POPULATION AGEING IN SCOTLAND - IMPLICATIONS FOR HEALTHCARE EXPENDITURE

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[1] Victor Hawthorne carried out the original Midspan studies. Pauline MacKinnon is the Midspan administrator.

[2] The LSCS is supported by the ESRC/JISC, the Scottish Funding Council, the Chief Scientist's Office and the Scottish Executive. The authors alone are responsible for the interpretation of the data. Census output is Crown copyright and is reproduced with the permission of the Controller of HMSO and the Queen's Printer for Scotland.

Publications, Working Papers and Presentations

The following publications, working papers and presentations are a result of the research conducted for this PhD.

Published

Geue C, Lewsey J, Lorgelly P, Govan L, Hart C, Briggs A. (2011). Spoilt for choice: Implications of using alternative methods of costing hospital episode statistics. Health Econ. DOI: 10.1002/hec.1785 (Chapter 4)

Working papers

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Geue C, Lewsey J, Lorgelly P, Govan L, Hart C, Briggs A. Costing hospitalisations: Issues with Scottish Hospital Episode Statistics. Health Economists' Study Group, Cork, June 2010.

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Conference presentations

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Abstract

Population ageing is a major concern for developed countries in terms of public expenditure required to pay for health care (HC). The broad aim of this thesis is to contribute to and expand the debate on the independent effects that population ageing and the time immediately before death (TTD) have on HC expenditure in Scotland. This study analyses, for the first time in Scotland, how HC expenditure projections are influenced through the application of two approaches; the first only accounting for an increasing proportion of the elderly population, and the second also implementing a TTD component.

Several issues that are under-researched or have not been addressed in TTD studies previously, are explored and alternative approaches are presented. Utilising two large linked datasets this thesis addresses important methodological issues. Alternative methods to cost inpatient hospital stays are examined as this has pivotal implications for any analysis undertaken to estimate the independent effect of TTD and age on HC expenditure. Explanatory variables that have previously not been considered, such as health risk and health status measures at baseline, are included in these analyses. The issue of sample selection, arising through the inclusion/exclusion of survivors in a TTD study is investigated and the impact of individuals' socio-economic status on costs is examined.

The analysis of alternative costing methods clearly showed that any inference that can be made from econometric modelling of costs, where the marginal effect of explanatory variables is assessed, is substantially influenced by the chosen costing method. The application of a Healthcare Resource Group (HRG) costing method was recommended. This study found that TTD, age and the interactions between these two factors were significant predictors for HC expenditure. The analysis further identified some of the health status and health risk measures to be important predictors of future HC

expenditure. An examination of how sample selection impacts on estimated costs at the end of life showed that if survivors were excluded from the analysis, costs might be overestimated.

Drawing on a representative sample of the Scottish population, the investigation of the association that the socio-economic status had with HC costs suggested that less is spent on individuals from more deprived areas. This might partly be explained through the decreased probability of accessing hospital services for individuals from more deprived areas. Furthermore, results showed that projected HC expenditure for acute inpatient care for the year 2028 was overestimated by ~7% when an approach that only accounts for the higher proportion of elderly people in a population in the future is being used as compared to an approach that also accounts for the effect that remaining TTD has on costs.

Table of Contents

List of Tables

List of Figures

Abbreviations

BMI: Body Mass Index

CIS: Continuous Inpatient Stay

DRG: Diagnosis Related Group

DWP: Department for Work and Pensions

FCE: Finished Consultant Episode

FEV: Forced Expiratory Volume

GDP: Gross Domestic Product

GEE: Generalised Equation Estimation

GLM: Generalised Linear Model

GP: General Practitioner

GROS: General Register Office for Scotland

HC: Health Care

HCE: Health Care Expenditure

HRG: Healthcare Resource Group

ICD-9; ICD-10: International Classification of Diseases

ISD: Information Services Division

LOS: Length of Stay

LTC: Long-term Care

MCBS: Medicare Current Beneficiary Survey

MLC: Morbidity and Life Circumstances

NHS: National Health Service

NHSCR: National Health Service Central Register

NRAC: National Resource Allocation Committee

NRS: National Records of Scotland

OLS: Ordinary Least Squares

OPCS4: Office of Population, Censuses and Surveys Classification of Surgical Operations and Procedures (4th revision)

ORLS: Oxford Record Linkage Study

PAC: Privacy Advisory Committee

SBP: Systolic Blood Pressure

SIMD: Scottish Index of Multiple Deprivation

SLS: Scottish Longitudinal Study

SMR01: Scottish Morbidity Records (specifically acute inpatient and day cases)

SNT: Scottish National Tariff

SUR: Seemingly Unrelated Regression

TTD: Time to Death

Author’s Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Signature:

Printed name: Claudia Geue

1 INTRODUCTION

1.1 Introduction

Population ageing is a major concern for developed countries in terms of public expenditure that will be required in the next decades to pay for pensions, health care (HC) and other social services or benefits. With a very large population cohort, i.e. the 'baby boomers', approaching the age of 65 the issue of population ageing and its possible impacts on public expenditure requirements is a very immediate and topical one. In recent years there has been an increasing interest from policy makers and academics in analysing the main driving forces of demand for HC services and associated expenditure, in addition to changes in the demographic pattern.

There is an ever growing literature on the various factors to explain, estimate and project HC spending. In one of the first contributions, Fuchs found that cross-sectional differences in HC expenditures by age overestimated the changes that would result from an ageing population (Fuchs, 1984). After Fuchs's initial research that showed how determinants other than population ageing might influence HC expenditure, many studies followed. There is now a large body of evidence that the time immediately before death (time to death, TTD) seems to be a period that is characterised by a very high demand for HC and subsequently high costs, in addition to age. However, there does not seem to be a consensus on the degree of the relative importance of TTD in explaining increasing HC costs as individuals get older. Some research has found that patient age becomes an insignificant predictor for HC expenditure once TTD is included (Zweifel et al., 1999). Less strong findings merely support the argument that age alone is not solely responsible for increased HC spending and that TTD is also an important predictor (Seshamani and Gray 2004b).

