63
state 2		+	- 3.36/-2.63	- 3.36/-2.63
state 3			+	- 3.36/-2.63
Health at 65	-	+1.26/+0.91	-	

and expected health care expenditures over remaining lifetime at 65 in 2050. Second, we describe the cross sectional age profile of population health. Third, we discuss the growth in aggregate health care expenditures between 2010 and 2050.

5.5.1 Individual health

Healthy remaining life expectancies at 65 for men in 2050 are depicted in Figure 5.2. In the baseline scenario, healthy life expectancy is equal to that in 2010. In the extension of morbidity scenarios (1 and 1++) life expectancy is either 21.1 or 24.1, but the proportion of remaining life spent in each state is equal to the baseline scenario. As a result, the *absolute number* of years spent in poor health increases. The compression of morbidity scenarios (2, 2+, and 2++) show an increase in the number of years spent in state 1 and 2 as a result of decreasing transition probabilities for poorer health outcomes. In comparison to scenario 2, in which only transition probabilities are modified, scenario 2+ with a change in both initial health as well as transition probabilities shows a larger number of years spent in state 1. In the dynamic equilibrium scenarios (3, 3+, 3++), time spent in state 2, with a high probability of having one or more chronic disease, but only moderate disability, increases whereas time spent in state 3 remains constant. In scenario 3, the time spent in state 1 is equal to the baseline scenario. In scenario 3+ the time spent in state 1 is shorter, due to the increasing proportion of 65-year olds in initial health state 2. In the extreme version of each scenario, we see more or less the same pattern as in the normal versions, but with an extension of life expectancy to 24.1 years.

5.5.2 Individual health care expenditures over remaining lifetime

Figure 5.2 also shows the individual expected health care expenditures in each health state for men at 65 over remaining life in 2050, for hospital care, home care, and institutional LTC separately. Remaining lifetime expenditures show some considerable differences between scenarios, especially between the compression of morbidity scenarios and the others. Hospital expenditures are 23,000 euros in the baseline scenario. Hospital expenditures are 5,000 euros higher in scenario 1 and 7,000 euros higher in scenario 1++. In the improvement of health scenarios (2), hospital expenditures are slightly higher than in the baseline scenario, whereas expenditures are lower in the other two variants (about 20,000 euros in both 2+ and 2++). Hospital expenditures range from 29,000 euros (3) to 32,000 euros (3++) in the dynamic equilibrium scenarios.

Home care expenditures over remaining lifetime are 24.500 euros in the baseline scenarios. Expenditures are higher in all other scenarios. Of the other scenarios, expenditures are lowest in the different versions of scenario 2 (27,000-30,000 euros), and range from 36,000 to 46,000 euros in the other scenarios. Institutional LTC expenditures are again lowest in the baseline scenario (36,000 euros). In the other scenarios,

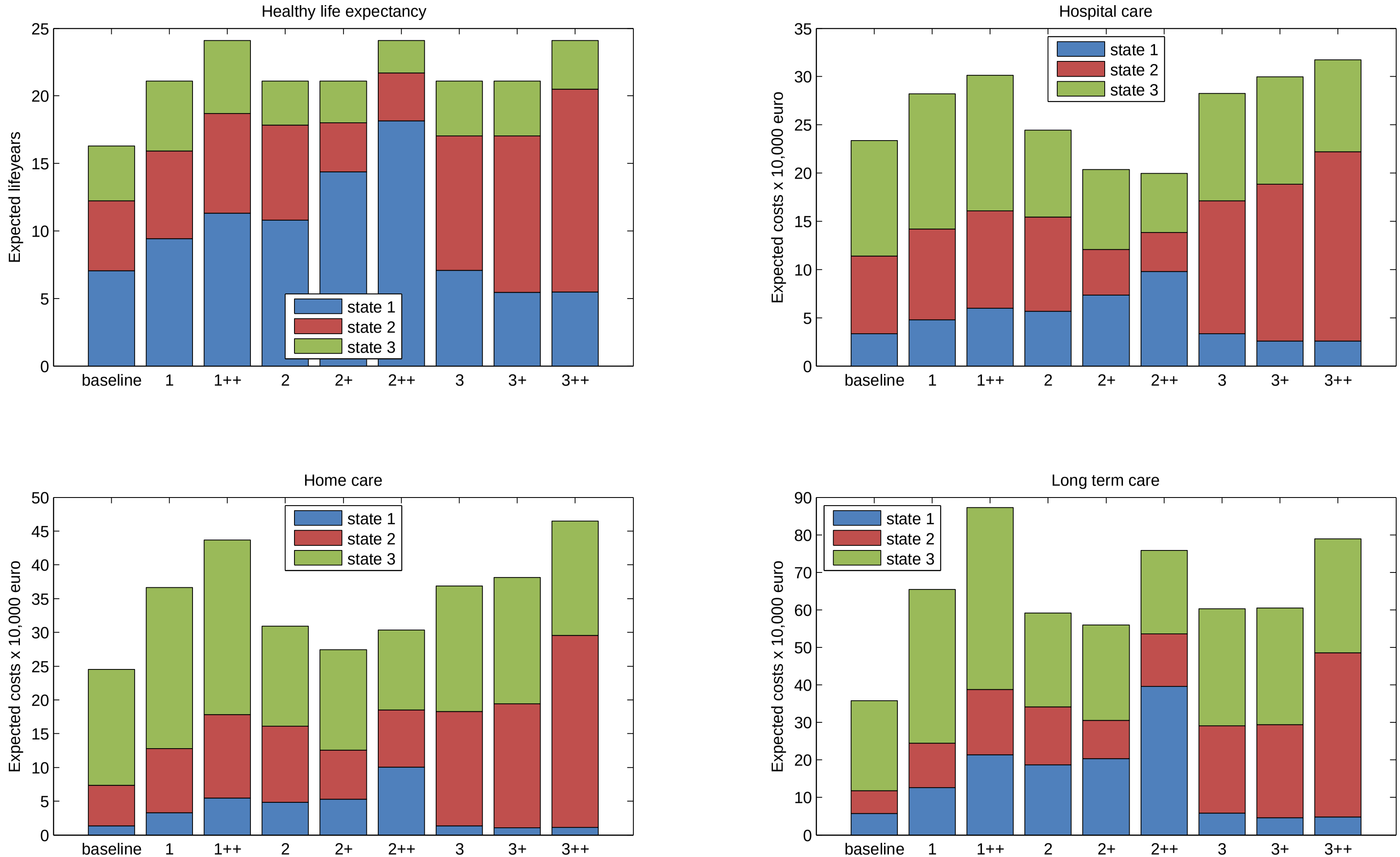

Figure 5.2: Expected lifeyears and expenditures at 65 for men under different scenarios.

expenditures range from 55,000 euros (2+) to 86,500 euros (1++). In contrast to hospital and home care, the extreme versions of all scenarios result in higher lifetime LTC expenditures compared to other versions of the same scenario.

5.5.3 Population health

Figure 5.3 shows the health composition of the older population in 2010, and in 2050 for each scenario. All scenarios show the well known baby boom effect: the broadest part of the pyramid moves upward over time. The population pyramids in the extension of morbidity scenarios (1,1++) show the same form as in 2010, only broader. The compression of morbidity scenarios (2,2+,2++) show an increase of the proportion of individuals in state 1, mainly at the younger ages at the bottom of the pyramid. The dynamic equilibrium scenarios (3,3+,3++) show an increase of the number of people in state 2, especially at the middle and top of the pyramid. When we compare the scenarios where only the transition probabilities are changed to the scenarios where the initial age profile is also changed, we can see that in the latter a larger part of the health changes occurs at the bottom of the population pyramid. Scenarios with a higher remaining life expectancy (1++,2++,3++) mainly have a larger number of people at the top of the population pyramid.

5.5.4 Aggregate expenditures

The projections of total health care expenditures over the years 2010 to 2050 are depicted in Figure 5.4. Of the scenarios with the more conservative life expectancy prediction, scenario 3+ (dynamic equilibrium) and 1 (expansion of morbidity) result in the highest hospital expenditures, closely followed by 3. The equally high prevalence of chronic diseases in scenario 1 and 3 seems to be more important than the lower prevalence of severe disability in scenario 3. Scenarios 2 and 2+, where the prevalence of chronic diseases is lower, result in considerably lower hospital expenditures. The large difference between 2 and 2+ is also noteworthy. The extreme life expectancy variants of scenarios 1 and 3 are, slightly, above their standard counterparts. The extreme scenario 2++ lies below 2 and 2+.

Whereas hospital expenditures decrease or stabilize after 2040, home care and institutional LTC expenditures rise over the whole time interval in all scenarios, except the baseline. Home care expenditures are highest in scenario 3+, followed by 1 and 3. Scenarios 2 and 2+ are related to lowest expenditures. However, scenario 2 surpasses the baseline scenario around 2043. Again, the more extreme life expectancy versions of scenarios 3 and 1 are above their counterparts, especially 3++. Institutional LTC expenditures are highest in scenario 1. Scenarios 3+ and 3 are second and third, but the difference with 1 is relatively larger than for hospital and home care. Here, the lower prevalence of disability in scenario 3 compared to 2 does have a strong effect on expenditures. Although expenditures in scenarios 2 and 2+ are lowest, the difference

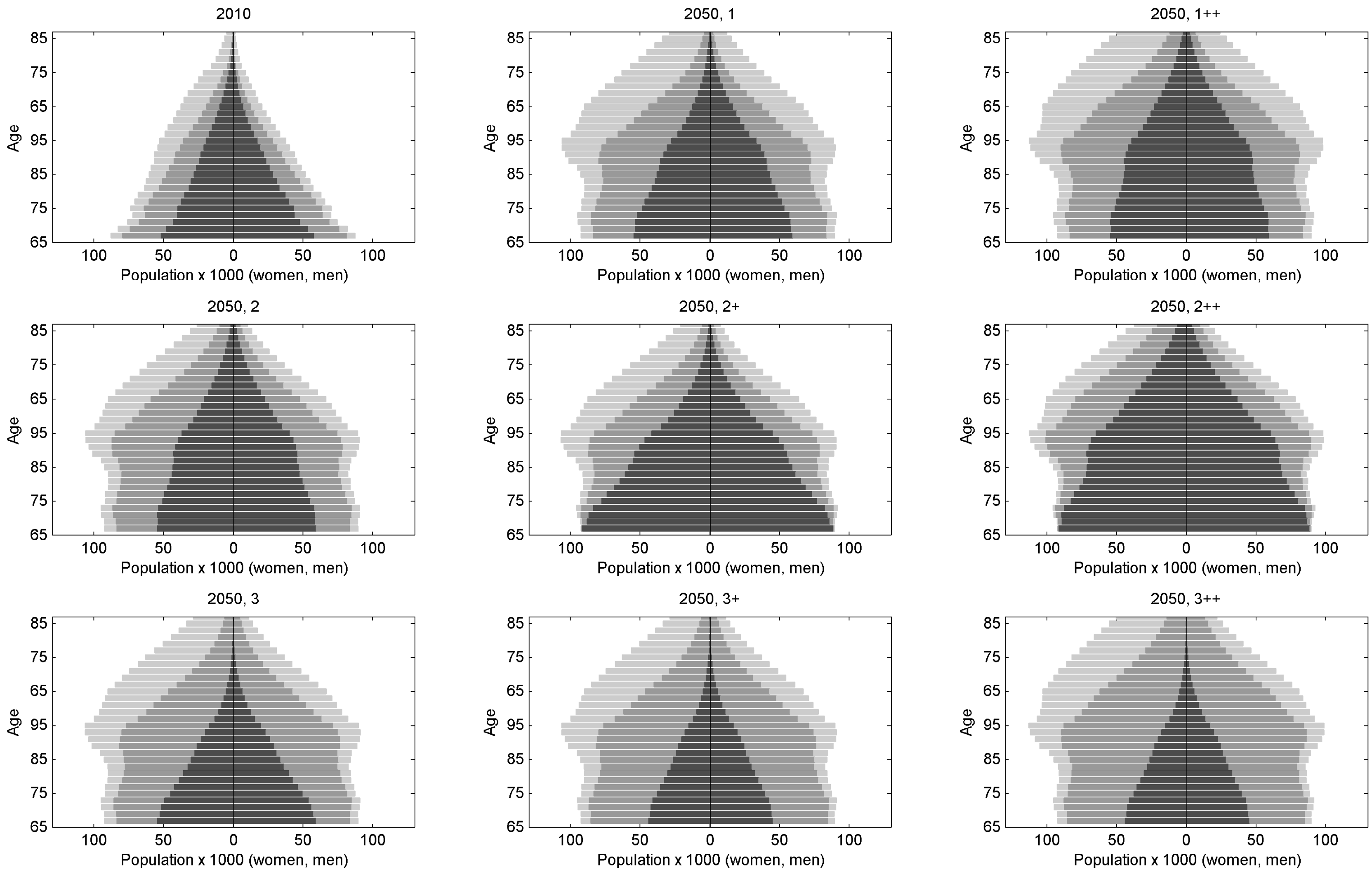

Figure 5.3: Health compositions of the population in 2010 and projection for 2050 under different scenarios (women left, men right). Darkest color indicates best health state.

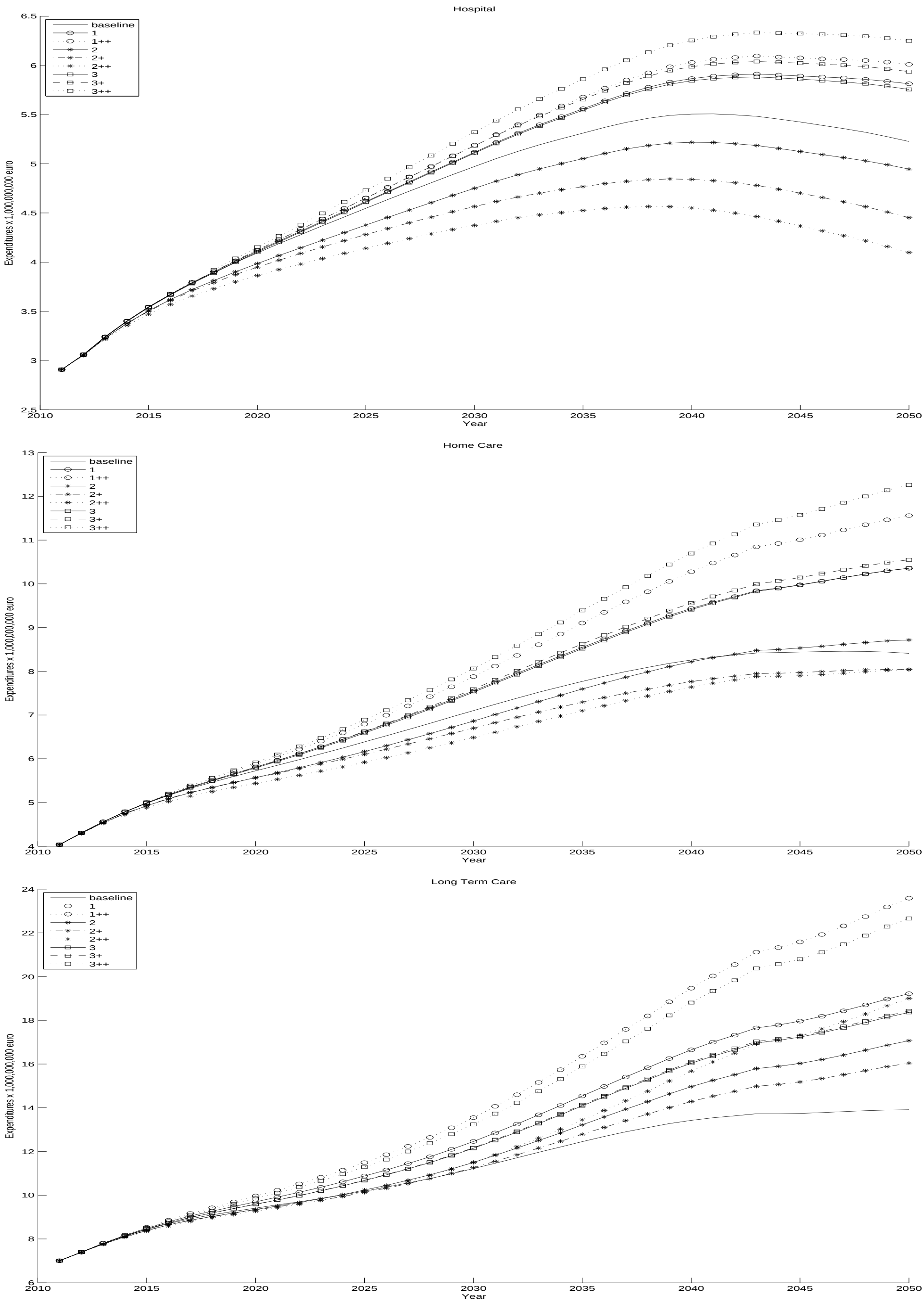

Figure 5.4: Predictions of expenditures between 2010 and 2050, for hospital care, home care, and long-term care, for each scenario.

Table 5.4: Average annual expenditure growth rate in 2010-250

Scen.	Hosp	home	LTC
baseline	1.52	1.90	1.77
1 expansion	1.79	2.45	2.62
1+ expansion	1.88	2.74	3.16
2 compression	1.37	1.99	2.31
2+ compression	1.10	1.78	2.15
2++ compression	0.88	1.78	2.59
3 dynamic equi.	1.77	2.45	2.50
3+ dynamic equi.	1.85	2.50	2.51
3++ dynamic equi.	1.98	2.89	3.05

with the other scenarios is smaller than for hospital and home care. For institutional LTC, there is a relatively large difference between the conservative life expectancy scenario 1 and 3 and the extreme versions 1++ and 3++. LTC expenditures in 2++ are lower than 2 and 2+ , but they surpass expenditures in scenario 2+ around 2050. Table 5.4 shows annual growth rates for all scenarios. Not including the baseline scenario, growth rates range from 0.88 (2++) to 1.98 (3++) for hospital care, 1.78 (2++) to 2.89 (3++) for home care, and 2.15 (2+) to 3.16 (1++) for institutional LTC.