A multitude of methods, sample populations and HC settings have been used to explain the relationship between ageing, TTD and HC expenditure, making it difficult to draw consistent conclusions. Analyses have been undertaken in many countries, all showing very different characteristics of how HC is being funded, delivered and the precision with which HC utilisation is being measured. So far, however, there has been no comprehensive and robust analysis of the impact of population ageing and TTD on HC expenditure in Scotland.

This thesis is the first empirical study to estimate the relationship between TTD, age and HC expenditure in Scotland utilising two large linked datasets of acute inpatient care records and survey data. This is guided by an extensive review of existing methods in the research area on an international level. Outlining gaps in existing studies and introducing approaches to improve current methods, this thesis seeks to contribute to the discussion around the role that TTD has to play in determining future HC expenditure in Scotland.

1.2 Objectives of this thesis

The overall aim of this thesis is to contribute to the debate on the independent effects that population ageing and the time immediately before death have on HC expenditure in Scotland, thereby investigating issues that remain under-researched or have not been adequately addressed. As life expectancy in the Scottish population increases, it is important to understand whether additional years of life gained would be spent in ill health, thereby placing financial pressure on HC service provision, or whether these additional years are healthy, meaning less pressure on existing HC budgets. It is also vital to ascertain whether the demand for HC is concentrated in specific population groups, categorised for instance by their socio-economic status.

Scotland has the advantage of having good quality and extensive, longitudinal data on HC resource use which can be linked to survey data. These data will be exploited in this thesis to answer the following research questions:

1. What is the independent effect of TTD and age on expenditure for acute inpatient care in Scotland?

2. How are HC expenditure projections influenced when using a model accounting for TTD versus a model that only accounts for the increasing proportion of elderly individuals?

3. How do previously unconsidered explanatory variables, such as health risks and health status measures impact on HC expenditure as the population ages and approaches death?

4. How does sample selection, in particular the inclusion/exclusion of surviving sample members due to right censoring, impact estimated costs?

5. What is the association between socio-economic status and HC expenditure at the end of life?

6. How do different methods to cost inpatient hospital stays affect cost estimates and what marginal effect do various explanatory variables have?

1.2.1 Objective 1: Effect of TTD and age on HC expenditure in Scotland

This thesis estimates the independent effects that TTD and age have on HC expenditure in an acute inpatient care setting in Scotland.

1.2.2 Objective 2: HC expenditure projections

This analysis addresses the issue of a possible overestimation of future HC costs if remaining TTD is not accounted for. Results are to inform policy makers when faced with HC budgeting decisions. The importance of drawing on a representative sample of the Scottish population is discussed, as reliability of results needs to be ensured.

1.2.3 Objective 3: Impact of health measures on HC expenditure

A longitudinal dataset (Renfrew/Paisley study) covering a period of 35 years is utilised, including baseline survey data linked to subsequent hospital admissions and death records. The breadth of the Scottish data mean that explanatory variables that have previously not been considered can be included, such as health risk and health status measures at baseline, thus allowing an examination of the importance of these factors and their impact on future HC expenditure.

1.2.4 Objective 4: Right censoring of survivors

This objective seeks to address the relationship between TTD, age and HC expenditure in Scotland over the last three years of life; in doing so an approach is introduced to include surviving sample members with an unknown TTD at censoring. Differences in estimated costs are compared under different sampling scenarios, highlighting the importance of the choice that is made in terms of the sample.

1.2.5 Objective 5: Effect of socio-economic status on HC expenditure

This part of the thesis uses the Scottish Longitudinal Study (SLS), linked to hospital admissions. The SLS is an anonymised 5.3% representative sample of the Scottish population (~270,000), drawn from the Scottish Census and started in 1991. It is important to ascertain whether the patterns of ageing and TTD in terms of HC costs are the same for different socio-economic groups. This is especially relevant in Scotland, which is characterised by a high proportion of people living in deprived areas, which is usually argued to translate into health inequalities.

1.2.6 Objective 6: Alternative methods to cost acute inpatient stays

This thesis will review health economic costing methodologies in order to distinguish between costs per event (episode), per diem or per Continuous Inpatient Stay (CIS) and any additional costs that are incurred through “expensive” interventions. This will take account of the fact that patients with the same diagnosis may receive different treatments and therefore incur different costs. In the absence of a ‘gold standard’ to estimate the economic burden of disease, a decision about the most appropriate costing method is required. Researchers have employed various methods to cost hospital stays, including per diem or Diagnosis Related Group (DRG) based costs. Alternative methods differ in data collection and costing methodology. Using data from Scotland as an illustrative example, costing methods are compared, highlighting the wider implications for other countries with a publicly financed health care system.

In order to address the main objectives 1 and 2 in this thesis, the methodological issues that have been presented as objectives 3 to 6 need to be addressed. Three empirical chapters (4, 5 and 6) are presented and the overall structure of this thesis that is to support investigation of the research questions is presented below.

1.3 Structure of the thesis

Chapter 2 outlines how population ageing is expected to affect demographics in Scotland. An overview of HC costs and resource allocation in Scotland is given, emphasizing the role that population characteristics play when assessing need.

In Chapter 3 a review and critical assessment of all relevant literature that analysed HC expenditure in relation to population ageing is presented, concentrating on the area of the literature that examined remaining TTD in addition to age and its association with HC costs. Important methodological issues and gaps are highlighted informing and motivating the empirical analyses in subsequent chapters.

Chapter 4 examines alternative costing methods for acute inpatient care episodes, addressing research objective 6. Results from this analysis are fundamental as they provide guidance for the costing undertaken in the subsequent empirical chapters of this thesis (Chapters 5 and 6).

Chapter 5 uses an empirical example (Renfrew/Paisley study) to estimate the effect that previously unconsidered covariates have on HC expenditure towards the end of life. These are health status and health risk measures at baseline and their impact and importance to predict future hospital costs is assessed. In addition, the implications that the inclusion/exclusion of surviving sample members in a TTD study has on estimated costs are analysed. Chapter 5 focuses on employing a method to correct for limitations arising in other studies that have faced the challenge of how to include surviving sample members with an unknown TTD. In order to provide results regarding the magnitude of the over- or under-estimation of costs at the end of life, costs will be estimated for different sample scenarios. This chapter addresses research objectives 1, 3 and 4.

Investigating objectives 1, 2 and 5, Chapter 6 utilises a representative sample of the Scottish population, the SLS. It builds on the analyses and conclusions derived from the two subsequent empirical chapters and utilises an appropriate costing method as well as a method to account for right censoring of survivors in the sample. In addition the analysis tests the impact that the socio-economic status has on HC expenditure for acute inpatient care, an issue that is of special interest and importance in Scotland. Exploiting the fact that the SLS is representative of the Scottish population, this chapter finally presents the methods and results for projecting future HC expenditure as outlined in objective 2. This is carried out by comparing two methods, thereby assessing the importance of including TTD in any such predictions.

Chapter 7 summarises and discusses the main findings of the analyses in the empirical chapters and highlights the wider implications these results may have. It also presents the conclusions derived from this work. Limitations of the thesis are discussed and the scope for future research is presented.

2 POPULATION AGEING AND HC EXPENDITURE IN SCOTLAND

2.1 Introduction

This chapter describes and defines in detail, how the two main factors that are analysed in this thesis, population ageing and HC expenditure, are measured in Scotland. It provides the foundations for the subsequent analyses and discussion in this thesis.

First, a summary is provided of the main assumptions when talking about population ageing in Section 2.2. An assessment of how population numbers, and particularly the elderly proportion of the population, are expected to change in Scotland over the next decades is provided in Section 2.3. Section 2.4 outlines the main components of HC expenditure in Scotland and introduces the allocation formula for HC resources within the hospital sector. This section also introduces the current thinking on TTD in resource allocation. In Section 2.5 a short overview of the organisation and cost for LTC is presented. A description of how HC resource utilisation can be measured in Scotland is provided in Section 2.6.

2.2 Population ageing

Population ageing will occur in virtually every country over the next decades although with a varying pace and at different levels. It is the process through which the proportion of older people in a population becomes larger. Population ageing is usually described as an increase in the proportion of people over the age of 65 in a population (Payne et al., 2007). It can also be expressed as an increase in median age. Population projections suggest that the median age of the world population will increase from 27

years (in year 2000) to 36 years by 2050. This would mean that half of the world's population will be older than 36 years (UN, 2002).

In general, population ageing is caused by a decline in the number of births, decreasing mortality, and to a lesser degree by migration. Declining births rates have been identified as one important reason for population ageing, with fertility being well below the replacement level in nearly all industrialised nations (UN, 2002), i.e. the birth rates are smaller than the death rates.

The main cause for population ageing alongside decreasing births rates is decreasing mortality rates, leading to longer life expectancy on average (at any age) (Howse and Harper, 2008). On a global level, life expectancy at birth has increased by about 20 years over the last five decades (UN, 2002). This increasing life expectancy can be observed to a greater extent in developed countries, whereas in less developed countries a huge variation in life expectancy exists (UN, 2002). As mortality is being shifted towards older ages, the survival curve follows a more and more rectangular shape. This rectangularisation of the survival curve is mainly due to an increased life expectancy through disease control and the elimination of premature death.

The curve becomes almost square with a probability of survival close to 1 which then suddenly drops to 0 (Manton, 1982). One example, of the rectangularisation of the survival curve, using data from Sweden is presented below in Figure 2.1 (Yashin et al., 2002).

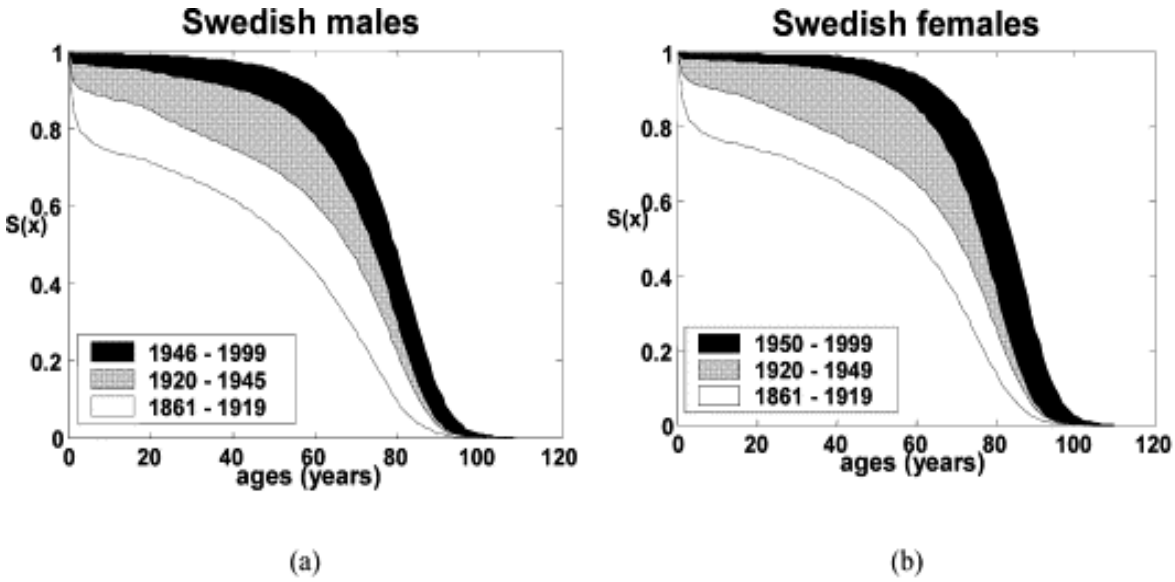

Figure 2-1 Example of rectangularisation of the survival curve. Reprinted from (Yashin et al, 2002) with permission