5.6 Discussion

The effect of population aging on health care expenditures depends on the relationship between longevity and the diverse aspects of health. We have analyzed the consequences of different health scenarios using a measure of health that combines a broad set of health indicators. The scenarios are based on the three commonly used hypotheses on morbidity: an expansion of morbidity, a compression of morbidity, and a dynamic equilibrium. The way the scenarios are implemented is extreme: in each scenario, adjustment of the selected health parameters explains the total change in life expectancy. In reality, it might be more likely that life expectancy gains are a result of a mix of scenarios. Extreme scenarios, therefore, show the boundaries of the effect of health on health care expenditure growth. We first discuss individual lifetime health care expenditures. Second, we turn to the role of health for aggregate health care expenditure growth. Third, we discuss the results on population health from a broader societal perspective. Finally, we discuss some limitations of the paper.

First, the individual lifetime expenditures show substantial differences between scenarios: lifetime hospital expenditures in the expansion of morbidity scenario (1) are up to 1.5 times larger than in the compression scenario (2). For institutional LTC, the relative differences are somewhat smaller, but still significant. This finding seems to be in contrast with other studies that find small differences in lifetime expenditures between different health scenarios (Lubitz et al., 2003; Goldman et al., 2005). However, the limited effect of health found in these studies is caused by the life extending effect of health. The same effect can be observed here: the extreme life expectancy version 2++ of scenario 2 is associated with better health but also a higher life expectancy. Indeed, scenario 2++ shows some savings in lifetime hospital expenditures compared to scenario 2, but these saving are offset by an increase in expected institutional LTC use at older ages. The differences in lifetime expenditures are mostly found when comparing two different health scenarios *given* a particular life expectancy.

Second, the average annual growth rate of health care expenditures in the Netherlands during the past few years has been around 4 percent. When we compare this number to the growth rates reported in Table 5.4, we confirm earlier findings that aging is not the only major factor behind health care expenditure growth. The growth rates for LTC and home care are somewhat high compared to earlier research (De Meijer et al., 2012). However, our higher finding seems to be related to the long time span of the study. Growth in these two sectors seems to accelerate up to 2040. The long-term care volume projections by Eggink et al. (2012) for 2010 to 2030 are within the range of our scenario projections over the same period.

The growth rates and time trends in aggregated expenditures again show substantial differences between health scenarios, especially in the long run. Again, differences are generally larger between health scenarios with the same life expectancy than between versions of the same health scenarios with different life expectancy. These findings show the added value of using scenario analysis based on multidimensional aspects of health instead of only mortality. To a certain extent, our findings supplement the conclusion of the time to death literature that increases in life expectancy do not have to lead to substantial increases in health care expenditures: increases in life expectancy, and even in healthy life expectancy, can be achieved without large consequences for health expenditure growth. That life expectancy gains can be achieved without costs increases, is also shown by Michaud et al. (2011) who found that increasing life expectancy in the U.S. by gradually moving American cohorts to the health status enjoyed by Western Europeans could lead to substantial health care savings between 2004 to 2050. However, such effects will only be achieved when increasing life expectancy is indeed a result of health improvements. Although the most optimistic health scenario is clearly associated with lower aggregated expenditures, a postponement effect for institutional LTC seems to be visible. By 2050, there is relatively large proportion of very old people in good health. Since these individuals will eventually transition to worse health states, LTC expenditures can be expected to rise further after 2050.

The scenario that seems to be related the closest to findings in the empirical literature is the dynamic equilibrium scenario (3). Number of years spent with chronic diseases and mild disability seems to be increasing, while time spent in severe disability seems to be rather constant (Crimmins and Beltrán-Sánchez, 2010; Hoeymans et al., 2012; Robine and Michel, 2004; Van Gool et al., 2011). Since some health trends are far from clear, policy makers could use our scenarios as bandwidth for the effect of health changes and aging on expenditure growth. For example, based on the scenarios it is likely that demand for hospital care will peak around 2040, while the demand for LTC will continue to grow at least until 2050. This difference in demand for different types of care should be taken into account when planning health care capacity. The findings also suggest some room for health interventions that can help to contain health care costs. The fact that in the dynamic equilibrium scenarios intuitional LTC expenditures grow more slowly compared to the expansion of morbidity scenarios indicates the need for limiting the disabling effect of chronic diseases.

Third, the scenarios that include changes in the initial health profile of new cohorts indicate that initial health differences have persistent effects on health during old age. This result underlines the importance of lifestyle interventions aimed at younger generations for the health of the future older population. Figure 5.3 shows the importance of a healthy older population from a broader policy perspective. The scenarios result in very different health compositions of the older population. In terms of for instance labor participation, the compression scenario, and even the dynamic equilibrium scenario, which leads to more chronic diseases but not necessarily to severe limitations that prevent participation, are much more beneficial than an expansion of morbidity.

Finally, like most studies on the relationship between health and expenditures, we have not modeled the reverse relationship between expenditures and health. Just as poor individual health leads to health care expenditures, health care use can also improve health. The relationship between collective health care expenditures and life expectancy is not entirely clear. In the past, health care seems to have had a relatively small contribution to life expectancy, although there is evidence that the effect has been stronger in recent years (Mackenbach et al., 2011). The most straightforward way to include health effects of expenditures to our model, would be to make additional hypotheses about future health care growth and its consequences on initial health and transition probabilities. Since we are mainly interested in the effect of health on expenditures, and the inclusion of additional health care scenario would mean additional complexity, we have chosen not to do so. For the same reason of avoiding additional complexity, we have not included additional scenarios on education level or partner status. Although these variables are included in the model, we have kept them at baseline level.

5.7 Conclusion

The effect of population aging on health care expenditure growth, and especially rising life expectancy, depends on trends in diverse aspects of underlying health. Therefore, predictions of the effects of aging have to explicitly consider the relationship between health and longevity. In this study, we have performed scenario analysis based on three commonly used hypotheses about this relationship, using a combined measure of health. Based on a growth of remaining life expectancy at 65 from 18.6 to 21.1 for men, and from 20.1 to 24.6 in 2050, there is more than one percentage point difference in annual health care expenditure growth rates between the most optimistic and the most negative scenario. Hospital expenditures are predicted to decline after 2040, whereas home care and institutional LTC will continue to rise up at least up to 2050. There seems to be some room for health improvement policies to contain expenditure growth, although potential effects should not be exaggerated. When associated with improvement in underlying health, additional life expectancy gains only have a limited effect on expenditure growth.

5.8 Acknowledgements

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Chapter 5. The effect of trends in health and longevity on health care expenditures in the older population. A scenario analysis.

Chapter 6

Health, work, and participation in the older population

Abstract

Given the aging of the Western population, the effect of health on social participation of older people is of great relevance. Participation can take the form of formal work, but also includes other societally relevant activities such as provision of informal care or volunteer work. In this paper, we estimate two dynamic models of the relationship between health and participation in the Dutch 55 to 65 year old population. The first model concerns the relationship between health and work, while in the second model we use a broad indicator of participation, also based on caregiving and volunteer work. To capture relevant interactions between different aspects of health, we use a latent health variable, based on a range of observed health indicators. We find that it is mostly the disabling effect, rather than the mere presence, of chronic diseases that influences participation. We also find some evidence of a positive effect of participation on health, although when we correct for unobserved individual characteristics, this effect is no longer significant.

Based on
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6.1 Introduction

One of the most important benefits of health is that it enables people to participate in society. Participation is not limited to having a paid job, but includes a number of activities with a societal relevance, such as providing informal care, or doing volunteer work. Given that the (relative) number of older people is growing in most Western countries, the relationship between health and participation of individuals at older ages is of special relevance. When health improvements allow individuals to continue working at older ages, some of the pressures on the labor market due to population aging might be alleviated. At the same time, the societal effects of population aging, such as an increasing need for care, will also depend on other forms of participation, like the provision of informal care (Colombo et al., 2011). Although improvements of health might be expected to offset some of the negative effects of population aging, the relationship between health and participation is not straightforward. In this paper, we investigate this relationship for the Dutch population between 55 and 65 years of age. We focus on three issues. First, we investigate the relevance of different health dimensions for participation. Health consists of many different dimensions, including the presence of chronic diseases, disability, and mental problems. Not all of these dimensions are likely to be equally relevant for participation. Second, we consider reverse causal effects between participation and health. Health might not only influence participation, participation might also have an effect on health. Such dual causality has to be taken into account to properly estimate the effect of health on participation. Third, we investigate the relationship between health and work, but also introduce a broader measure of participation, including provision of care and volunteer work.

There is substantial research on the effect of poor health on labor participation and early retirement. In their overview of the literature, Currie and Madrian (1999) conclude that the evidence suggest that poor health is negatively related to labor outcomes, specifically for older workers. Many studies use a single health indicator, mostly self-reported health or disability. In some cases, this indicators is corrected for justification bias, by letting employment status influence health reporting (Lindeboom and Kerkhofs, 2009) or by using a "health-stock" based on other health variables that function as instruments for self-reported health (Bound et al., 2010; Hagan et al., 2008; Roberts et al., 2010). As noted by Erdogan-Ciftci et al. (2011), however, these studies assume that a, cleansed, version of self-reported health is the accurate variable to use in employment models. However, there is no health indicator that can be considered true health for employment outcomes a priori. Instead, different health indicators are related to different dimensions of health that might be relevant for employment. Kerkhofs et al. (1999) estimate a retirement model using a range of health constructs and find that the effect of health depends on the specification of the health variable. McLellan (1998) investigates the health effect on labor supply of middle aged men in the U.S. He differentiates between severe health events, affecting functional limitations, the onset of chronic diseases, and accidents. The effect of severe health events affecting functioning is found to be stronger than the effect of chronic diseases. Given the different effect of aspects of health, it can be beneficial to combine health indicators to obtain relevant and meaningful interactions between health dimensions.

The influence of work, or retirement, on health has also been extensively investigated. Based on the retirement adjustment theory (Atchley, 1976), a negative relationship between retirement and health is often assumed. According to this theory, retirees have to adjust to their loss of job and income, and adjustment problem might lead to health problems or unhealthy behavior. However, retirement or job loss, might also have some beneficial health effects, such as having more time to adhere to medical advise. Rijs et al. (2011) discuss a number of studies on the general effect of retirement and health that find either no effect or a positive effect. Lindeboom (2012) discusses the empirical economic literature on the effects of work on health. He finds that, generally, cross section studies find a negative effect of (early) retirement on health. However, health and work are jointly determined, in the sense that both factors can influence eachother. Moreover, unobserved individual effects, for instance related to lifestyle, might influence both health and work outcomes. Lindeboom (2012) reports that studies that correct for this possible endogeneity using an instrumental variable approach find no, or a positive effect of retirement on health. Following an earlier study by Stern (1989), Cai and Kalb (2006) estimate a simultaneous equation model of health and work, and find mixed results on the effect of no work on health, depending on age and sex. As one of the few studies, Haan and Myck (2009) use a panel dataset to explicitly estimate time dynamics in both health and labor participation, while correcting for unobserved heterogeneity. They find evidence of a negative effect of non-employment on health.

Besides work, there are other forms of participation that have a societal value. Social participation is a broad concept that includes both recreational and productive social activities outside the house that allow (older) individuals to meet others. The first form of participation is mostly directed at improving one's own well being and self-development, while in the latter, the individual contributes his or her resources to individuals or groups in the community through involvement in voluntary and political associations (Klumb and Baltes, 1999). We will focus on the second form of social participation, and we will consider the relationship between informal caregiving, volunteer work and health. Concerning the relationship between caregiving and health, there seems to be consensus that caring for (older) individuals with poor health or disability is burdensome and stressful and can contribute to morbidity. Empirical studies tend to find a negative effect on morbidity (e.g. (Schulz and Beach, 1999)), or health (e.g.(Hughes et al., 1999)). However, there are also empirical studies finding a positive effect on health or mortality, such as Brown et al. (1999).

The relationship between informal care provision and labor participation has been investigated in a number of studies, mostly focusing on the general population and not necessarily older people. These studies generally use either cross-section data comparing labor participation between carers and non-carers, or direct questions to caregivers whether they would work if they didn't have to provide informal care (Leigh, 2010). Some studies use panel data combined with simultaneous equation strategies, estimating labor participation and informal caregiving jointly (Henz, 2004; Leigh, 2010; Mentzakis et al., 2009; Knoef and Kooreman, 2011; Soldo and Wolf, 1994). In general, studies correcting for reverse causality and unobserved heterogeneity find smaller negative effects of informal care provision on labor participation than univariate studies. Although some studies include a health indicator as explanatory variable, this variable is most often only self-reported health, and the longitudinal dynamics between health and informal care provision are seldom explored. Studies on the relationship between volunteer work tend to find a positive effect on health (Morrow-Howell et al., 2003; Piliavin and Siegl, 2007; Young and Glasgow, 1998) and mortality (Musick et al., 1999; Harris and Thoresen, 2005). Two studies that control for possible endogeneity also find a positive effect of volunteer work on mortality (Luoh and Regula Herzog, 2002; Aoki, 2011)

Although research on a number of aspects of the relationship between health, work, and other forms of societal participation is quite extensive, three important insights are missing. First, most studies on health and participation use a single health indicator. This indicator, generally, is self-assessed health or self-assessed labor related health. However, to assess the influence of health on (labor) participation a broader health measure, that captures essential interactions between different aspects of health, is needed. For instance, the influence of chronic diseases on participation will likely depend on the disabling effect of those diseases. When factor analysis or latent class analysis is used to combine health, the risk of self-justification bias in the health indicator will also be limited. Second, most studies focus on the relationship between health and a particular form of participation. Since the relationship between health and those different aspects of participation are likely to be related, and tradeoffs between different forms of participation can be expected, a joint analysis can be beneficial. Third, although dual causality between health and labor participation has been investigated, few studies use panel data to estimate time dynamics, especially for other forms of participation besides work.

In this paper, we develop two joint models of health and participation of the 55 to 65 year old population. In the first model we focus on the relationship between health and formal work. In the second model, we include a variable based on four aspects of participation: formal work, provision of domestic care, provision of personal care, and volunteer work. In the dynamic models, lagged values of health and (labor) participation influence eachothers current values. To enable the inclusion of different dimensions of health, we model health as a latent discrete variable, based on a set of health indicators. We extend the health and work model by adding an unobserved individual effect that is correlated between outcomes to control for unobserved individual effects.

6.2 Methods

6.2.1 The basic dynamic model

We model the dynamic relationship between health and employment using an intertemporal model. Both health, h, and employment, w, are defined as discrete variables with J, respectively K states. We discuss the definition of the health variable in Section 6.2.3. The employment variable has three states: "fulltime employment", "part time employment", and "no employment". In the second part of our analysis, the employment variable is replaced by a "latent participation" variable that is also discussed in Section 6.2.3. The basic idea of the dynamic model is that health and employment of individual i at time t both depend on values of health and employment at time $t-1$. The general form of the model can be described as

$$\begin{aligned} P(h_{i,t} = j | h_{i,t-1}, w_{i,t-1}, x_t^h) &= F_{h,j}(h_{i,t-1}, w_{i,t-1}, x_{i,t}^h) \\ P(w_{i,t} = k | w_{i,t-1}, h_{i,t-1}, x_t^w) &= F_{w,k}(w_{i,t-1}, h_{i,t-1}, x_{i,t}^{w'}), \end{aligned} \tag{6.1}$$

where x_t^h and x_t^w a set of covariates, for health, respectively employment. Just as Haan and Myck (2009) we opt for an intertemporal model where health and work are influenced by their lagged values, instead of a simultaneous model where current values of health and work are allowed to influence eachother. Although joint modeling methods for discrete variables are available (Schmidt and Strauss, 1975), such models can be hard to estimate in practice. Furthermore, it is difficult to find the necessary appropriate exclusion restriction needed to estimate a joint model. Also, in our data health and work are observed once every three years at the same time, making the identification of the exact timing of the events impossible. Therefore, the intertemporal model seems to provide a more clear interpretation compared to a true simultaneous model (Haan and Myck, 2009).

We specify the functional forms of the health and the employment equations as multinomial logit models. The specification is

$$\begin{aligned} P(h_{i,t} = j | h_{i,t-1} = l, w_{i,t-1} = m, x_t^h) &= \frac{\exp(\gamma_{l,j}^h + \delta_{m,j}^h + x_{i,t}^{h'}\beta_j^h)}{\sum_{q=1}^{J} \exp(\gamma_{l,q}^h + \delta_{m,q}^h + x_{i,t}^{h'}\beta_q^h)} \\ P(w_{i,t} = k | h_{i,t-1} = l, w_{i,t-1} = m, x_t^w) &= \frac{\exp(\gamma_{l,k}^w + \delta_{m,k}^w + x_{i,t}^{w'}\beta_k^w)}{\sum_{r=1}^{K} \exp(\gamma_{l,r}^w + \delta_{m,r}^w + x_{i,t}^{w'}\beta_r^w)}. \end{aligned} \tag{6.2}$$

The effect of lagged health, when $h_{i,t-1} = l$ on current health is determined by variables $\gamma^h_{l,1}, .., \gamma^h_{l,J}$ and on current employment by $\gamma^w_{l,1}, .., \gamma^w_{l,K}$. The effect of lagged employment, when $w_{i,t-1} = m$, is given by $\delta^h_{m,1}, .., \delta^h_{m,J}$ for current health and $\delta^w_{m,1}, .., \delta^w_{m,J}$ for current work status.