Population ageing will have effects in many areas of public life. For instance, it will impact on labour market participation and the share of the population in receipt of transfer payments, i.e. pensions. This could potentially cause an accelerated financing problem: a higher share of older individuals, whose demand for transfer payments increases, especially for HC (as has been argued in the literature), and a decreasing share of the population funding these payments through taxes or compulsory insurance contributions. Another layer that population ageing may add to this overall workforce problem is a possible decline in the NHS workforce, i.e. the staff that delivers HC (Wiener and Tilly, 2002, Segal and Bolton, 2009). Two scenarios could unfold alongside each other: a) a decrease in services provided and/or b) an increased financial incentive to either retain existing staff or to attract new staff into the HC sector.

The main challenge for policy makers in the future will therefore be to allocate available scarce resources so that the populations' demand is met. The challenge policy makers are faced with is to accurately quantify this future demand. An increasing demand for HC services has been identified as the main contributor for increasing costs. This assumption is based on the general perception that health deteriorates with increasing age and therefore more older people will mean more use of HC services, and an increasing proportion of older people will necessarily lead to a higher demand for HC and consequently higher HC expenditure (Payne et al., 2007).

2.3 Population ageing in Scotland

2.3.1 Population numbers

As outlined earlier, several factors contribute to an ageing population, including the number of births and the number of deaths. Figure 2.2 shows the actual and predicted number of births and deaths in Scotland between 1951 and 2033. Since the 1960s there has been first a sharp decline in the total number of births (1965 until 1978) followed by a less severe decline from 1979 onwards. The total number of deaths in Scotland has fluctuated around 60,000 per year with a slight decline from the year 2000 onwards. Deaths are expected to reach 60,000 again by 2033.

Until about 2026 the number of births is projected to exceed the number of deaths. After 2026 however the number of deaths is expected to outweigh the number of births, which will lead to fertility falling below the replacement level.

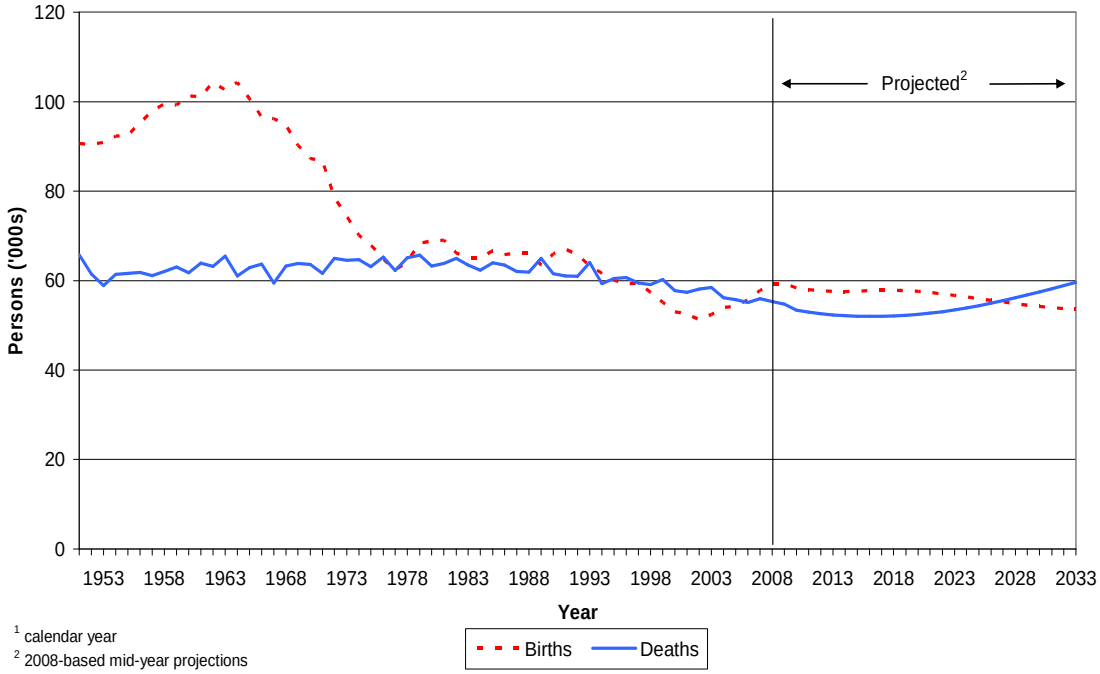

Figure 2-2 Births and deaths, actual and projected, Scotland, 1951-2033 (GROS, 2010)

Population numbers are also, to a lesser degree, influenced by migration. Net migration is calculated by subtracting the number of people leaving a country (emigrants) from the number of people entering a country (immigrants). Figure 2.3 shows the net migration for Scotland, which was negative until the 1990s but with an increasing trend until 2008, after which time net migration is projected to decrease slightly to remain at a constant positive level from about 2013 onwards, with about 12,000 more people coming into Scotland annually than leaving the country.

Together, the natural change (births minus deaths) and migration act to increase population numbers until 2026. Beyond 2026, the number of deaths is projected to exceed the number of births with a constant positive net migration rate (GROS, 2009).