6.2.2 Joint model with correlated random effects

An issue of concern in the above model is the possibility of unobserved individual effects that jointly influence health and work (or participation). In the presence of such effects, estimates of the effect of health on work and vice versa might be overestimated. A way of controlling for unobserved individual effects is the use of a random effects model. Given the limited number of waves available in our dataset we will only estimate such a model for the health and work relationship, for which more waves are available, and use it mainly as a robustness check for the results based on the model in Equation (6.2). Just as Haan and Myck (2009), we use a discrete random effect. We define the random effects through the discrete latent variable ξ_i, with types $s = 1, .., S$. When individual i is of type s, the random effects are defined as $u^h_{i,j} = u^h_{s,j}$ for the health equation and $u^w_{i,k} = u^h_{s,k}$ for the work equation. Including these effects in Equation (6.2), the joint model becomes

$$\begin{aligned} P(h_{i,t} = j | h_{i,t-1} = l, w_{i,t-1} = m, u^h_i, x^h_t) &= \frac{\exp(\gamma^h_{l,j} + \delta^h_{m,j} + u^h_{i,j} + x^{h'}_{i,t}\beta^h_j)}{\sum_{q=1}^J \exp(\gamma^h_{l,q} + \delta^h_{m,q} + u^h_{i,q} + x^{h'}_{i,t}\beta^h_q)} \\ P(w_{i,t} = k | h_{i,t-1} = l, w_{i,t-1} = m, u^w_i, x^w_t) &= \frac{\exp(\gamma^w_{l,k} + \delta^w_{m,k} + u^w_{i,k} + x^{w'}_{i,t}\beta^w_k)}{\sum_{r=1}^K \exp(\gamma^w_{l,r} + \delta^w_{m,r} + u^w_{i,r} + x^{w'}_{i,t}\beta^w_r)}. \end{aligned} \tag{6.3}$$

Whereas the basic model can be estimated as two separate multinomial logit models, the joint model has to be estimated jointly because of the included correlation between the health equation and the work equation through the latent variable. Let $\pi = \pi_1, .., \pi_S$ be the probability vector describing the probabilities that $\xi_i = s$. Let $P(h_{i,t} = j)$ and $P(w_{i,t} = k)$ be the conditional probabilities of health and work as described in Equation (6.3). Then, the likelihood function becomes

$$L = \prod_{i=1}^N \sum_{m=1}^M \pi_m \prod_{t=1}^T \prod_{j=1}^J \prod_{k=1}^K P(h_{i,t} = j) P(w_{i,t} = k)) I(h_{i,t} = j \& w_{i,t} = k), \tag{6.4}$$

where I() is an indicator function.

We use the Expectation Maximization (EM) algorithm to maximize the log-likelihood of the joint model. Jointly with the health and work equations we also estimate two additional models for the initial health and initial work condition. A well known problem with dynamic random effects model is that the unobservable individual effects are often correlated with the initial observations at $t = 0$. Ignoring this correlation can lead to severe estimation bias. Therefore, we follow the approach of Heckman (1981) and correct for this correlation by regressing the initial observations on the same variables included in the dynamic model, with the exception of the lagged values of health and work, and on the random effects (Alessie et al., 2004). This method is found to work reasonably well even for a small number of waves (Heckman, 1981; Akay, 2009). Standard errors for the coefficients of the joint model are obtained using 500 bootstrap runs.

6.2.3 Latent health and participation

To accommodate for a large set of health variables in a single model, we also specify a discrete latent variable for health. The use of the latent variable allows us to incorporate the interactions between different aspects of health and participation in a parsimonious way. The states of this latent variable are related to outcomes of a set of observed health indicators: chronic diseases, upper body performance, functional limitations, activity limitations, self-perceived health, depressive symptoms, and cognitive impairments. Each of these J observed indicators y^j is related to the latent variable in the following way:

$$P(y^j_{i,t} = k|\pi^1_{i,t}, .., \pi^M_{i,t}) = \sum_{m=1}^{M} \pi^m_{i,t} P(y^j_{i,t} = k|\eta_{i,t} = m), \tag{6.5}$$

where $\pi^m_{i,t} = P(\eta_{i,t} = m)$. In other words, the state of the latent variable $\eta_{i,t}$ determines the probabilities of observing a particular value of a health indicator. An advantage of modeling health by using a discrete latent variable instead of a continuous one, is that the use of a discrete variable results in a number of distinct states or classes that can often be interpreted to be related to a specific health domain. The use of latent class analysis is most attractive if the states of the latent variable have a natural interpretation (Deb and Trivedi, 2002). Since the definition of the latent states is determined by the data, states of the latent variable can in some cases related to specific aspects of the data, such as outliers, without a clear interpretation. Therefore, the interpretation of the latent states should be supported both by a priori reasoning and by meaningful a posteriori differences (Deb and Trivedi, 2002). Observations are classified as belonging to the state $\eta_{i,t} = m$ for which the posterior membership probability is largest. Then, we can replace h in Equation (6.2) and (6.3) by η.

The same procedure is also used to define a broad indicator of participation in the second part of our analysis. Participation decisions in different domains, such as formal work, volunteer work, and informal caregiving, are not independent, and individuals most likely determine the amount of participation in each field simultaneously. Such a decision process can be modeled by including all possible interaction between the (discrete) participation variables, or by using a simultaneous equation framework. However, those approaches require a large number of parameters that have to be estimated. Instead, we use the latent variable approach as a data driven way to model the most common combinations of different forms of participation. The data provides information on the number of hours spent on different forms of participation. We use this information to construct discrete participation variables for each form of participation. The reasons to use discrete variables is that it allows us to differentiate between an individual's decision to participate in a particular form at all, and the (conditional) choice of number of hours he or she participates. Although this can also be done by using two-part models, using discrete variables of which one states is equal to no participation (zero hours) is a relatively easy and parsimonious way to incorporate this distinction in our model.

6.3 Data

We use data from the Longitudinal Ageing Study Amsterdam (LASA). LASA is an ongoing longitudinal study on predictors and consequences of changes in well-being and autonomy in the older populations (Huisman et al., 2011). The study follows a representative sample of adults ≥ 55 in the Netherlands over a long period of time. Respondents are interviewed every three years. The LASA sample consists of two cohorts. The first cohort started in 1992 with almost 4500 respondents born between 1903 and 1937. In 2002, a new cohort was added. This cohort consisted of 1000 respondent born between 1938 and 1947. We use the second to seventh wave of LASA. Since the mandatory pension age in the Netherlands was 65 during the study period, we only include individuals younger than 65 in our analysis. This means that the youngest respondents can be followed over a maximum of four waves. Respondents with only a single observation under the age of 65 are excluded. The number of included individuals in the resulting unbalanced sample is reported in Table 6.1.

We focus on three types of outcomes: health, work, and participation. For health and participation we construct new variables based on the latent class model described in Section 6.2.3. The underlying health and participation indicators are discussed here.

6.3.1 Health

Seven indicators of health and disability are used, covering physical as well as mental aspects of health. Table 6.6 in Appendix 6.A provides an overview. Self-perceived health is measured by an indicator in which the respondent is asked to rate his own health on a five point scale ranging from excellent to poor. Physical functioning is measured by a self-reported indicator as well as an objective indicator. The first indicator consists of three items, each pertaining to a mobility activity in daily life: walking up and down a 15-step staircase without stopping, using private or public

Table 6.1: Estimation sample. LASA respondents between 55 and 65.

Variable	Observation	Mean	St. Dev.
$\Delta(woman)$	First	0.53	0.50
$\Delta(woman)$	Last	0.53	0.50
age	First	58.46	2.01
age	Last	63.26	1.21
$\Delta(partner)$	First	0.85	0.35
$\Delta(partner)$	Last	0.82	0.38
$\Delta(children)$	First	0.90	0.30
$\Delta(children)$	Last	0.90	0.30
$\Delta(high\ edu)$	First	0.54	0.50
$\Delta(high\ edu)$	Last	0.54	0.50
$\Delta(\eta = 1)$	First	0.48	0.50
$\Delta(\eta = 1)$	Last	0.41	0.49
$\Delta(\eta = 2)$	First	0.29	0.46
$\Delta(\eta = 2)$	Last	0.35	0.48
$\Delta(\eta = 3)$	First	0.22	0.42
$\Delta(\eta = 3)$	Last	0.25	0.43
$\Delta(no\ work)$	First	0.57	0.50
$\Delta(no\ work)$	Last	0.81	0.39
$\Delta(parttime\ work)$	First	0.18	0.39
$\Delta(parttime\ work)$	Last	0.12	0.33
$\Delta(fulltime\ work)$	First	0.25	0.43
$\Delta(fulltime\ work)$	Last	0.07	0.26
$\Delta(no\ dom.\ care)$	First	0.90	0.30
$\Delta(no\ dom.\ care)$	Last	0.91	0.28
$\Delta(little\ dom.\ care)$	First	0.04	0.19
$\Delta(little\ dom.\ care)$	Last	0.04	0.19
$\Delta(much\ dom.\ care)$	First	0.06	0.24
$\Delta(much\ dom.\ care)$	Last	0.05	0.22
$\Delta(no\ pers.\ care)$	First	0.73	0.44
$\Delta(no\ pers.\ care)$	Last	0.76	0.43
$\Delta(little\ pers.\ care)$	First	0.16	0.36
$\Delta(little\ pers.\ care)$	Last	0.12	0.33
$\Delta(much\ pers.\ care)$	First	0.11	0.31
$\Delta(much\ pers.\ care)$	Last	0.12	0.32
$\Delta(no\ vol.\ work)$	First	0.57	0.50
$\Delta(no\ vol.\ work)$	Last	0.52	0.50
$\Delta(little\ vol.\ work)$	First	0.26	0.44
$\Delta(little\ vol.\ work)$	Last	0.28	0.45
$\Delta(much\ vol.\ work)$	First	0.16	0.37
$\Delta(much\ vol.\ work)$	Last	0.20	0.40
no. of waves work		2.70	0.61
no. of waves part.		2.62	0.49

transportation, and to cut one's own toenails. The indicator is a total score, ranging between 1 (no limitations) and 4 (limitations for all three activities) (Kriegsman et al., 1997). The second indicator is a performance test, measuring the time it takes for the respondent to put on and take off a cardigan. Respondents are assigned a score between 1 and 4, depending on the quartile their time falls into. Respondents who are not able to perform the test are assigned the score 5. Limitations in daily activities are measured with the Global Activity Limitation Indicator (GALI) (Van Oyen et al., 2006). Respondents are asked whether health problems limit their daily activities. The three answer categories are "no", "slightly", and "severely". The presence of chronic diseases is also self-reported. The indicator has a four point scale, ranging between no chronic disease and more than two chronic diseases. The mental aspect of health included in the study are depressive symptoms and cognitive impairments. For depressive symptoms the Center for Epidemiological Studies Depression Scale (CES-D) is used (Radloff, 1977). The CES-D scale is a widely used self-reported measure of depression. The score ranges between 0 to 60. Respondents scoring more than 16 are indicated as having clinically relevant symptoms of depression. Cognitive impairments are measured by the Mini Mental States Examination (MMSE) (Folstein et al., 1976). Respondents are placed on a scale of cognitive functioning between 0 and 30, where a lower score indicates worse functioning. The commonly used cut-off point is 24.

6.3.2 Work and participation

In LASA, respondents are asked whether they have a paid job at present, and if so, for how many hours per week. We construct a discrete variable with three states: no work, parttime work, and fulltime work. No work is defined as working less than half a day (4 hours) per week. Parttime work is defined as working between 4 and 32 hours, and fulltime work as more than 32 hours.

For the second part of the analysis, we use three forms of participation besides work: provision of domestic care, provision of personal care, and participation in organizations. Question concerning caregiving are incorporated in the last three waves of the data. Therefore, only the respondents from waves 5 to 7 are included. For domestic care, it is asked whether the respondent recently gave regular domestic care to somebody outside the own household. Domestic care is described as doing groceries, taking care of hot meals, taking care of breakfast, cleaning, doing the laundry, doing the dishes, vacuuming, chores in the house, putting the trash outside, and making beds. Respondents who provide domestic care are asked to whom and how many hours each week. For personal care, it is also asked whether the respondent gave this care to someone in the own environment (including the household) on a regular basis. Personal care was described as washing (face/hands), dress and undress, sit down and stand up, eating and drinking, going to the toilet, washing (douche, bath), walking the stairs, move indoors and outdoors, take in medicine, and put on elastic stocking).

Questions concerning membership and participation in organizations are asked in all LASA waves. Respondents are asked whether they are a member of a formal organization. Respondents who answer yes are asked about the type of organizations they are a member of, including trade unions, sports clubs, religious organizations, action committees, and more. They are also asked whether they perform any administrative work (e.g. being chairman, treasurer) and volunteer work (e.g. making coffee, organizing playing card matches) for these organizations. In addition, participation in administrative work and in volunteer work is recorded in minutes. For each of the three forms of participation we define a three state discrete variable, with no participation, less than half a day (4 hours), and half a day or more per week.

6.3.3 Covariates

We include the following covariates in the analysis: age, sex, partner status, having children, and education level (low or high). All variables are dummies, except for age. High education is defined as intermediate training or higher. We transform the age variable as $(age - 54)/(65 - 54)$. To accommodate for calendar year effects affecting labor participation, such as policy changes, wave dummies are included in the work and participation equation.

6.4 Results

6.4.1 Health and labor participation

Health

We estimate the latent health variable using the full LASA sample of individuals between 55-70. An important choice that has to be made is selecting the number of states of the latent variable. This choice is based on assessment of model fit and interpretability of the model. To assess the fit, Table 6.2 shows the values of the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) for a two, three, and four state specification of the latent variable. Both criterions try to weight model fit and number of parameters (lower values of BIC or AIC are preferred). The loadings of the health indicator variables on the latent health variable are depicted in Figure 6.1. The figure shows the expected values of each health indicator, for each value of the latent state. For ease of comparison, the outcomes for each indicator are standardized to lie between 0 (best outcome) and 1 (worst outcome).

The four state specification has the lowest AIC and BIC values. When we consider the loadings, we can see that the two-state specification results in: state 1 related to good expected health outcomes, and state 2 related to moderate or poor expected outcomes. The three state specification results in: state 1 related to good

Table 6.2: Model fit for latent health variable with different number of states

			AIC	BIC
2 states	π_1	0.58	67343	67595
	π_2	0.42		
3 states	π_1	0.36	61093	61474
	π_2	0.36		
	π_3	0.28		
4 states	π_1	0.27	56958	57441
	π_2	0.27		
	π_3	0.26		
	π_4	0.20		

expected health outcomes, state 2 related to presence of chronic diseases, moderate self-perceived health, but low probability of disability, and state 3 related to presence of chronic diseases as well as a high probability of disability. The four state specification resembles the three state specification, with an additional differentiation between state 3 and 4 in the level of disability and depressive symptoms. Given the relatively small sample size, and the fact that the inclusion of an additional state requires the estimation of quite a large number of additional parameters in the dynamic model, we opt for a three state specification. Although the four state specification show a better model fit, the three state model seems to capture the main interactions between the health variables, specifically between presence of chronic diseases and disability.

Dynamic model of health and work

The standard intertemporal model of health and work is reported in Table 6.3. In the health equation, there is a strong relationship between health state in the previous wave and current health. Being in state 2 or 3 has a significant positive effect on remaining or going to state 2 or 3. The influence of work at wave $t-1$ on poorer current health is negative, but only significant for the effect of fulltime work for health state 3. Although, conditional on lagged health, the effects of the others covariates are not significant, the direction of the effects is mostly as expected.

In the work equation, the effect of work status at wave $t-1$ is strong: individuals with work at $t-1$ have a higher probability of having work at t. The effect of health status is as expected: compared to being in good health at $t-1$, being in poorer health at $t-1$ has a negative effect on the probability of having work at t. This effect is stronger for health state 3 compared to state 2. The effects are only significant for

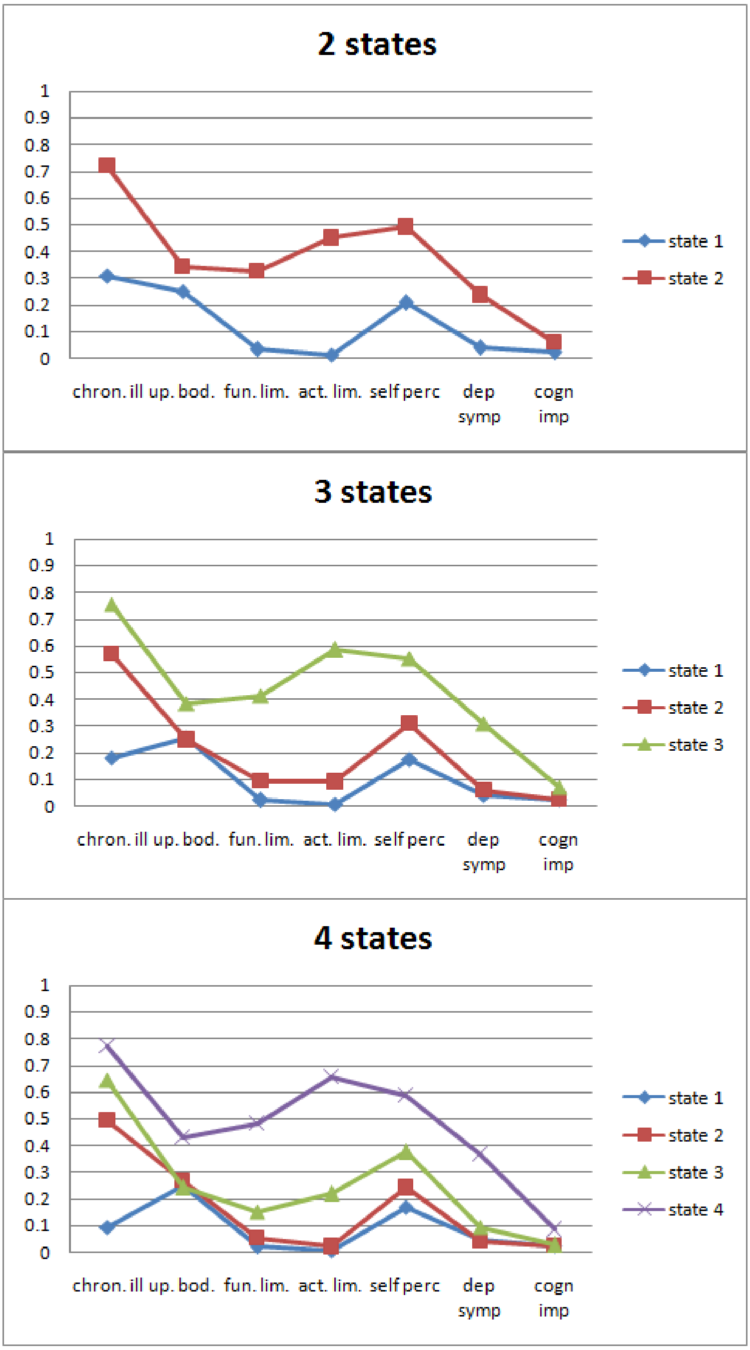

Figure 6.1: Standardized loadings of the health indicators for specification of the latent variable with different number of states. Estimated using the < 71 LASA sample.

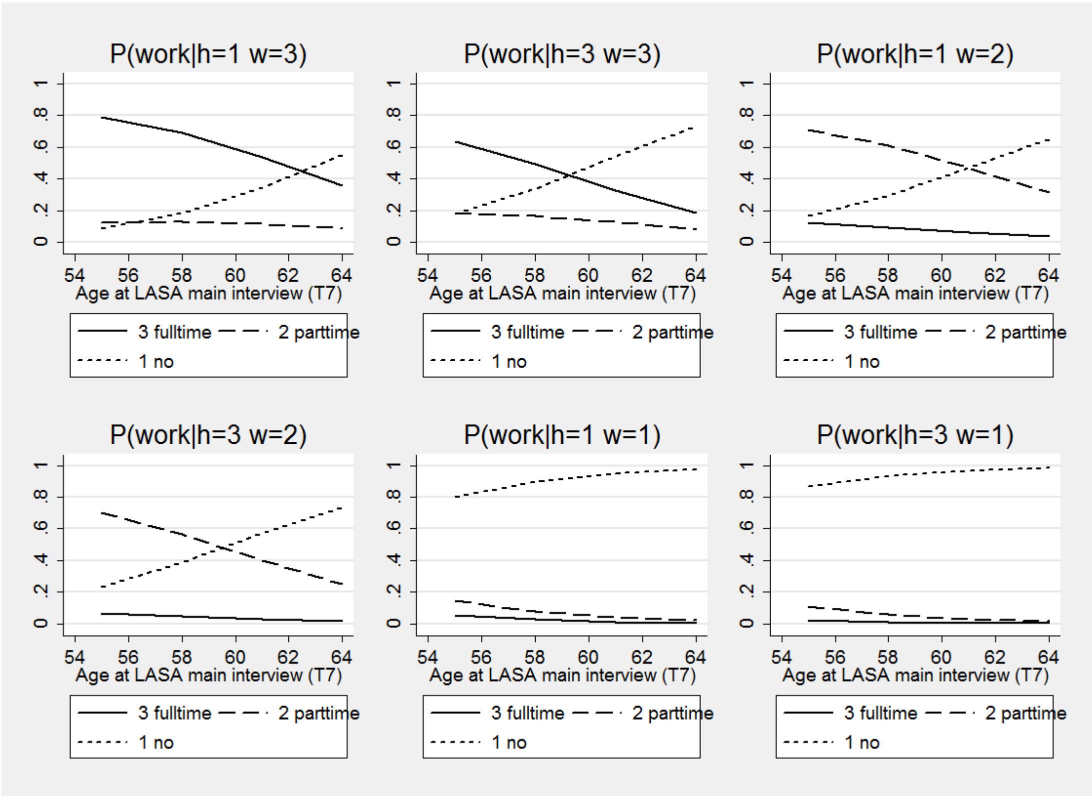

Figure 6.2: Age profile of probability of work status given lagged health (h = 1 best, h = 3 worst) and lagged work (w = 1 no, 2 parttime, 3 fulltime). All other variables are set at baseline level.

fulltime work. The effects of the other covariates is mostly as expected, in particular a strong significant negative effect of age on the probability of having work.

To assist in interpretation of the model, the age profile of probability of work status is plotted in Figure 6.2 for different combinations of lagged health (good health state 1, and poor health state 3) and lagged work status (3 fulltime work, 2 parttime work, 1 no work). All other covariates are set at baseline value. As can be expected the probability of fulltime and parttime work decreases with age. Being in good health at $t-1$ has a relatively large effect on the probability of remaining at work for those who have work at $t-1$, but only a small effect on the probability of work for those who do not work at $t-1$.

Table 6.3: Regression results for health and work. Standard model and joint model including correlated random effect. η is the latent health indicator, with $\eta = 1$ being the best health states and $\eta = 3$ the poorest. π_2 is the probability of belonging to state 2 of the discrete random effect variable. Bootstrapped standard errors for the joint model.

	Standard model		Joint model	
	Coef.	p-val.	Coef.	p-val.
Health				
State 2				
$\Delta(woman)$	0.142	0.293	0.349	0.083
age	0.487	0.192	1.225	0.035
$\Delta(partner)$	-0.241	0.188	-0.447	0.113
$\Delta(children)$	0.017	0.940	0.009	0.975
$\Delta(highedu)$	-0.165	0.186	-0.446	0.067
$\Delta(\eta_{t-1} = 2)$	1.874	0.000	0.927	0.092
$\Delta(\eta_{t-1} = 3)$	2.646	0.000	1.233	0.064
$\Delta(work_{t-1} = part.)$	-0.129	0.425	0.058	0.820
$\Delta(work_{t-1} = full.)$	-0.099	0.555	0.219	0.449
c	-1.208	0.003	-1.864	0.003
Mass point 2			2.853	0.090
State 3				
$\Delta(woman)$	0.069	0.683	0.388	0.201
age	-0.173	0.707	0.867	0.206
$\Delta(partner)$	-0.363	0.103	-0.716	0.087
$\Delta(children)$	0.035	0.900	0.033	0.937
$\Delta(highedu)$	-0.444	0.005	-0.905	0.002
$\Delta(\eta_{t-1} = 2)$	2.394	0.000	0.768	0.290
$\Delta(\eta_{t-1} = 3)$	4.751	0.000	2.552	0.008
$\Delta(work_{t-1} = part.)$	-0.397	0.057	-0.112	0.750
$\Delta(work_{t-1} = full.)$	-0.877	0.000	-0.361	0.392
c	-1.629	0.001	-2.872	0.001
Mass point 2			4.242	0.036
Work				
Parttime				
$\Delta(woman)$	-0.068	0.705	-0.064	0.715
age	-2.680	0.000	-2.673	0.000
$\Delta(partner)$	-0.278	0.255	-0.282	0.263
$\Delta(children)$	0.352	0.227	0.352	0.221
$\Delta(highedu)$	0.235	0.162	0.232	0.211
$\Delta(wave = 3)$	0.522	0.085	0.525	0.110
$\Delta(wave = 4)$	1.099	0.039	1.101	0.039
$\Delta(wave = 6)$	0.731	0.001	0.732	0.001
$\Delta(wave = 7)$	1.026	0.000	1.027	0.000
$\Delta(\eta_{t-1} = 2)$	-0.091	0.622	-0.123	0.677
$\Delta(\eta_{t-1} = 3)$	-0.353	0.116	-0.402	0.371
$\Delta(work_{t-1} = part.)$	3.174	0.000	3.178	0.000
$\Delta(work_{t-1} = full.)$	2.081	0.000	2.088	0.000
c	-1.924	0.001	-1.935	0.001
Mass point 2			0.061	0.924
Fulltime				
$\Delta(woman)$	0.222	0.398	0.221	0.443
age	-3.227	0.000	-3.281	0.000
$\Delta(partner)$	-0.036	0.914	-0.016	0.964
$\Delta(children)$	0.016	0.965	0.017	0.965
$\Delta(highedu)$	0.228	0.278	0.248	0.274
$\Delta(wave = 3)$	0.652	0.107	0.664	0.160
$\Delta(wave = 4)$	1.256	0.162	1.290	0.778
$\Delta(wave = 6)$	0.948	0.000	0.951	0.000
$\Delta(wave = 7)$	0.911	0.006	0.902	0.014
$\Delta(\eta_{t-1} = 2)$	-0.427	0.072	-0.305	0.367
$\Delta(\eta_{t-1} = 3)$	-0.940	0.003	-0.750	0.188
$\Delta(work_{t-1} = part.)$	2.392	0.000	2.375	0.000
$\Delta(work_{t-1} = full.)$	4.883	0.000	4.865	0.000
c	-3.297	0.000	-3.261	0.000
Mass point 2			-0.251	0.902
π_1			0.574	0.000
π_2			0.426	0.000
Log.-Lik.	-1512	(health)	-4460	
	-844	(work)		

Joint model of health and work

Table 6.3 also shows the regression results for the joint model with correlated random effects. The regression equations for the initial conditions are reported in Appendix 6.B Table 6.7. We have opted for a discrete random variable with two points of support mass. Again, this decision is motivated by the size of the data and computation time. Although a latent variable with two states might not fully capture all unobserved heterogeneity, the results provide an indication of the effect of controlling for unobserved individual effects. In the health equation in Table 6.3, mass point 2 is related to poorer health outcomes than mass point 1 (the baseline value). In the work equation, mass point 2 is related to smaller probability of fulltime work compared to mass point 1, although not significantly. The effect of the lagged values of health and work are considerably smaller when the random effects are included, and no longer significant. Specifically, the effect of lagged health on work is no longer significant. This finding might be partially explained by the relatively small number of available waves, which means that the number of observed individuals with for instance initial poor health, and good health in later waves is small.

6.4.2 Health and participation

Participation indicator

As indicator for participation, we specify a latent variable based on the four observed indicators of participation; formal work, personal care, domestic care, and volunteer work. Table 6.4 shows the model fit for a two, three, and four state specification of the latent participation variable, and Figure 6.3 shows the loadings of the participation indicators on the states of the latent variable. The four state model has the lowest AIC and BIC values. The loadings in the two state specification result in one state associated with a moderate probability of formal work, and low probability of personal and domestic care, and one state associated with a lower probability of work, but a higher probability of providing care. The three state specification shows state 1: relatively high probability to work, and low probabilities for providing care. State 2: low probability of working and providing care. State 3: low probability of working, but moderate probability of providing care, especially domestic. The three states specification shows little differentiation regarding volunteer work. The four state specification mainly seems to add additional differentiation between individuals with low probability of participating on all indicators, and individuals with low probability of participating except for volunteer work. We opt for a three state variable. Although somewhat of a simplification, we will further refer to these states as "state 1, propensity to formal work", "state 2, no participation", "state 3, propensity to care".

Figure 6.3: Standardized loadings of the participation indicators for specification of the latent variable with different number of states. Estimated using the < 65 LASA sample.

Table 6.4: Model fit for latent participation variable with different number of states. π_i indicates the fraction of individuals classified in state i.

			AIC	BIC
2 states	π_1	0.51	6624	6715
	π_2	0.49		
3 states	π_1	0.34	5391	5529
	π_2	0.33		
	π_3	0.33		
4 states	π_1	0.25	4527	4708
	π_2	0.25		
	π_3	0.25		
	π_4	0.25		

Dynamic model of health and participation

The regression results of the intertemporal model of health and participation are reported in Table 6.5. In the health equation, health status at $t-1$ again has the expected effect on current health status. There are no significant effects of participation, except for a positive effect of state 2 (no participation) on the poorest health state. In the participation equation, we also see the expected effects of lagged participation. Poor lagged health (state 3) has a significant effect on the probability of being in participation state 2 (no participation). The effect of health state 2 is in the same direction, but smaller and not significant. Age has a significant effect on the probability of being in participation state 2 (no participation) and 3 (propensity to care) instead of state 1 (propensity to formal work).

We also plot the age profile of probability of participation status in Figure 6.4. The figure shows the age specific probability of being in a particular participation state, given lagged values of health (1 best, 3 worst) and participation (1 propensity to formal work, 2 no participation, 3 propensity to care). All other variables are kept at baseline values. The results show a decreasing probability of being in state 1 (propensity to formal work) with age. The figure also shows that poor health at $t-1$ lowers the probability of state 1, both for individuals already in state 1 at $t-1$, as well as for individuals in other states at $t-1$. Individuals in state 3 (propensity to care) have a relatively high probability of transitioning to state 2 and especially 1 (formal work). Health at $t-1$ has only a small influence of going from state 1 (formal work) or 2 (no participation) to state 3 (care).

Table 6.5: Regression results for health and participation. η is the latent health indicator, with $\eta = 1$ being the best health states and $\eta = 3$ the poorest. $Participation$ is the latent participation variable with states 1 (propensity to formal work), state 2 (no participation), and state 3 (propensity to care).

	Coef.	p-val.
Health		
State 2		
$\Delta(woman)$	0.009	0.959
age	-0.111	0.827
$\Delta(partner)$	-0.122	0.639
$\Delta(children)$	0.139	0.637
$\Delta(highedu)$	-0.065	0.720
$\Delta(\eta_{t-1} = 2)$	1.823	0.000
$\Delta(\eta_{t-1} = 3)$	2.774	0.000
$\Delta(participation_{t-1} = 2)$	0.259	0.221
$\Delta(participation_{t-1} = 3)$	-0.068	0.765
c	-1.092	0.032
State 3		
$\Delta(woman)$	0.173	0.480
age	-0.308	0.647
$\Delta(partner)$	-0.098	0.777
$\Delta(children)$	0.676	0.127
$\Delta(highedu)$	-0.360	0.127
$\Delta(\eta_{t-1} = 2)$	2.723	0.000
$\Delta(\eta_{t-1} = 3)$	5.367	0.000
$\Delta(participation_{t-1} = 2)$	0.738	0.010
$\Delta(participation_{t-1} = 3)$	0.318	0.302
c	-3.618	0.000
Log lik.	-728.363	
Participation		
State 2		
$\Delta(woman)$	0.061	0.759
age	3.027	0.000
$\Delta(partner)$	0.283	0.334
$\Delta(children)$	0.002	0.994
$\Delta(highedu)$	-0.254	0.203
$\Delta(wave = 7)$	0.138	0.527
$\Delta(\eta_{t-1} = 2)$	0.377	0.079
$\Delta(\eta_{t-1} = 3)$	0.849	0.001
$\Delta(participation_{t-1} = 2)$	2.532	0.000
$\Delta(participation_{t-1} = 3)$	1.145	0.000
c	-2.892	0.000
State 3		
$\Delta(woman)$	0.533	0.015
age	2.887	0.000
$\Delta(partner)$	-0.286	0.343
$\Delta(children)$	0.718	0.064
$\Delta(highedu)$	-0.296	0.174
$\Delta(wave = 7)$	-0.269	0.271
$\Delta(\eta_{t-1} = 2)$	0.412	0.082
$\Delta(\eta_{t-1} = 3)$	0.696	0.015
$\Delta(participation_{t-1} = 2)$	1.387	0.000
$\Delta(participation_{t-1} = 3)$	1.747	0.000
c	-3.496	0.000
Log.-Lik.	-784.602	

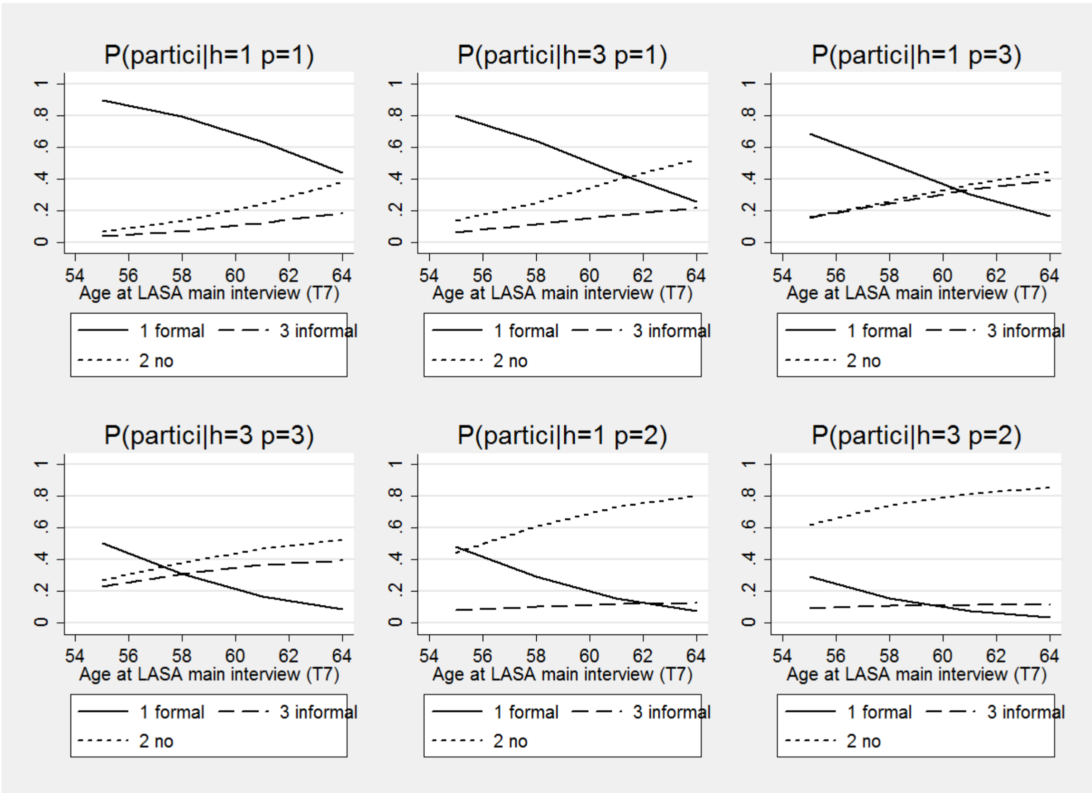

Figure 6.4: Probability of participation outcomes given lagged values of health (1 best, 3 worst) and participation (1 is formal work, 2 no participation, 3 caregiving).