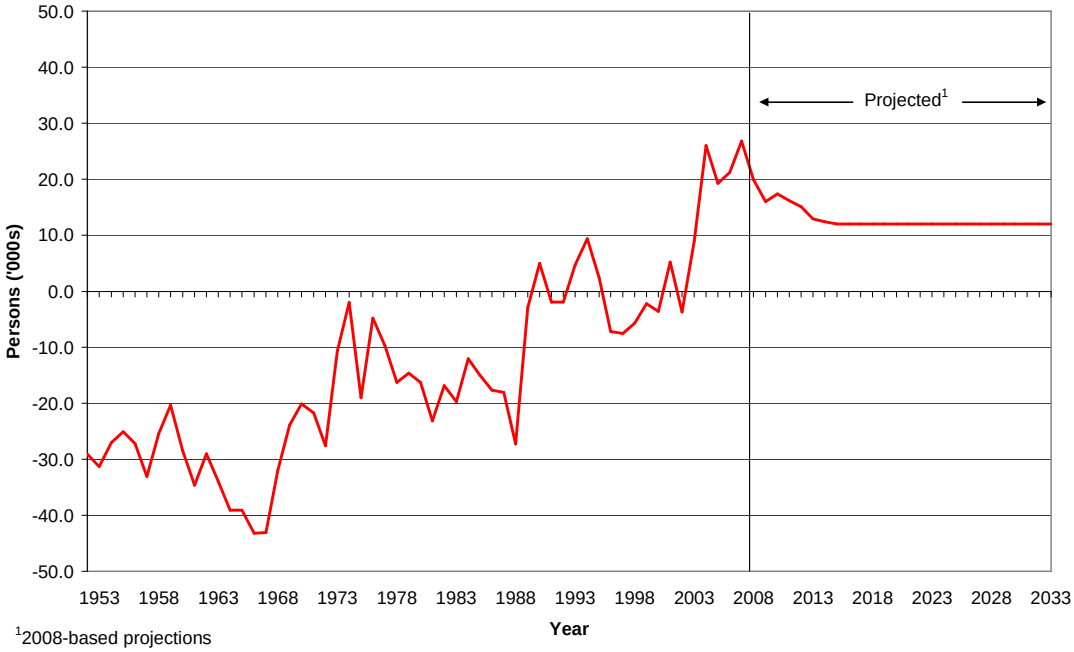

Figure 2-3 Estimated and projected net migration, Scotland, 1951-2033 (GROS, 2010)

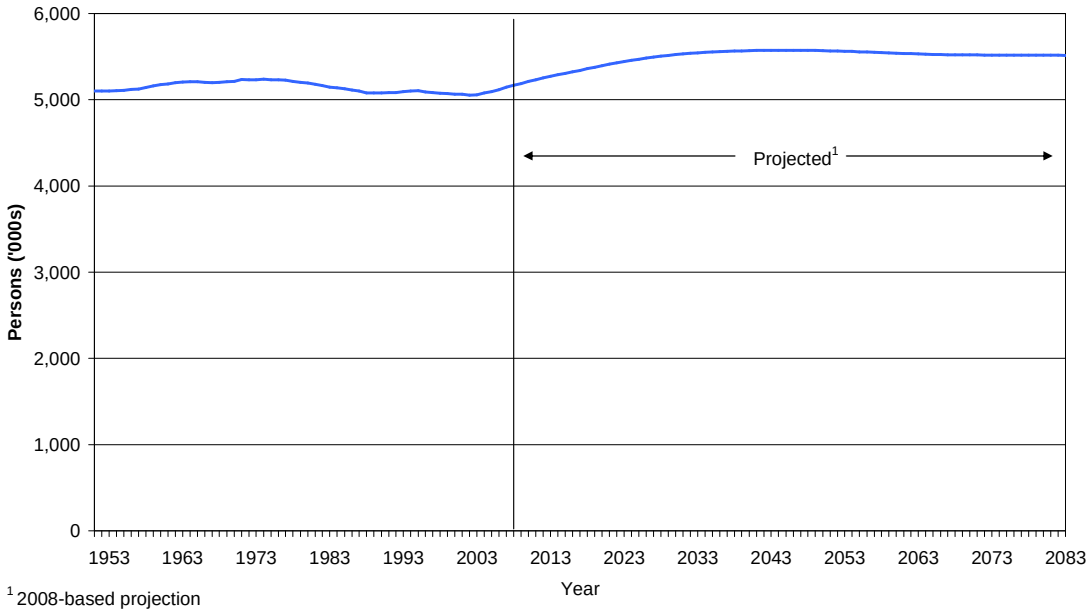

Figure 2-4 Estimated population of Scotland, actual and projected, 1953-2083 (GROS, 2010)

Compared to the rest of the UK, population ageing in Scotland will be even more pronounced due to differences in the demographic pattern. The first element to take into consideration when analysing the age structure, is the total size of the population. The following projections from the then General Register Office for Scotland (GROS)[3] are based on 2008 population estimates. According to these, the Scottish population is expected to rise from 5.17 million in 2008 to 5.36 million in 2018 and after that to 5.54 million in 2033 (GROS, 2009). After 2033 though, Scotland's population numbers are expected to decline slowly, but to remain above current figures (Figure 2.4).

2.3.2 Age composition

More important than total population numbers when analysing aspects and implications of population ageing is the age composition of the population.

The population pyramids in Figures 2.5 and 2.6 below show the changing age structure of Scotland's population and compare the most recent structure with the projected structure in 2031. Historically, a pyramid shaped diagram showed a very high number of young people at the bottom of the scale and a decreasing number of people as age increased. Figure 2.5 shows the population structure for 2011, where a pyramid shape is no longer present, indicating an increasing number of people at the top end of the scale (older people) and a decreasing number of people at the bottom end (younger people). These differences are even more pronounced for the projected composition of Scotland's population in 2031 (Figure 2.6).

3 From the 1st April 2011 the General Register Office for Scotland has merged with the National Archives of Scotland to become the National Records of Scotland (NRS).

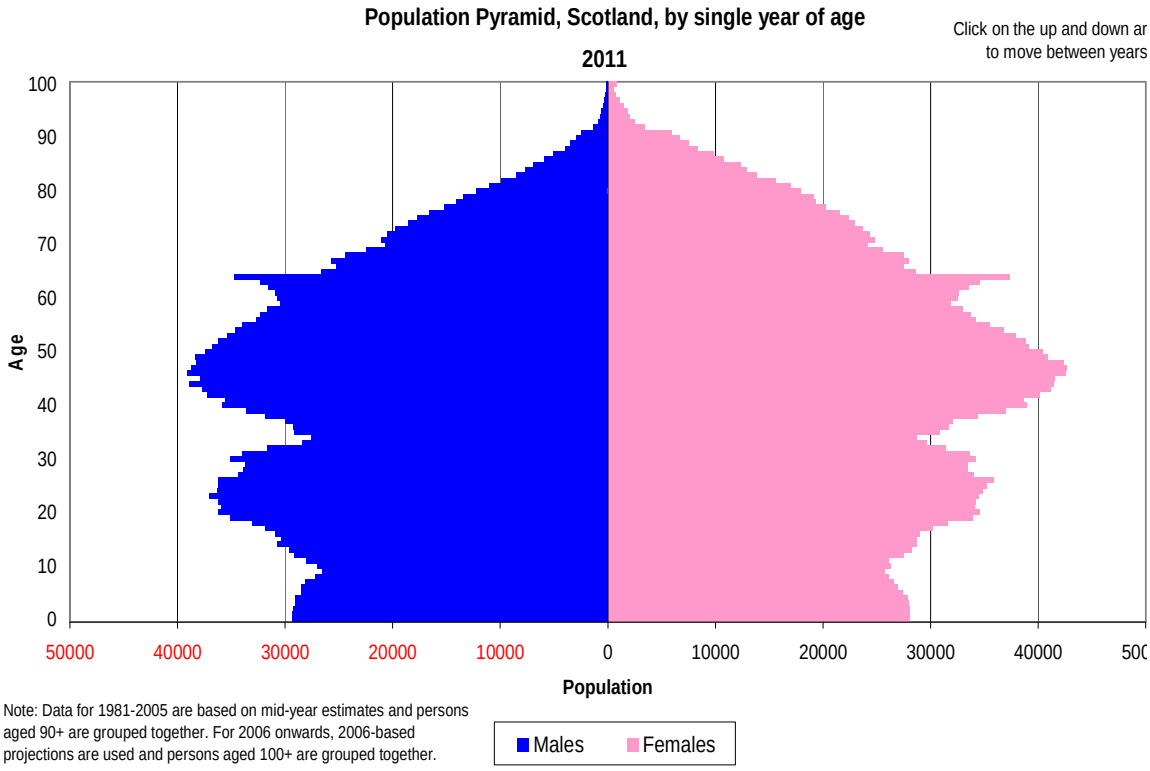

Figure 2-5 Population pyramid 2011, (GROS, 2011)

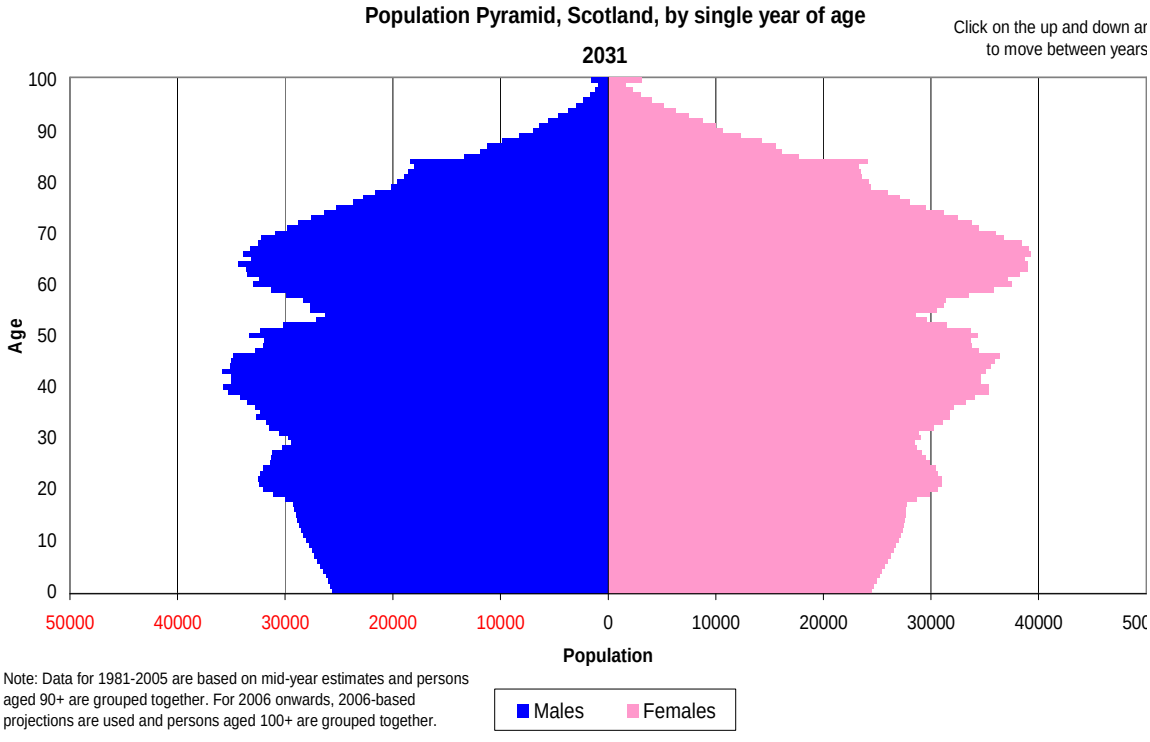

Figure 2-6 Population pyramid 2031, (GROS 2011)

Between 2008 and 2018, the number of children under the age of 16 is expected to increase from 0.91 million to 0.92 million (1% increase). This is followed by a decrease and expected to reach 0.90 million by 2033 (1.5% decline compared to 2008 figures) (GROS, 2009). Over the same period the number of people aged 75 and older is projected to increase from 0.39 million to 0.48 million, an increase of 23% (2008-2018). Thereafter, this number is projected to continue increasing until it has reached 0.72 million, in 2033. This translates into an increase of 84% from 2008 figures (Figure 2.7) (GROS, 2009).