6.4.3 Simulations

To gain further insight in the relationship between health and participation, we simulate different health and participation paths for a man of 55 with different initial health and participation states. All other covariates are again kept at their baseline value. For the health and work model we use the standard model. Although we have found evidence for unobserved individual effects, the simulation based on the standard model provides a more complete view on the total association between health and work. Figure 6.5 shows the probability that a 55 year old man with a particular initial combination of health and work will be in a certain health state in consecutive ages up to 64. Given that the model is based on three-year transitions, the probabilities in the intervening years are based on linear interpolation. The top two graphs shows expected health states for a man in initial good health. As can be seen, probability of remaining in good health is high. There is a 80 percent probability that a man in initial good health at 55 will be in good health at 64. Not having work at 55 has only a small negative effect on the probability of being in good health at consecutive ages. The two lower graphs show health paths for an individual in poor initial health. The graphs show a substantial probability of health improvement, either to state 2 or 1, in consecutive ages. The figure also shows that the probability of health improvement is considerably smaller for individuals without work at 55.

Figure 6.6 shows the simulated work paths for a 55 year old man. The two top graphs concern an individual with fulltime work at 55. The probability of having work declines rapidly with age. Initial poor health decreases the probability of fulltime work in consecutive ages. For individuals without employment at 55, the probability of having work at consecutive ages is small, and mostly concerns parttime work. Initial health has a small influence on work at consecutive ages, but initial good health does raise the probability of parttime work at consecutive ages somewhat.

Figure 6.7 shows the simulated health path based on the health and participation model. The resulting paths are quite similar to those in Figure 6.5. We can see that the effect of participation state on health at consecutive ages is small for individuals with initial good health at 55. For individuals in initial poor health, being in participation state 2 (no participation) has a negative effect on health in consecutive ages. In the related simulation of probabilities of participation in Figure 6.8, it is visible that poor initial health at 55 has a negative effect on the probability of being in state 1 (propensity to formal work) between 55 and 64 for all initial participation states. Individuals in initial participation state 3 (propensity to care), have a relatively small probability of remaining in that state during consecutive ages. Initial health differences have a small influence on that probability. However, individuals in initial state 3 and in poor health have a considerably higher probability of going to state 2 (no participation) instead of 1 (formal work) compared to the same individuals in initial good health.

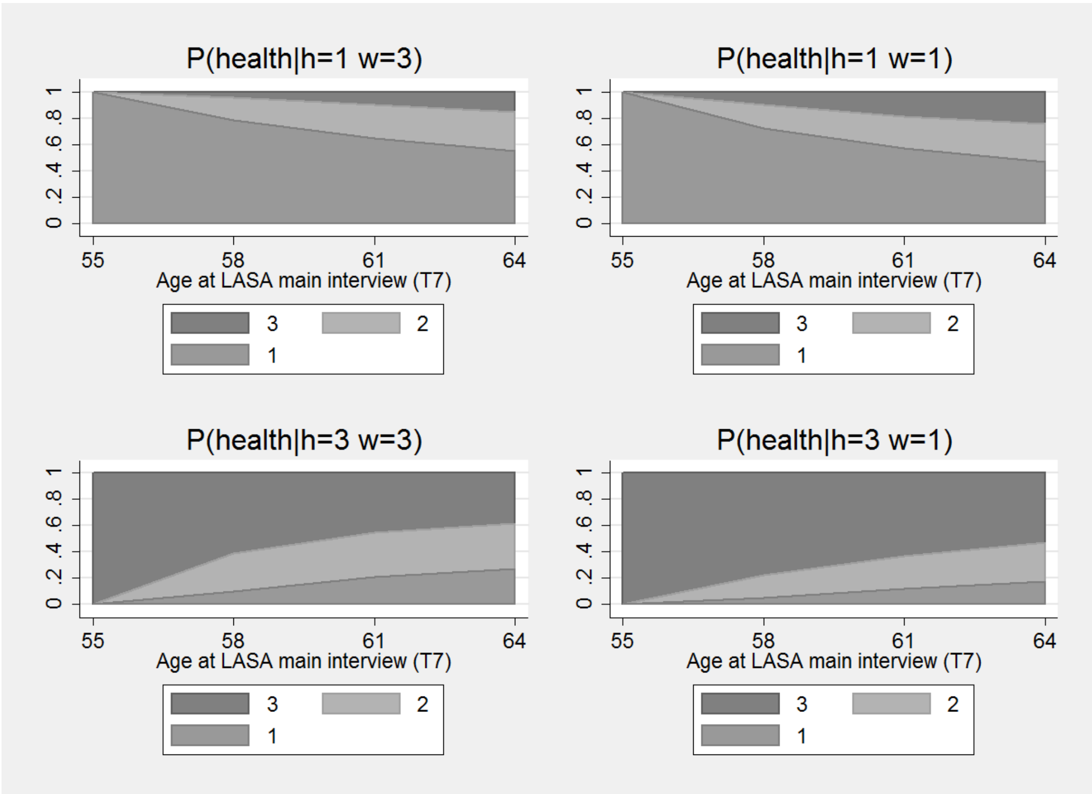

Figure 6.5: Probability that a man of 55 in good health (h=1) with fulltime work (top left), good health and no work (top right), poor health (h = 3) and work (bottom left), or poor and and no work (bottom right) will be in a particular health state at consecutive ages.

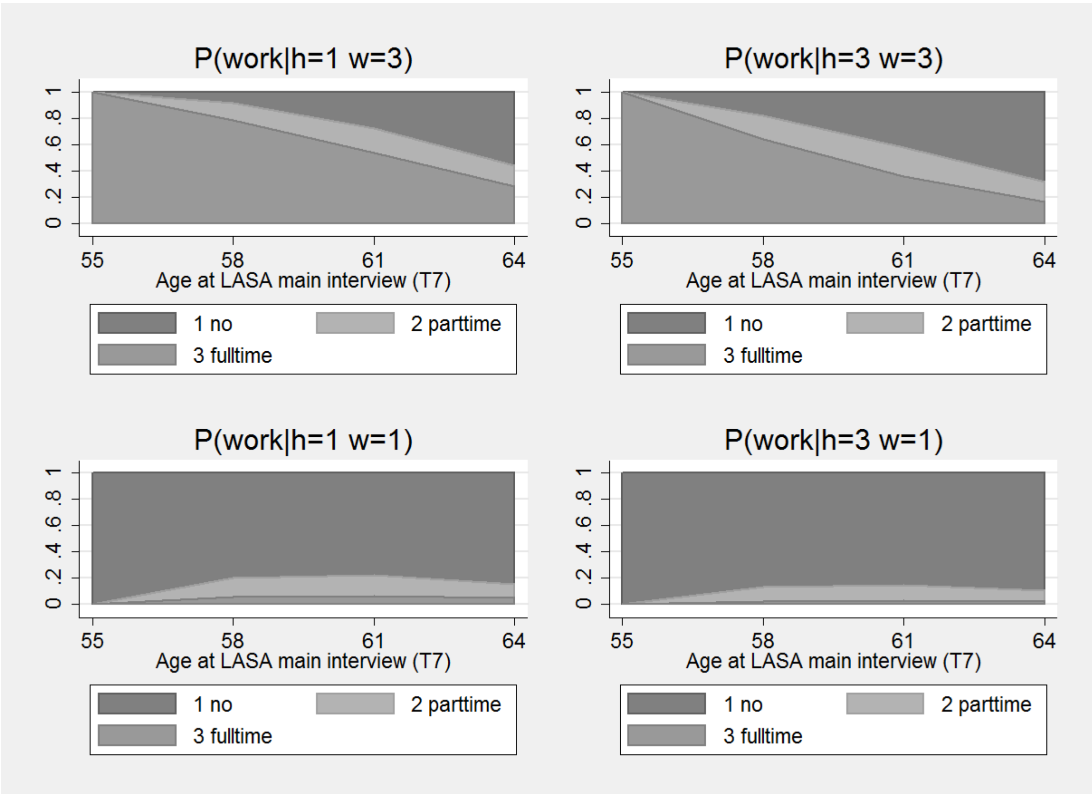

Figure 6.6: Probability that a man of 55 with work and good health (top left), work and poor health (top right), no work and good health (bottom left), or no work and poor health (bottom right) will have work at consecutive ages.

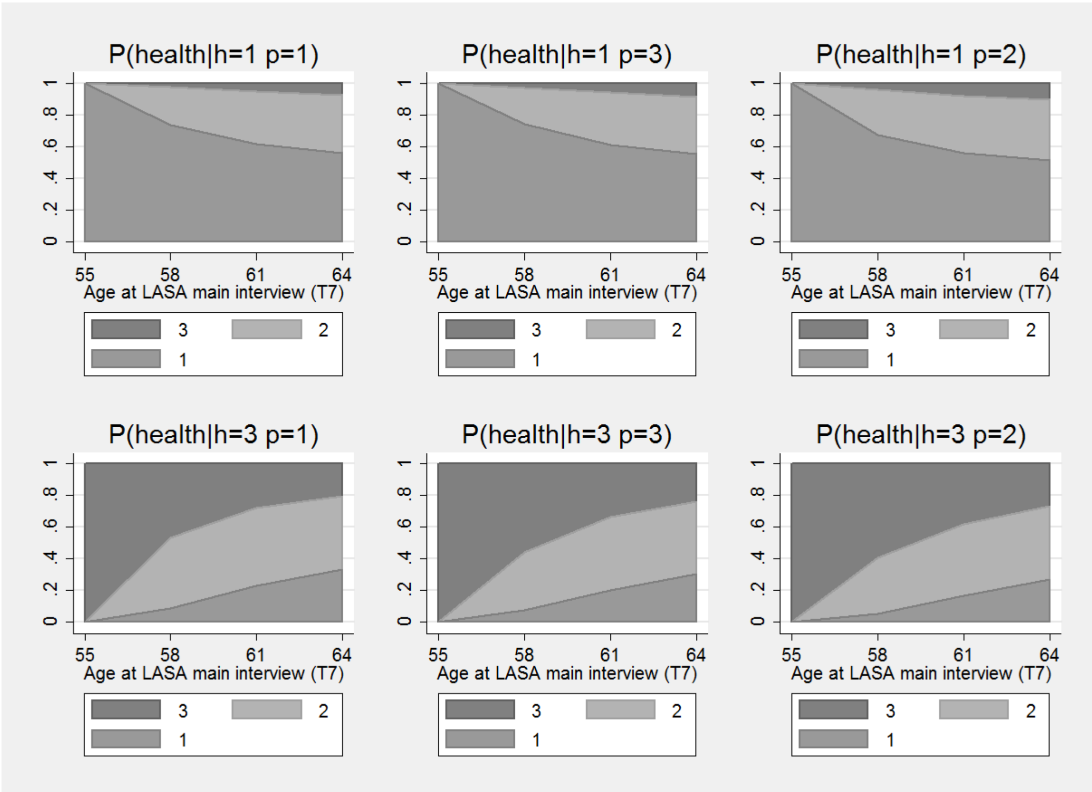

Figure 6.7: Probability that a man of 55 in good health (h = 1) with propensity to formal work (p = 1) (top left), good health (h = 1) and propensity to care (p = 3) (top middle), good health (h = 1) and no participation (p = 2) (top right), poor health (h = 3) and propensity to formal work (p = 1) (bottom left), or poor health (h = 3) and propensity to care (p = 3) (bottom middle), or poor health (h = 3) and no participation (p = 2) (bottom right) will be in a particular health state at at consecutive ages.

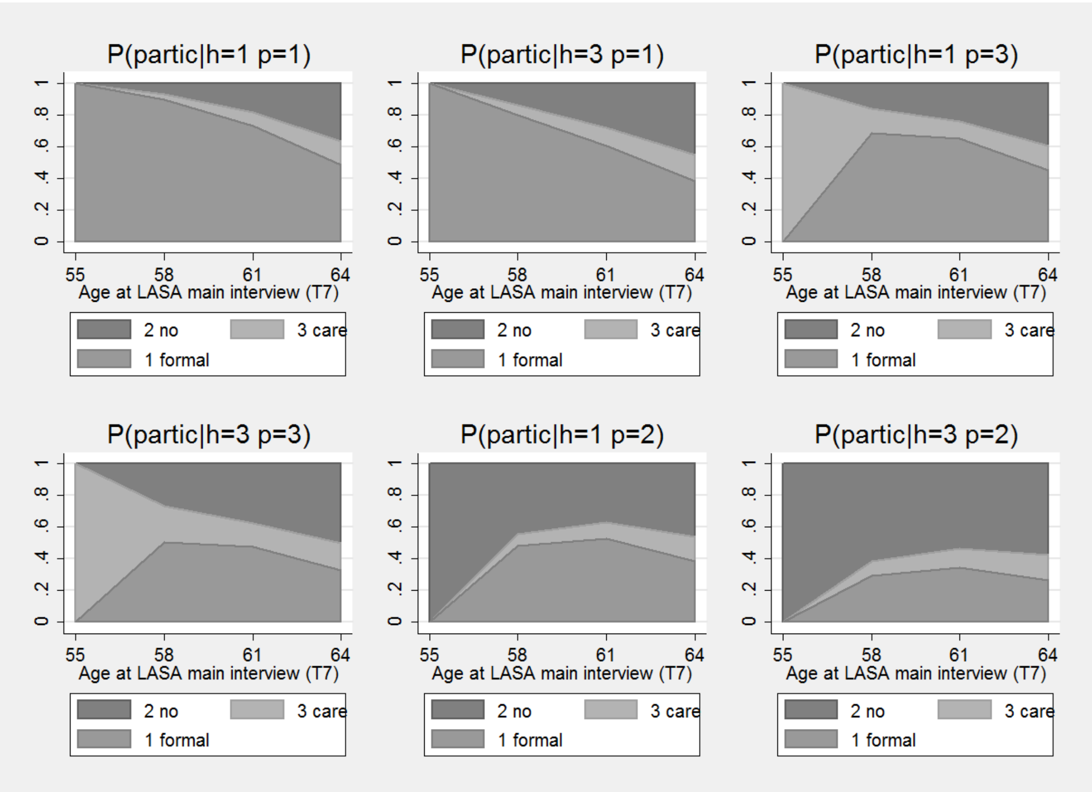

Figure 6.8: Probability that a man of 55 with propensity to formal work (p = 1) and good health (h = 1) (top left), propensity to formal work (p = 1) and poor health (h = 3) (top middle), propensity to care (p = 3) and good health (h = 1) (top right), propensity to care (p = 3) and poor health (h = 3) (bottom left), no participation (p = 2) and good health (h = 1) (bottom middle), or no participation (p = 2) and poor health (h = 3) (bottom right) will be in a particular participation state at consecutive ages.

6.5 Discussion

In the light of population aging, the relationship between health and participation is of importance. We have estimated dynamic models of health and participation to investigate this relationship for the Dutch population between 55 and 65. Our approach is novel in two ways. First, we use a latent health variable that incorporates different dimensions of health that might be relevant for participation. Second, we have extended our model of health and work to a more broad measure of participation, including informal care and volunteer work. What has our approach added? First, we discuss the main findings on the relationship between health and work. Second, we consider the results on health and the more broad measure of participation. Finally, we give some policy implications.

First, we have opted for a three state latent health variable. The definition of the variable is based on seven health indicators, including self-perception of health, chronic diseases, limitations and mental and cognitive impairments. The three state definition has resulted in a differentiation between individuals in good health, individuals with chronic diseases but without disability, and individuals with chronic diseases and disability. Although a 4 state specification leads to more differentiation in the level of disability and depressive symptoms, we have opted for the three state version because of the small sample size. When we consider the dynamics of health, we have found that good health is quite persistent: most individuals in good health at 55 will still be in good health at 65. In contrast, individuals in poor health at 55, with chronic diseases that lead to limitations, have a high probability of health improvement, at least to a less disabling state. We have found some evidence for an influence of work status on health. However, when we control for possible endogeneity, results are no longer significant. Here, our results differ from Haan and Myck (2009), but are in line with other studies controlling for endogeneity between health and work (Lindeboom, 2012). No general influence of employment status on health was found by Rijs et al. (2011) using the LASA study. The relatively small number of 55 to 65 year olds in the sample, the small number of waves, and the three year distance between waves might partially explain the non significant result.