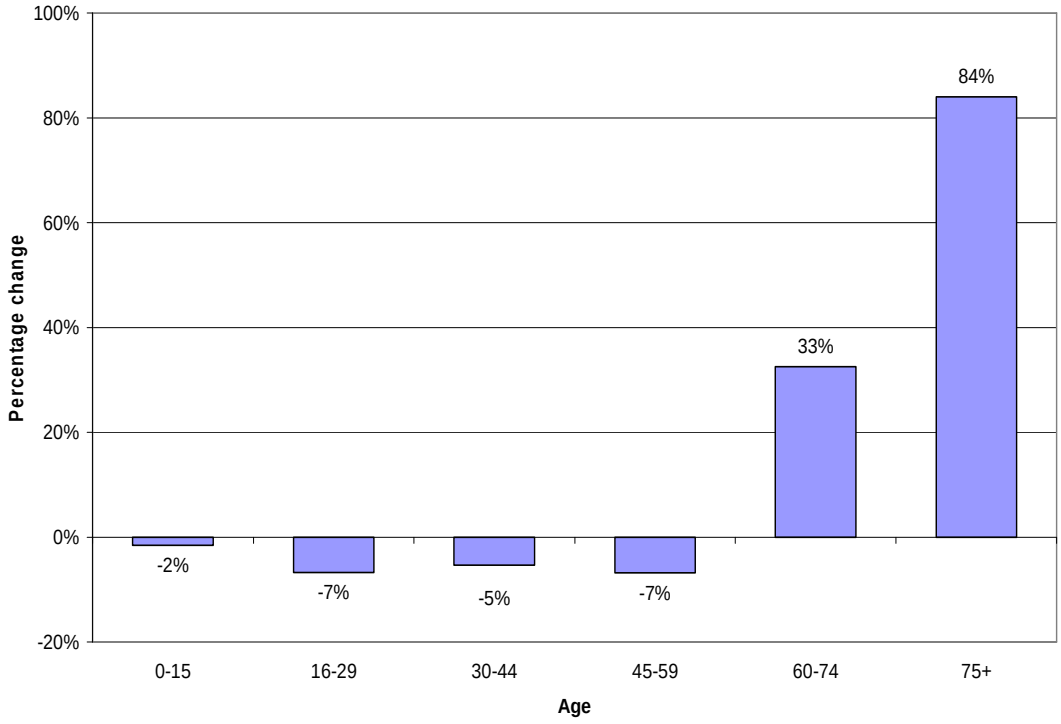

Figure 2-7 Projected percentage change in Scotland's population by age group, 2008-2033, (GROS, 2010)

In light of these developments, it has previously been anticipated that the costs of HC (along with other public expenditure costs, like social security and social care) will increase (Dang et al., 2001); an assumption that is discussed in detail in Chapter 3.

2.4 Health care costs in Scotland

2.4.1 ‘Costs Book’

NHS Scotland is divided into 14 health boards, which provide HC services to the population in their area. Each of the 14 health board’s annual accounts, which includes their net operating costs, provide the basis for the ‘Scottish Health Service Costs’, also known as the ‘Costs Book’ (ISD, 2011). The Costs Book is the only source that has published detailed cost information for the NHS Scotland. Cost information is mainly derived from health boards’ financial returns data. About 94% (~£9.7 billion) of all operating costs of the NHS Scotland are contained within the Costs Book. Costs include all hospital services, community services and family health services (ISD, 2011). In addition to cost information, information on patient demographics is also published in the Costs Book.

Costs for hospital services encompass a variety of services, including surgery provided by consultants at large urban hospitals (inpatient services) as well as outpatient clinics at rural community hospitals. Total costs of £5.5billion were incurred in the hospital sector in the financial year 2009/2010. Community services include services provided by district nurses, health visitors, prevention services, screening programmes and health promotion; in 2009/10 £1.4billion was allocated to this HC setting. Family health services are all Primary Medical Services provided by GPs, opticians, dentists and pharmacists, totalling about £2.3billion in 2009/2010 (ISD, 2011).

Figure 2.8 shows the share of costs for each of the different sectors covered in the Costs Book for the financial year 2009/2010. With a share of close to 60%, costs for hospital care are the main contributor to total HC costs in Scotland.

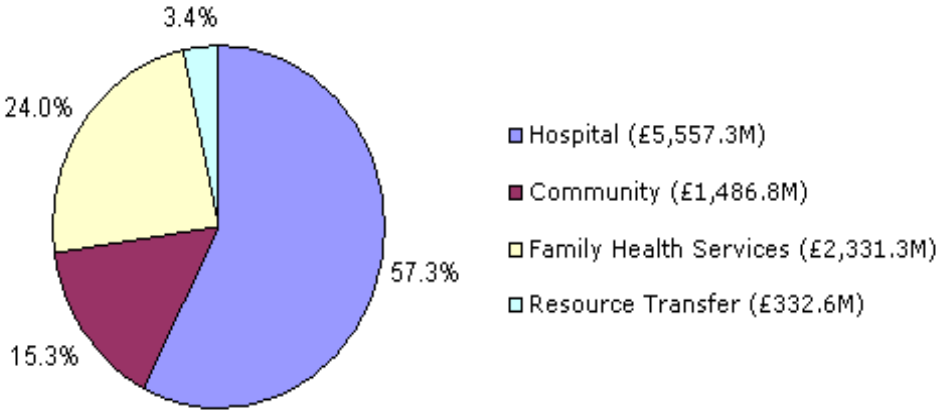

Figure 2-8 Overall health care costs in Scotland in 2009/10 by health care sector (ISD, 2011)

Costs of NHS Scotland are produced through a top-down approach, so that these are mainly based on the annual HC budget for Scotland, which is determined by Ministers during the Spending review process. The annual budget for hospital and community health services and GP prescribing is allocated to each of the 14 health boards based on a formula that adjusts for relative need of the population in each of the health boards. This allocation formula is discussed below. The Costs Book reflects how the annual budget is distributed over different HC services, with acute inpatient care comprising the largest sector. It also provides information on how, within each service, costs are cascaded down to specialty specific costs in the case of hospital care.