Regarding the results for work, we first of all have found, as expected, a strong negative relationship with age. Furthermore, we have found that poorer health decreases the probability of work. This effect is strongest and most significant for health state 3, related to chronic diseases and disability. Here, the multidimensional approach of health is beneficial, since it is mostly the disabling effect of diseases rather than the mere presence of chronic diseases, that is related to lower labor participation. We find that better health results in a higher probability that an individual who has a job, remains at work. Instead, the effect of better health on individuals without work is limited. We do find some effect on the probability of parttime work. Other factors, such as institutional changes, seem to play an important role in determining labor participation. These might be partially captured by the wave dummies in the work regression. We indeed find that observations in later years have a higher probability of work, but a clear time trend is not visible. We have included women as well as men in the model. The effect of sex on employment, conditional on lagged employment, is not significant. However, judging from the large significant negative effect of women on fulltime work in the initial conditions equation in Appendix 6.B, the number of women with a fulltime job at the first observation is significantly smaller than the number of men. Preliminary analysis based only on men showed almost the same results as the model for both men and women reported here. Therefore, the results are not necessarily indicative for scenarios with a large increase of labor participation of older women. When we control for unobserved endogeneity in the joint model, the effect of health on work keeps the same sign, but is no longer significant. Small sample size and long distance between waves might again partially explain this result.

Second, to include a broader measure of participation we have again opted for a latent variable approach. The available observed participation indicators are formal work, personal care, domestic care and volunteer work. The three state specification that we have chosen results in one state related to a high probability of formal work, a second state related to no participation except for volunteer work, and a third state related to the provision of informal care. In case of the latent health variable, an interpretation in terms of underlying unobserved "true" health that manifests itself in different observed health indicators seems intuitive. In case of the latent participation variable, interpretation is less straightforward. We use the latent variable mainly as a data-driven way to capture the most important correlation between the different forms of participation. For ease of interpretation, we have referred to the three states as propensity to work, no participation, and propensity to care. The idea behind these names is that individuals belonging to for instance state 1, have a desire or ability to work formally, but this not necessarily mean that they actually work. Actual working status is then determined by external factors, such as the employment rate. This interpretation is intuitive but has to be done with care.

In the dynamic model of health and participation, the effect of participation on health is generally small. There is a significant effect of being in state 2 (no participation) on going to poor health. Although this finding might partially be due to unobserved individual characteristics, individuals with low social participation seem to have an additional health risk. The effect of health on participation should be differentiated by initial participation state. For individuals in state 1 (propensity to formal work) better health increases the probability of remaining in that state. For individuals in state 2 (no participation), better health increases the probability of going to state 1. In both cases, health has little influence on the probability of going to state 3 (propensity to care). For initial state 3, health has a small influence on the probability of remaining in that state, but does influence the probability of going to state 1 and 2.

Finally, our results show that good health is a necessary but not sufficient condition for labor participation of the older population. Additional policy measures, such as financial incentives for employers or older workers, are needed to stimulate labor participation of older individuals. Based on the multidimensional approach to health in this paper, health policy to improve employment of older workers should not focus on the prevention of chronic diseases per se, but rather on their disabling effect. When we consider other forms of participation, health seems to have little influence on provision of informal care. Also, there seems to be little risk that increased labor participation in the age group 55 to 65 decreases the supply of informal care, since care provision seems to be driven mostly by need. Also, there is a relatively large number of individuals between 55 and 65 without formal work or other forms of participation. It should be noted that this might be different for older age groups. Health does play an important role in the return of informal care givers to formal work. We have found indications that non-employment, or low social participation, is associated with health risk. This risk should be addressed by health and social policy jointly. In short, although health plays a role in providing the conditions for higher participation of the older population, expectations of the effect of health improvements without additional social policy should not be too high.

6.A Overview of the health indicators

Table 6.6: Health indicators in the LASA survey

Indicator	Description	Categories
Chronic diseases		No disease One Two More than two
Upper body performance	Time putting on-off cardigan	first quartile second quartile third quartile fourth quartile cannot
Functional limitations	Climb staircase Cut toenails Use own or public transportation	No limitations 1 limitation 2 limitations 3 limitations
Activity Limitations	Health problems limit daily activities	No Slightly Severely
Self-perceived health		Excellent Good Fair Sometime good/bad Poor
Depressive symptoms	CES-D scale (0-60) Cut-off at 16	No Yes
Cognitive impairments	MMSE (0-30) Cut off at 24	Unimpaired Impaired

6.B Estimation results: initial conditions

Table 6.7: Regression results for initial health and work status in the joint model. η is the latent health indicator, with $\eta = 1$ being the best health states and $\eta = 3$ the poorest. Bootstrapped standard errors.

Health			Work		
	Coef.	p-val.		Coef.	p-val.
State 2			Parttime		
$\Delta(woman)$	0.388	0.085	$\Delta(woman)$	0.101	0.605
age	0.721	0.261	age	-2.392	0.000
$\Delta(partner)$	-0.370	0.272	$\Delta(partner)$	-0.137	0.580
$\Delta(children)$	-0.252	0.448	$\Delta(children)$	-0.463	0.106
$\Delta(highedu)$	-0.620	0.018	$\Delta(highedu)$	0.463	0.007
			$\Delta(wave = 5)$	0.986	0.000
c	-1.046	0.046	c	-0.106	0.816
Mass point 2	2.809	0.017	Mass point 2	-0.848	0.019
State 3			Fulltime		
$\Delta(woman)$	0.015	0.964	$\Delta(woman)$	-2.558	0.000
age	-0.021	0.980	age	-4.729	0.000
$\Delta(partner)$	-0.594	0.616	$\Delta(partner)$	-0.585	0.061
$\Delta(children)$	0.365	0.522	$\Delta(children)$	-0.134	0.712
$\Delta(highedu)$	-0.929	0.036	$\Delta(highedu)$	0.562	0.002
			$\Delta(wave = 5)$	0.698	0.000
c	-2.063	0.188	c	2.463	0.000
Mass point 2	4.169	0.163	Mass point 2	-1.341	0.030

Chapter 7

General Discussion

7.1 Research aims

In this thesis, I have set out to gain insight in the longitudinal relationship between longevity and health of the older population, and the consequences of this relationship for health care expenditures and (labor) participation. In the introduction, I have formulated the following aims:

1. To investigate the relationship between different dimensions of health of older individuals. And to combine relevant health variables in an indicator of health, with a meaningful interpretation, that can be applied for the analysis of dynamic interactions between health and other outcome variables, and that is usable to operationalize health scenarios.

2. To model and estimate the individual longitudinal relationship between health and health care expenditures for older people, in order to investigate dynamics in health, longer life, and health care expenditures.

3. To operationalize health scenarios, based on the existing hypotheses on longevity and health, and to use the models from 2 to gain insight into population effects of these health scenarios on health care expenditures.

4. To model and estimate the longitudinal relationship between health and forms of social participation, such as labor participation and informal care provision, in the older population.

In addition, I would explore new techniques that allowed me to fulfill these aims using large microdatasets. Now, I will reflect on the results in the light of these aims.

7.2 Main findings

The many faces of health

The first aim of this thesis has been to do justice to the multidimensional nature of health, and to include a broad health measure in the analysis. This aim was motivated by the heterogeneous nature of health, especially for the older population. As the human body ages, organs wear and the body's ability to fight diseases declines. As a result, the prevalence of (chronic) diseases and health impairments increases with age. In turn, these impairments can lead to limitations in performing physical and mental actions used in daily life. Although health generally decreases with old age, individual trajectories of impairments and disability differ substantially between individuals (Nusselder et al., 2006). Also, health is more than not being ill. There is a large diversity in health disorders, ranging from purely physical limitations to problem with cognitive and mental functioning. Furthermore, as discussed in Chapter 5, trends in different aspects of health tend to diverge. A multidimensional of approach of health is thus required. At the same time, it is difficult to include large sets of separate health indicators in a statistical analysis of the relationship between health and societal outcomes. Therefore, a parsimonious approach, that combines or summarizes different health aspects, is needed.

In this thesis, latent class analysis is applied to combine information from different discrete health indicators. These indicators cover subjective and objective, physical and mental aspects of health and disability. Latent class analysis is widely used in the social sciences to capture dependencies between two or more variables, through an unobserved variable (Hagenaars and McCutcheon, 2002). The latent variable used in the thesis is discrete. The states of the variable determine the likelihood of a particular health outcome for all health indicators. The usefulness of the resulting health measure depends on whether the states can be given a meaningful a posteriori interpretation in terms of health (Deb and Trivedi, 2002), and can be successfully implemented in individual and aggregate analysis of health and outcomes such as health care expenditures. The three state model estimated in Chapter 4 indeed seems to be related to the underlying health indicators in a meaningful way. The first state is related to good health for all indicators. The second state is related to a high probability of chronic diseases, but only a moderate probability of disability, and a low probability of mental or cognitive problems. The third state is related to poor health for all indicators, especially also a high probability of disability and mental or cognitive problems.

The latent variable thus relates well to two important aspects of health for the aging. First, the latent variable differentiates between physical and mental impairments. Second, the variable distinguishes between the presence of chronic diseases and their disabling effect, which can be seen as different consecutive stages in the process of disablement (Verbrugge and Jette, 1994). The second distinction has also proven to be instrumental in the modeling of different morbidity scenarios in Chapter 5. As discussed earlier, there are three commonly used scenarios for the relationship between longevity and health: compression of morbidity, expansion of morbidity, and a dynamic equilibrium, with a tradeoff between the increasing age-specific prevalence of diseases and a decreasing severity of those diseases. Instead of focusing on a limited selection of health indicators, the hypotheses could be operationalized using interactions between different health aspects. Especially for the dynamic equilibrium scenario, where the difference in the disabling effect of chronic diseases between states 2 and 3 enabled the modeling of a simultaneous increase in the prevalence of chronic diseases and a decrease in their severity, the combined health indicator proved to be useful.

There are two modeling choices that I want to reflect on. First, the use of a relatively broad measure of health. I have already discussed the advantage of such measures in capturing relevant aspects of health in the older population. A disadvantage is that there is relatively little room for detail. There is substantive research applying models based (large) sets of chronic diseases combined with lifestyle, e.g. (Van Baal et al., 2008). These models can be used to simulate the effect of specific lifestyle interventions on the prevalence of particular diseases. Such an analysis is much more difficult using the model from Chapter 4. Combination of these two kinds of models can therefore be fruitful. Second, the use of a *discrete* health variable. In many economic applications, health is treated as a continuous variable. This approach is in line with an interpretation of health as a capital stock (Grossman, 1972). As I have argued, there is reason to treat health not as a continuous variable, but as a variable with different stages related to different health domains. This multidimensional treatment of health contrasts with most empirical literature using a continuous latent variable, which is based on a single measure of health. In reality, the differentiation between health states is probably even more gradual than in the latent model from Chapter 4. In that sense, the model is a compromise between parsimony and detail in health.

There are a few applications that combine discrete health indicators using a continuous latent variable, or factor. However, these models are not classification models, in that they do not result in distinct groups that can be given a meaningful interpretation in terms of different health dimensions. The Grade of Membership (GoM) method developed by Manton (1982), and applied by for instance Portrait et al. (2000), is closely related to the discrete latent variable. In addition, this method also estimates individual 'grades' of membership, allowing each individual to partially belong to more than one state. Compared to latent class analysis, the advantage of GoM is that it conceptually allows for more differentiation in health between individuals through the individual membership probabilities. However, since the latent class analysis relates the latent variable to the observed indicators in terms of probability, the latent class analysis actually also allows for differentiation between individuals within a particular latent health state. Furthermore, latent class analysis can be more easily combined with the analysis of time dynamics.

The relationship between health and health care expenditures

The relationship between (aspects of) health and health care expenditures has been studied in a number of different ways, focusing on for instance individual determinants (inequality) of health care use (Van Doorslaer et al., 2004), or costs of illness (Rice, 2000). What the approach in this thesis adds, is again the use of a broad concept of health. Given that health of the older population can best be defined in terms of combinations of different health aspects, instead of separate diseases or impairments, the same is true for its consequences for health care expenditures. There is indeed evidence, that different aspects of health are relevant for different types of health care expenditures. The analysis in Chapter 3, using four separate health indicators, provides some additional indications of the relevance of different health domains for health care expenditures. Not only do the findings show larger differences in the relationship between health and hospital costs between indicators, also the interaction effects between health, age, and sex are different.

The usefulness of a combined health approach can be made clear by comparing the multidimensional approach in this thesis with traditional cost of illness studies. The aim of such studies is to gain insights in the societal burden of diseases by looking at their effects on costs. These insights are complementary to epidemiological studies, since the cost effect of a disease might differ from its health burden, for instance mortality. In fact, a result of these studies is that not the most lethal, but the most disabling diseases result in highest costs. A step further is to not consider the cost effects of an individual diseases, but to look at the combined effect of two or more diseases (Wong et al., 2011b). The analysis in this thesis can then be seen as yet another step, concentrating on combinations of health aspects instead of diseases only. Such combined analysis can lead to new insights that are missed by focusing on diseases only. For instance, Chapter 5 shows that future hospital expenditures will be strongly related to the prevalence of chronic diseases. Instead, long-term care expenditures will depend much more on the effect of these diseases on disability and cognitive impairments.

Longitudinal dynamics in health and health care expenditures

To understand how health influences the relationship between longevity and health care expenditures, insight is needed in the longitudinal dynamics of both. Studies of longitudinal dynamics in health in an economic context have been rather limited. Halliday (2008) and Lange and McKee (2011) use time series techniques to analyze dynamics in health, but these are based on self-perceived health, respectively a continuous latent variable. They therefore share the same disadvantages in terms of a multidimensional treatment of health. Longitudinal research on health care expenditures is also limited. Wong (2012) uses a non-parametric method to construct lifecycle paths of health care expenditures, but this approach lacks a direct link with health. The latent Markov model developed in Chapter 4 provides an alternative way to model dynamics in health and health care expenditures, or other outcomes. The model has the advantage that lifecycle patterns in health care expenditures can be directly linked to patterns in health. It is based on a multidimensional concept of health, but at the same time allows for relatively parsimonious modeling of time dynamics between the different health indicators.

Health economic research on the consequences of longevity has been mostly based on time-to-death studies, explicitly linking costs to proximity to death (Zweifel et al., 1999). The general finding of these studies is that longevity gains have a small impact on health care expenditures, since they merely shift costs to later ages. A number of objections have been raised against the time-to-death approach. The most important in the light of this thesis is that the time to death approach ignores the underlying dynamics in health that cause the relationship between mortality and health care expenditures. Especially, in long-term care, where costs are much more determined by the disabling effect of diseases and not their mortality, proximity to death is not a very good explanatory variable. The seminal study by Lubitz et al. (2003) relates differences in (initial) health directly to life expectancy as well as costs. They find that, in the US, initial differences in self-perceived health do not result in large differences in costs over remaining lifetime. This result is due to the fact that initial better health is related to longer life, and postponement of costs.

Chapters 3 and 4 investigate whether the findings of Lubitz et al. (2003) can be generalized for different measures of health, for different age groups, and for different types of care. A tradeoff between lower current costs and additional costs in later years is indeed found for different health indicators in Chapter 3, and the combined latent variable in Chapter 4. However, time patterns of costs do differ substantially based on the health indicator used. The postponement of costs due to better initial health is found for different initial ages, but the effect on costs over total remaining lifetime differs for values of initial age in Chapter 4. For initial age 65, cumulative costs are almost equally high for each initial health state. For older ages, initial better health results in higher costs over remaining lifetime. The results also show a tradeoff between cure and long-term care. Better initial health at 65 seems to lead to lower costs in the hospital sector, even over remaining lifetime, but also to higher expected costs in long-term care later in life.

Dynamics in health, work, and participation

In Chapter 6, the approach of using a multidimensional concept of health is extended to the societal participation of older individuals. The relationships between health and labor participation, as well as between health and a broader definition of participation, including caregiving and volunteer work, are investigated. The findings show a negative effect of poor health on labor participation, as well as participation in general. This effect is the most pronounced for the combination of chronic diseases with disability. Mere presence of chronic diseases has only a weak effect on participation. There are also some indications that participation has a positive effect on health. I want to discuss two issues. First, the chapter focuses on participation of 55 to 65 year olds. With plans to raise the pension age in many Western countries, an important question is how health can enable individuals to continue work at ages older than 65. Findings for the 55 to 65 year old group can provide an indication of the relationship between health and participation at these older ages. For instance, the rising prevalence of chronic diseases among the older population is not necessarily a problem for increasing participation, as long as disabling effects are limited. Also, living longer in good health is a necessary, but far from sufficient condition for increased (labor) participation. However, empirical results for older ages can add additional insights. For this purpose, differences in pension age between countries, or gradual increases of the pension age can be utilized.

Second, one of the motivations to consider other forms of participation is the possible negative effect of increased labor participation on other societally valuable activities such as informal caregiving and volunteer work. The results in Chapter 6 did not show strong trade off effects: informal caregiving seems to be mostly determined by need, and volunteer work seems to be largely independent of other forms of participation. Also, there is a relatively large part of the population between 55 and 65 that does not engage in any of the forms of societal participation. Again, extrapolation of the results to older ages should be done with care. At older ages the need to provide informal care, for example to a spouse, is likely to be much higher and can be in conflict with increased demand for formal work. Extension of a broad concept of both health and participation to more formal models of individual decision making under budget constraints, such as Bound et al. (2010) or Knoef and Kooreman (2011), can be beneficial.

New data, new techniques

The two main goals of this thesis, to use a broad health measure and to study longitudinal effects, result in possibly conflicting data demands. The use of a broad health measure requires detailed health information, often only available in cross section surveys or small panel surveys, whereas longitudinal, lifecycle, analysis requires preferably large datasets with continuous, or at least regular, time measurements. To fulfill both goals, I have combined survey data with registry data. To make full use of such combined datasets, modeling choices have to be made that sometimes differ from common practice. In other instances, changes to existing techniques have to be implemented. I will focus here on the modeling of individual transitions in health when only repeated cross section data of different individuals, or longitudinal survey data with large time intervals is available. In both cases, combining health data with registry data can possibly improve current methodologies based on interpolation techniques, e.g. (Lièvre and Brouard, 2003).

In Chapter 3, I combined repeated cross section health surveys with longitudinal survey data on hospital use. This way, baseline health could be related to costs of hospital use over seven years. By using a stacked dataset, where the oldest health survey is used to estimate costs over seven years, and the more recent only for one year, full use could be made of the available data. The implementation of a discrete survival model, where the observation period was cut up into yearly intervals, allows the use this stacked data design without creating survival bias. The latent Markov model introduced in Chapter 4 is the main technique employed in this thesis to capture the relationship between different dimensions of health in a parsimonious way. Although latent Markov models are quite commonly used in a number of fields, and latent class models have been employed in health economics, the use of such models for the analysis of dynamics in sets of health indicators is quite novel. A specific addition is again the combination of registry data with survey data. To accommodate the estimation of one-year transition probabilities using a survey with three-year waves, health care use information from a hospital registry dataset was added. The additional information from this dataset could thus be used to provide information on the state of the latent variable in years for which no survey data is available.

7.3 Further research

Even more faces of health

Through the whole of this thesis, I have argued for the use of a broad concept of health. It is important to realize that the indicators included in the definition of the latent variable in Chapter 3 are not necessarily the right set for any analysis. The usefulness of an indicator will depend on the subject and purpose of the analysis. For the analysis of something like the effects of incidental health shocks, the health concept used in this thesis is not very appropriate. Instead, the latent health variables describe consecutive stages of health related to aging. As such, the health variable used here could be seen as an important building block for a concept of health that can be applied over the whole lifecycle. Possible extensions of the current health concept can be thought of. I will give two examples: One is providing even more detail to the health of the older population. The other is extending the health concept to other parts of the lifecycle. First, the current health variable for the older population could be extended by including frailty. Gerontologists have introduced this term to identify a state of age-related increased risk of ill health and disability. Most commonly, this state is thought of in a clinical way, primarily related to a loss and dysfunction of skeletal muscle and bone (Fried et al., 2001). Recently, broader definitions, including social aspects, have also been operationalized, e.g. (Gobbens et al., 2010). One advantage of the inclusion of frailty related indicators might be that they provide additional explanation of the age effect in long term care use, which is not fully captured by health and disability. Indicators related to the concept of frailty are available in more recent waves of the LASA survey, and could thus be relatively easy be used in the Dutch context.

Second, the latent health variable can be adapted to also describe health at earlier stages of life. The difference between the indicator used for the total older population in Chapter 4, and the indicator used for the 55 to 65 population in Chapter 6 already shows that the relevance of different health dimensions is age-specific: for the relatively younger population cognitive impairments are of much less importance. For even younger ages, between 0 and 55, other aspects of health will be important. At these ages, most individuals are in good health, while a small group will have severe health impairments and disabilities, related to genetic diseases or severe injuries. Although small in size, this group might have a severe impact on for instance health care expenditures. For labor participation, mental impairments might play an important role. Furthermore, to link health-related behavior at earlier stages in life to chronic diseases later in life, lifestyle aspects could be included.

Health and health care expenditures

As discussed in Chapter 2, there is a gap between studies focusing on individual determinants of health care expenditure and macro studies based on aggregated data and time series techniques. Lorenzoni and Oderkirk (2012) discuss a great variety of health care forecasting models used in different OECD countries. They distinguish between predictions made by microsimulation models, such as those in Chapter 5, and predictions based on macro models. Generally, macro models have the best prediction performance. At least for short and medium time horizons, and with the absence of structural breaks (Przywar, 2010). However, the usefulness of prediction models should not only be assessed based on prediction performance. Lorenzoni and Oderkirk (2012) state that medium and long-term forecasts should identify where a society may be heading in the future if current trends continue, and should clarify the factors that are driving health care expenditures. Furthermore, these models can provide clearer picture of societal consequences of health and health care spending. To answer question such as “what are the consequences of different health trends on long term health care spending?”, or “in which sector of the health care system will costs be rising the most?”, micro models are very useful. Because changes in health, or other variables, can be implemented at the individual level, microsimulation is well equipped to simulate “what if” scenarios relevant for policy makers. Although macro and micro studies are thus complementary, benefits might be achieved by combining both approaches (Lorenzoni and Oderkirk, 2012).

An area where the use of a broader measure of health can be beneficial is the research on how individual preferences for health drive the observed relationship between national income growth and health care expenditures. In their influential study, Hall and Jones (2007) model health as a luxury good, of which individuals want to spend an increasing share of their growing income. The idea is that the relative marginal utility of health increases compared to other consumption goods, mainly because of the life extending effect of health. The definition of health in studies like Hall and Jones (2007) is rather limited. Most often, mortality, or a measure directly related to mortality is used. This concept of health might not be appropriate for the different ways that health plays a role in these models: Health is not only assumed to extend life, but also to add utility itself, to interact with the utility of other consumption goods, and to influence productivity. As I have found, different aspects of health are relevant for all these different roles, and trends in these different aspects do not coincide. For instance, a health measure based directly on mortality will not accurately capture the trend in those aspects relevant for the intrinsic value (utility) of health, such as disability. Therefore, measures of health are needed that can capture the relevant aspects for all the different domains. However, the need for parsimonious models is even more pressing in these complex dynamic models that often have to rely on data calibration. Therefore, the approach of this thesis, to model different dimensions of health through a single latent variable, might actually be a good starting point.

How do dynamics in health relate to longevity and health care expenditures?

An important issue for research on the longitudinal relationship between health and health care expenditures is the identification of causal effects. It is likely that the relationship between health and health care use goes both ways: health affects the amount of care used, but the amount of care used also influences health, and survival. Therefore, the results in this thesis are based on associations between health and health care expenditures rather than strict causal effects of health on expenditures. This is also the case for most related studies, including the time to death literature (Zweifel et al., 1999) and health-based projection models (Goldman et al., 2005). In order to identify causal effects, researchers have to look for changes in health independent of health care use. In the context of labor market outcomes, Garcia-Gomez et al. (2013) look for instance at the effect of acute hospitalizations, that are most likely not caused by previous health care use. Although such analysis can be very effective in identifying effects of particular health shocks, a disadvantage is that they can seldom be extrapolated to effects of changes in more general measures of health such as used in this thesis. This makes using such estimates in projection models difficult. Also, for changes in the health of the older population, which often can be better described as a gradual process instead of a shock, it will be difficult to find useful instruments. A promising approach might be to use changes in the macro health care budget or financing system. Mackenbach et al. (2011) find strong indications that the relaxation of the Dutch health care budget in 2001, and a resulting increase of health care for the elderly, has led to an increase in life expectancy. Use of these kinds of natural experiments might aid in identifying causal effects of health care expenditures on health and vice versa.

Data and techniques

Although the availability of large, combined, microdatasets has considerably improved the possibilities for research in health and economics, more can be desired. Through the Social Statistics Database, Statistics Netherlands has been able to make a large collection of nationwide datasets, such as for hospital admissions (LMR) and long-term care use (CAK), accessible to researchers. However, other datasets have not been made available yet, or only for very specific purposes. For health care research, the national health care insurance files are the most important. Moreover, health research in the Netherlands could benefit from a large, longitudinal health survey. The currently available data consists of a large cross sectional survey by Statistics Netherlands, and several smaller, often irregular, longitudinal surveys for specific subpopulations. Analysis of time trends and dynamics in different health aspects could be considerably improved if repeated detailed health measurements for a sufficiently large and representative sample of the Dutch population would be available. The results of this thesis, and that of others, have shown that using and combining detailed health information is worthwhile for scientific as well as policy purposes.

In the meanwhile, optimal use has to be made of the data that is available. I have explored a number of techniques for this purpose, but many more can be thought of. I will give three examples. First, several techniques have been developed to enable the use of repeated cross section data as a quasi panel. e.g. (Van de Kassteele et al., 2012; Pelzer et al., 2002). These techniques rely on relatively strong assumptions that allow the combination of observations from sufficiently similar individuals. The combination of repeated cross sections with registry data could considerably improve these techniques. Second, time trends in health are often estimated based on cross sectional data. Given a lack of sufficiently large survey datasets, repeated cross section techniques and/or combining cross section data with longitudinal registry data could improve estimation of health trends. Third, the analysis in Chapter 6 is based on longitudinal survey data only. Since labor participation and health are simultaneously observed, and only at three year intervals, the identification of causal effects is difficult. The additional use of health care registry data, could enable the identification of health shocks, and thus shed more light on the direct causal relationship between health and labor participation.

7.4 Policy recommendations

Several policy recommendations can be given based on the research in this thesis. I focus on three themes. The first theme elaborates on the meaning of a broad view on health for health policy. I also discuss how the findings on the effect of health on health care expenditure influence the role of health interventions. The second theme focuses on changes to the health care system. Here, I link some of the subjects treated in this thesis, such as the relationship between health and other determinants of health care expenditures, and the longitudinal dynamics in health, to possible changes in the way health care is provided and financed. The third theme focuses on how policy can assist in utilizing the benefits of healthy aging.

Rethinking health and health policy

A broad perspective on health in policy is needed. Health is more than the mere absence of disease. Health consists of a large number of overlapping aspects, and as I have shown in this thesis, different combinations of these aspects are important for the use of cure, long term care, or participation. Health policy should be based on an integrated approach towards the different domains of health. Moreover, although a more strict focus on particular aspects of health can sometimes be necessary, in general health policy should be assessed on its effect on social well being. Given that a larger share of national income will be spent on health care in the future, we have to make sure that it is spent where effects on well being are largest. In some cases this could actually mean less treatment instead of more. Focus on domains of health related to (labor) participation of older individuals and self-reliance is necessary.

A broader view on the effects of health is also needed. It can be tempting to try to gain support for health improvement measures based on their potential for cost saving. However, as shown in earlier studies, smoking and obesity might actually lead to lower costs (Van Baal et al., 2008). I have found that the tradeoff between (lower) current expenditures and (higher) future expenditures due to longer life is also present for more general indicators of health. Despite the fact that some cost saving effects of better health scenarios are found in Chapter 5, health improvement is not the cure for health care expenditure growth that it is sometimes taken to be. Nevertheless, investing in prevention and health promotion is of importance. Again, health should be seen as a multidimensional concept, with different dimensions that are intertwined with different aspects of well-being, but also with different aspects of society. Although often difficult in practice, health policy should be concerned with the effects of such a broad concept of health beyond the health care sector, including well being, employment, and informal care provision. Such a perspective can point towards valuable interventions for society. A positive finding is that gains in life expectancy are generally not related to additional growth in health care costs. In some cases, interventions, aimed at improving quality of life without extending life, might actually have a cost containment effect. To be effective, policy makers should design these interventions to be close to what people themselves value as important, and to what they are able to incorporate in their daily life.

Rethinking the health care system

Even if we follow the reasoning of Hall and Jones (2007), and see rising health care expenditures merely as a result of an increasing societal willingness to pay for health, rising health care expenditures still pose a number of policy problems. These problems are not so much related to the level of health care expenditures, but to the distribution of contributions and benefits between (groups of) individuals. This subject touches on a number of issues, such as progressivity of collective finances as a whole, and the effect of income redistribution on economic growth, that are beyond the scope of this thesis. However, as concluded in Chapter 2, the distribution of collectively financed care between individuals depends to a large extent on health. I will therefore focus on the relevance of my findings on the longitudinal dynamics in health for the benefits of as well as contributions to the health care system.

The uneven distribution of health and disability between socioeconomic groups will put pressure on (intergenerational) solidarity. This will especially be the case when new medical technologies are mostly aimed at individuals in poor health, skewing the distribution of health care even further (Wong et al., 2012). However, the influence of health on life expectancy, and on expected costs at later ages, should also be taken into account when considering differences in health care use between socioeconomic groups. Given that better socioeconomic status is, cross sectionally, related to better health, it can be expected that higher socioeconomic groups use a large part of their life lifecycle health care consumption at older ages. Cross section estimates, based on the current age composition of the population, might therefore underestimate health care use of higher socioeconomic groups. Indeed, redistributions from high to low socioeconomic groups in the Dutch health care system are smaller when a lifecycle perspective is applied (Wouterse, 2008).

The more even distribution of health care expenditures over total lifetime also suggests policy options on the contribution side. When everyone is confronted with the same level of health care expenditures over his total life, it can make sense to replace the current collective pay-as-you-go system by a more individual health savings account system. Such a system enables people to save for health care expenditures in much the same way as they save for their pension. However, such accounts are associated with problems, such as the large unevenness in the distribution of lifecycle expenditures between individuals (Wong, 2012). As an alternative, cohort based financing of (additional) health care could be considered (Van Ewijk, 2012). Such a system would make the financing of health care less dependent on the current age profile of the population, while at the same time retaining the benefits of a collective insurance system.

The results of this thesis also point towards another aspect of health care. Due to the demographic and epidemiological trends analyzed in Chapter 5, the number of older people with one or more chronic diseases will increase substantially. The patterns of health over remaining lifetime in Chapter 4, show that most individuals are likely to be confronted with health impairments and disability at some point in their life. Combined with the increasing education level and income of the older population, these developments require the provision of health care that is in line with the needs and desires of individuals at different stages of their older life. Examples can be the development of assistive technology to enable older individuals to stay living at home, even with impairments.

Rethinking the link between health care and social security systems

A broader view on health and its effects also means that health is not only a concern of health policy, or the ministry of health, but is an integrated part of social policy. Cooperation and integration between different policy areas and ministries is needed. The findings in Chapter 6 provide an indication of the dual link between health and different forms of participation. The role of health in stimulating labor participation is thus a shared concern for social affairs as well as health policy. For instance, possible health benefits, or losses, from (social) policy measures deserve a larger role in societal cost benefits analyses than is now common practice. Labor policy should be focused towards capabilities and preferences of older individuals, and should include other forms of social participation besides work. Regarding the link between health and social affairs, the role of older individuals as informal care givers is especially important. An example of a concrete policy measure is providing a financial stimulus that allows individuals to work less in the last years of their career in return for informal care giving. Again, such policy could be integrated into a lifecycle approach towards health and work. Another example is the joint responsibility for creating a focus on interventions and technology that improve functioning at older ages. Such interventions can be beneficial not only in terms of health and health care costs, but also in stimulating social participation in the older population.

Summary

The aging of the population in most Western countries will put pressure on the financial sustainability of health care systems and other social arrangements. The growing relative number of older people will increase the demand for health care and will decrease the number of net contributors to social security systems. However, population aging, and especially increasing life expectancy, might also assist in solving some of these issues. When longer life implies a postponement, rather than an increase, in health care use, and older individuals can participate longer in society, the impact of population aging might be limited. In both of these cases, the relationship between longevity and health plays an important role. The underlying trends in health will determine how the age profile of health care use will change as life expectancy rises, and health of the older population will also influence their possibilities to participate in society. In this thesis, I focus on four issues regarding the economic consequences of healthy aging.

First, a broad measure of health is needed. Health is a multidimensional concept of which different elements might be relevant for different economic consequences. Moreover, the relationship between health and life expectancy tends to differ between different elements of health. Often the interest is on combination of different aspects of health, such as chronic diseases and their disabling effects, so that measures need to be developed that capture the most important dynamics. The second issue is the modeling of the relationship between different health dimensions and health care expenditures. The third issue is the longitudinal relationship between health and health care expenditures. Although on a cross section basis better health is associated with lower health care expenditures, the long-run relationship might be very different given the increased life expectancy, and possible postponement of health care costs, resulting from better health. Finally, this thesis is concerned with the dynamics between health, work, and other forms of social participation. Again, a broad definition of health is needed here, and longitudinal tradeoffs between health and different forms of participation have to be investigated. The aim of this thesis is to gain insight in the longitudinal relationship between longevity and health of the older population, and the consequences of this relationship for health care expenditures, labor participation,

and informal care provision. This general aim can be divided into the following four specific aims

1. To investigate the relationship between different dimensions of health of older individuals. And to combine relevant health variables in an indicator of health, with a meaningful interpretation, that can be applied for the analysis of dynamic interactions between health and other outcome variables, and that is usable to operationalize health scenarios.
2. To model and estimate the individual longitudinal relationship between health and health care expenditures for older people, in order to investigate dynamics in health, longer life, and health care expenditures.
3. To operationalize health scenarios, based on the existing hypotheses on longevity and health, and to use the models from 2 to gain insight into population effects of these health scenarios on health care expenditures.
4. To model and estimate the longitudinal relationship between health and forms of social participation, such as labor participation and informal care provision, in the older population.

Chapter 2 discusses the impact of population aging on health care expenditures. The contributions of the chapter are twofold. First, based on a conceptual model of health care expenditure, the relationship between aging, health and expenditures is discussed. Health care expenditure models solely based on age overestimate the effect of aging on health care expenditures. Models that include proximity to death as an explanatory factor show that longevity gains are paired with postponement of expenditure to later ages rather than increases in expenditures. However, proximity to death is only a proxy of underlying health. Studies that include more detailed information on health and disability are scarce but they show that the influence of age and mortality on health care expenditures is strongly diminished when health and disability are directly included. Second, aging and health are related to other determinants of expenditure growth, such as technological progress and collective income growth. The direct effect of population aging on health care expenditure growth is relevant, but modest: population aging explains 0.5-1.0 percent of the 4 percent real annual growth in health care expenditures. The strongest driver of health care expenditures seems to be technological innovation, facilitated by economic growth. Technological growth, however, interacts with age: aging reinforces the impact of technological change and vice versa. The direct influence of aging is strongest in long term care, where age is a significant determinant of expenditures, even when health and disability are included. The chapter concludes that models are needed that can capture dynamics in health and expenditures, and that although the direct effect of aging is modest, the strong interaction with other determinants means that the relationship between age and health care expenditure remains of importance.

Chapters 3 and 4 are both concerned with the estimation of the longitudinal relationship between health and health care expenditures. The first chapter considers the relationship between values of several health indicators at baseline with longitudinal costs of hospital use. The second chapter develops a latent Markov model to analyze the relationship between a joint measure of health with hospital and long term care expenditures over remaining lifetime. A central notion in both chapters is that initial gains in expenditures due to improvement in health might be offset by expenditures at later ages due to gains in life expectancy.

Chapter 3 investigates the relationship between baseline health and costs of hospital use over a period of eight years. Cross-sectional survey data is combined with information from the Dutch national hospital register. Four different indicators of health (self-perceived health, long-term impairments, ADL limitations and comorbidity) are considered. We find that for ages 50 to 70, differences in hospital costs between good health and poor health are substantial and persist during the whole time period. However, for higher ages expected hospital costs for individuals in poor health decline rapidly and become lower than those for people in good health after about six to seven years. The higher mortality rate among people in poor health is the primary cause here. Results are confirmed for all four health indicators.

Chapter 4 builds on the previous chapter and further investigates the dynamic relationship between several dimensions of health and health care expenditures for older individuals. Health data from the Longitudinal Aging Survey Amsterdam is combined with data on hospital and long term care use. A latent variable based jointly on observed health indicators and hospital expenditures is estimated. The health indicators cover physical as well as psychological health, disability, self perceived health, and objective measures. Annual transition probabilities between states of the latent variable are estimated using a Markov model. The resulting latent indicator has four states: good health, moderate health with high probability of chronic diseases but only moderate disability and low probability of cognitive impairment, poor health with high probability of disability and cognitive problem, and death. Initial differences in health and health care expenditures are associated with longer life spent in better health, but do not lead to large differences in expenditures over total remaining lifetime. Whereas hospital expenditures over remaining lifetime tend to be higher for individuals in initial poor health, long-term care expenditures are higher for individuals in initial good health. Both Chapter 3 and 4 show that initial differences in health are not associated with large differences in longitudinal health care expenditures. This result suggests that, although improvement of health is an important goal in itself, expectations of cost saving effects should be modest.

Chapter 5 uses the model from Chapter 4 to analyze the effects of several health scenarios on individual and aggregated health care expenditures over the next four decades. Using two values of future remaining life expectancy at 65, different health scenarios are analyzed. These scenarios are based on common hypotheses on the relationship between longevity and health: expansion of morbidity, compression of morbidity, and a dynamic equilibrium. The scenarios are used to predict health care expenditure growth in the Netherlands between 2010 and 2050. Hospital expenditures are predicted to decline after 2040, whereas home care and institutional long-term care will continue to rise up at least up to 2050. The chapter finds considerable differences in expenditure growth rates between scenarios with the same life expectancy in 2050 but different trends in health. Compression of morbidity generally leads to the lowest expenditure growth. The effect of additional life expectancy gains *within* the same health scenario is relatively small for hospital care, but considerable for long-term care. There seems to be room for health improvement policies to contain expenditure growth, although potential effects should not be exaggerated. When associated with improvement in underlying health, additional growth in life expectancy has only a limited effect on expenditure growth.

In **Chapter 6**, the use of a latent health variable, comprising many dimensions of health, is applied to another societal factor related to aging, namely societal participation of the older population. Participation can take the form of formal work, but also includes other societally relevant activities such as provision of informal care or doing volunteer work. Two dynamic models of the relationship between health and participation in the Dutch 55 to 65 year old population are estimated. The first model concerns the relationship between health and work, while in the second model broader indicator of participation, also based on caregiving and volunteer work, is used. The findings show that it is mostly the disabling effect, rather than the mere presence, of chronic diseases that influences work, as well as broader forms of participation in the older population. There are also some indications that participation has a positive effect on health, although part of this effect might be due to unobserved individual characteristics.

In **Chapter 7**, I reflect on the main findings in the thesis and provide suggestions for further research. I also reflect on ways to implement some of the findings, concerning the use of abroad definition of health as well as a lifecycle approach, into policy.

Samenvatting

De veroudering van de Westerse bevolking zet de financiële houdbaarheid van de zorg en andere sociale voorzieningen onder druk. De groei van het aantal ouderen ten opzichte van de rest van de bevolking zal de vraag naar zorg doen toenemen, terwijl tegelijkertijd het relatief aantal mensen dat netto bijdraagt aan sociale voorzieningen afneemt. Veroudering van de bevolking heeft echter ook positieve kanten die kunnen bijdragen aan het oplossen van de problemen. Zeker als veroudering van de bevolking het gevolg is van langer leven. Langer leven kan bijvoorbeeld betekenen dat zorgkosten worden uitgesteld, maar over het hele leven gelijk blijven. Ook zijn ouderen wellicht in staat om over een groter deel van hun langere leven maatschappelijk te participeren. Hierdoor kan een deel van de negatieve effecten van de vergrijzing worden beperkt. In beide gevallen speelt gezondheid een belangrijke rol. De onderliggende trends in gezondheid bepalen hoe het leeftijdsprofiel van zorggebruik verandert met de stijgende levensverwachting. Gezondheid bepaalt ook in grote mate of ouderen op hogere leeftijd kunnen blijven participeren. In dit proefschrift richt ik mij op vier onderwerpen die betrekking hebben op de economische gevolgen van gezonde veroudering.

Ten eerste vereist onderzoek naar gezond ouder worden een breed gezondheidsbegrip. Gezondheid is een multidimensionaal concept, waarvan verschillende dimensies van belang kunnen zijn voor verschillende economische onderwerpen. De relatie met levensverwachting is ook niet voor alle dimensies van gezondheid hetzelfde. Voor onderzoek naar economische onderwerpen is vaak niet een enkel aspect van gezondheid van belang, maar zijn we juist geïnteresseerd in combinaties van verschillende gezondheidsaspecten, zoals het effect van chronische zieketen op functionele beperkingen. Daarom moeten er nieuwe gezondheidsmaten worden ontwikkeld die de meest relevante interacties tussen diverse dimensies van gezondheid kunnen vangen. Het tweede onderwerp is het modelleren van de relatie tussen verschillende aspecten van gezondheid en zorguitgaven. Het derde onderwerp is de longitudinale relatie tussen gezondheid en zorguitgaven. Hoewel mensen in goede gezondheid op jaarbasis minder zorguitgaven hebben dan mensen in slechte gezondheid, wil dat niet zeggen dat het zelfde ook geldt over de rest van het hele resterende leven. Het kan immers ook zo zijn dat betere gezondheid nu alleen betekent dat zorgkosten worden doorgeschoven naar een later moment in het leven. Tot slot bekijk ik in dit proefschrift ook de dynamische relatie tussen gezondheid, werk en andere vormen van maatschappelijke participatie. Ook hier gaat de aandacht weer uit naar een brede definitie van gezondheid en langetermijn interacties. Het doel van dit proefschrift is om inzicht te krijgen in de longitudinale relatie tussen langer leven en gezondheid van ouderen, en de gevolgen van die relatie voor zorguitgaven en maatschappelijke participatie. Deze algemene doelstelling kan worden onderverdeeld in vier meer specifieke subdoelen

1. Het onderzoeken van de relatie tussen verschillende dimensies van gezondheid van ouderen en het combineren van relevante gezondheidsvariabelen in een gecombineerde indicator. Deze indicator moet een betekenisvolle interpretatie in termen van gezondheid hebben, en moet kunnen worden toegepast bij de analyse van dynamische interacties tussen gezondheid en economische uitkomsten. Ook moet de indicator kunnen worden gebruikt om gezondheidsscenario's te operationaliseren.

2. Het modelleren van de longitudinale relatie tussen gezondheid en zorguitgaven van ouderen op een individueel niveau, opdat de dynamiek in gezondheid, langer leven en zorguitgaven kan worden onderzocht.

3. Het operationaliseren van gezondheidsscenario's die gebaseerd zijn op bestaande hypothesen over de relatie tussen langer leven en gezondheid. En het gebruiken van de modellen uit doelstelling 2 om inzicht te krijgen in de effecten van deze gezondheidsscenario's op zorguitgaven op populatieniveau.

4. Het modelleren en schatten van de longitudinale relatie tussen gezondheid en verschillende vormen van maatschappelijke participatie, zoals arbeidsparticipatie en het verlenen van informele zorg.

Hoofdstuk 2 brengt de gevolgen van de veroudering van de bevolking voor de zorguitgaven in kaart. Het hoofdstuk richt zich op twee aspecten. Ten eerste worden aan de hand van een conceptueel model van de determinanten van zorguitgaven de bevindingen uit de literatuur over de relatie tussen veroudering, gezondheid en zorguitgaven besproken. Modellen die alleen gebaseerd zijn op leeftijd overschatten het effect van vergrijzing op zorguitgaven. Modellen die ook tijd tot overlijden meenemen laten namelijk zien dat levenswinst gepaard gaat met een uitstel van kosten in plaats van een toename. Tijd tot overlijden is zelf echter ook een beperkte indicator van onderliggende gezondheid. Studies die meer gedetailleerde gezondheidsmaten hanteren vinden namelijk dat de invloed van zowel leeftijd als tijd tot overlijden sterk afneemt wanneer wordt gecontroleerd voor gezondheid en beperkingen. Ten tweede is de vergrijzing slechts een van oorzaken van de stijgende zorguitgaven, maar hangt deze wel sterk samen met de andere determinanten van uitgavengroei. Het directe effect van vergrijzing is relevant maar beperkt: vergrijzing verklaart tussen de 0,5 en 1 procentpunt van de totale 4 procent jaarlijkse rëeele groei in zorguitgaven. De sterkste factor achter de stijgende zorguitgaven lijkt medische technologie te zijn, gefaciliteerd door economische groei. Vergrijzing versterkt echter de budgettaire impact van nieuwe medische technologieën, en nieuwe medische technologie kan ook weer leiden tot verdere levensverlenging. Het directe effect van vergrijzing is het sterkst in de langdurige zorg. De conclusie van het hoofdstuk is dat modellen voor zorguitgaven de dynamische relatie met gezondheid moeten meenemen. Het directe effect van vergrijzing is beperkt, maar de interactie met andere determinanten betekent dat vergrijzing een belangrijke rol zal blijven spelen.

Hoofdstukken 3 en 4 hebben beide betrekking op het schatten van de longitudinale relatie tussen gezondheid en zorguitgaven. Hoofdstuk 3 gaat over de relatie tussen op verschillende manieren gemeten initiële gezondheid en langdurige kosten van ziekenhuiszorg. In hoofdstuk 4 wordt een latent Markov model ontwikkeld om de relatie tussen een gecombineerde gezondheidsmaat met ziekenhuis en langdurige zorguitgaven over het resterende leven te analyseren. Een belangrijk aspect in beide hoofdstukken is de vraag of initiële winst in zorguitgaven door een betere gezondheid teniet worden gedaan door latere uitgaven als gevolg van langer leven.

Hoofdstuk 3 behandelt de relatie tussen gezondheid in het basisjaar en kosten van ziekenhuiszorg over de volgende acht jaar. Crosssectionele enquête data wordt gecombineerd met data van het Landelijk Medisch Register (LMR). De analyse wordt uitgevoerd voor vier verschillende maten van gezondheid: zelf ervaren gezondheid, langdurige beperkingen, beperkingen in dagelijkse bezigheden en comorbiditeit. De resultaten laten zien dat voor leeftijden tussen de 50 en 70 verschillen in zorgkosten tussen gezonde en ongezonde mensen aanzienlijk zijn en over de hele periode aanhouden. Voor hogere leeftijden nemen de verwachte kosten voor mensen in initiële slechte gezondheid echter sterk af over de tijd, en zijn na zes tot zeven jaar zelfs lager dan die van initieel gezonde mensen. De belangrijkste oorzaak van dit patroon is de hogere sterftekans van mensen in slechte gezondheid.

Hoofdstuk 4 bouwt voort op het vorige hoofdstuk en gaat dieper in op de dynamische relatie tussen verschillende dimensies van gezondheid en zorguitgaven van ouderen. Gezondheidsdata van de Longitudinal Aging Study Amsterdam (LASA) wordt gecombineerd met administratieve data over ziekenhuis en langdurige zorggebruik. Op basis van verschillende gezondheidsindicatoren en ziekenhuisgebruik wordt een latente variabele geschat. De gezondheidsindicatoren bestrijken fysieke en lichamelijke aspecten van gezondheid, beperkingen, zelf gerapporteerde en objectief gemeten gezondheid. Met behulp van een Markov model worden jaarlijkse transitiekansen tussen de verschillende staten van de latente variabele geschat. De resulterende maat heeft vier staten: goede gezondheid, matige gezondheid met een hoge kans op chronische ziekte maar niet op ernstige beperkingen, slechte gezondheid met een hoge mate van beperkingen en cognitieve problemen, en dood. Initiële verschillen in gezondheid zijn van invloed op zowel het totaal aantal resterende levensjaren als het aantal jaren in goede gezondheid, maar slechts in beperkte mate op totale zorgkosten. Kosten van ziekenhuiszorg zijn over het algemeen hoger voor mensen met een initieel slechte gezondheid, en kosten van langdurige zorg voor mensen in initieel goede gezondheid. Zowel hoofdstuk 3 als 4 laten zien dat goede gezondheid niet per se leidt tot lagere zorgkosten over het resterende leven. Dit resultaat suggereert dat, hoewel het verbeteren van gezondheid een belangrijk doel op zich is, de verwachtingen voor kostenbesparingen beperkt moeten zijn.

In **hoofdstuk 5** wordt het model uit het vorige hoofdstuk gebruikt om het effect van verschillende gezondheidsscenario's op individuele en collectieve zorguitgaven te analyseren. De scenario's zijn gebaseerd op bekende hypothesen over de relatie tussen langer leven en gezondheid: expansie van morbiditeit, compressie van morbiditeit, en dynamisch evenwicht. De scenario's worden gebruikt om de groei van de zorguitgaven in Nederland tussen 2010 en 2050 te voorspellen. Ziekenhuisuitgaven zullen stijgen tot 2040 en daarna afnemen. Langdurige zorguitgaven, daarentegen, zullen tot aan 2005 blijven stijgen. Groeipercentages verschillen aanzienlijk tussen scenario's met een zelfde ontwikkeling in levensverwachting maar andere trends in gezondheid. Compressie van morbiditeit leidt in het algemeen tot de laagste groei. Het effect van additionele levensverwachtingswinst binnen hetzelfde gezondheidsscenario is beperkt voor ziekenhuisuitgaven, maar sterker voor langdurige zorg. Er lijkt ruimte te zijn voor gezondheidsbeleid om zorguitgaven te beperken, hoewel het effect niet moet worden overschat. Wanneer levensverwachtingswinst gepaard gaat met verbetering van gezondheid is het effect op uitgavengroei beperkt.

In **hoofdstuk 6** wordt het gebruik van een latente gezondheidsvariabele gebaseerd op verschillende dimensies van gezondheid toegepast op een ander economisch relevant vraagstuk, namelijk maatschappelijke participatie van ouderen. Bij participatie kan gedacht worden aan formeel werk, maar ook aan het geven van informele zorg of het doen van vrijwilligerswerk. Er worden twee modellen geschat voor de relatie tussen gezondheid en participatie voor Nederlandse ouderen tussen 55 en 65. Het eerste model gaat alleen over de relatie tussen gezondheid en werk, terwijl in het tweede model een breder begrip van participatie, inclusief informele zorg en vrijwilligerswerk wordt gebruikt. De bevindingen laten zien dat vooral beperkingen als gevolg van chronische ziekten, en niet het hebben van een chronische ziekte op zich, van invloed is op werk en participatie. Er zijn ook aanwijzingen dat participatie een positieve invloed heeft op gezondheid, hoewel dit effect ook veroorzaakt kan worden door ongeobserveerde individuele eigenschappen.

In **hoofdstuk 7** reflecteer ik op de belangrijkste resultaten van het proefschrift en doe ik suggesties voor vervolgonderzoek. Ook ga ik in op de vraag hoe de bevindingen aangaande het gebruik van een breed gezondheidsbegrip en een levensloopperspectief kunnen worden geïmplementeerd in beleid.

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Curriculum Vitae

Bram Wouterse was born in 1985 in Heerlen. He studied econometrics & management science at the Erasmus University Rotterdam from 2003 to 2008. He obtained his bachelor degree in 2007 and his master degree in 2008. His master thesis was on the subject of solidarity in the Dutch health care system. From 2008 to 2013 he was employed at Tranzo, Tilburg University and at the National Institute for Public Health and the Environment. There, he performed his PhD research on the economic consequences of healthy aging, and he was involved in the Dutch Public Health Forecast 2014. Currently, he works as a researcher at the CPB Netherlands Bureau for Economic Policy Analysis.

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