2.4.2 Resource allocation

The Arbuthnott formula, which was introduced in 2000, was in place until 2008, when it was replaced by the National Resource Allocation Committee (NRAC) formula after an extensive review between 2005 and 2007. NRAC carried out the review and its recommendation on updates for the resource allocation formula were implemented from 2009 onwards (ISD, 2011). In general, resource allocation takes place after the total amount of money to be allocated has been determined through the Spending review

process, so that a given amount of money needs to be distributed. Resource allocation of the entire HC budget comprises the basis for HC costs that are later reported in the Costs Book, i.e. that part of the budget that was allocated to hospital services by health board and cascaded down to specialties and other services.

Arbuthnott Formula

From its introduction in 2000, the Arbuthnott formula allocated about 70% of the total HC budget to health boards (Fair Shares for All, 2000). The current NRAC formula updated, refined and improved the elements of the Arbuthnott formula, but fundamentally maintained its structure.

The Arbuthnott formula is a weighted capitation formula. It is used to calculate shares of the budget to be allocated to health boards rather than money (NRAC, 2007). Initial shares of the HC budget are calculated using information on the size of the population. The formula then seeks to adjust for relative need in a health board area to capture the composition and characteristics of a population beyond size. It also adjusts for any additional costs of delivering HC services in that area compared to the rest of Scotland. The main elements to capture relative need have been identified as: population size, the relative number of males and females in different age groups, an adjustment to take account of the additional costs of delivering HC services in remote and rural areas compared to the national average and, a measure of deprivation, the so called morbidity and life circumstances (MLC), which are based on the four indicators detailed below (Fair Shares for All, 2000).

Adjustment for age accounts for the fact that a Health Board with a higher proportion of elderly people will have a greater need for HC services. Adjustment for gender, for example, takes into account that a Health Board with a higher proportion of women in childbearing age will face a greater demand for HC services related to child birth (Fair Shares for All, 2000).

The resource allocation formula takes account of MLC in each Health Board. This is also known as the Arbuthnott Index, which is calculated using a combination of the following key components, which are closely linked to HC need:

• the mortality rate for people under the age of 65,

• the area's unemployment rate,

• the percentage of elderly people living on income support and

• the number of households with two or more measures of deprivation from the 1991 census (NHS Scotland Resource Allocation Committee (NRAC), 2007).

The choice of these indicators is based on the assumption that people in more deprived areas have a higher exposure to factors that have a negative impact on health, so that people in these areas tend to have a greater need for HC (Fair Shares for All, 2000). It is important to note that the 'Arbuthnott Index' is a measure of population characteristics that influence need; it is not a direct measure of need (Fair Shares for All, 2000). The 'Arbuthnott Index' is also responsive to changes in need over time. This is ensured by updating three of the four key components, i.e. the mortality rate for people under the age of 65, the area's unemployment rate, and the percentage of elderly people living on income support in each Health Board. Health Boards, for instance, with an index of less than zero (the index ranges from -4 to 4) have levels of deprivation and morbidity that are below the national average (Fair Shares for All, 2000).

Relative need of a population is estimated based on the assumption that service use reflects need and the Arbuthnott formula accounts for need in the following HC settings:

• acute inpatient care

• maternity care

• mental health

• geriatric care

• learning disabilities

• community services and

• General Practitioner (GP) prescribing.

In order to assess population need in each of these settings, the four elements, which have been described above are taken into account.

NRAC formula

NRAC reviewed each element of the Arbuthnott formula between 2005 and 2007 and proposed the following main updates to the existing formula:

• an updated method to measure population size

• a refinement of age bands that are used for age and gender adjustment from 8 to 20 categories, to obtain more precise indications for costs incurred by elderly people

• in terms of the MLC adjustment, the suggestion was to replace the Arbuthnott index with three separate indices to capture differences in costs by HC services and to factor

in ‘unmet’ need due to under-utilisation of acute services for circulatory diseases, as evidence showed that despite an increased need in deprived areas, these services were not used accordingly

• in terms of the unavoidable excess costs of delivering HC services in remote areas, it was recommended that for hospital services, an adjustment should be made based on the difference between local and national average costs by rural- urban category.

2.4.3 Resource allocation and TTD

The ‘Fair Shares for All’ report stated that mortality differences between Health Boards could be a proxy for need beyond the differences that had already been taken into account in terms of population size and population characteristics. The report also acknowledged evidence for an increase in resource utilisation as people approach death. Some first analyses undertaken showed that Health Boards with a higher mortality rate also had higher HC resource utilisation. Although TTD had been identified as a useful element of the resource allocation formula, it was decided not to include it as research in Scotland that provided evidence that TTD is an important predictor for HC expenditure alongside age, was at an early stage. Some disadvantages of including TTD in resource allocation had also been outlined, such as accounting for issues arising from utilisation of ‘mental health’ services, where TTD might not be as strong a predictor as in other HC settings (Fair Shares for All, 2000).

Following on from the 'Fair Shares for All' report, NRAC reviewed the components of the Arbuthnott Formula and specifically, how TTD is currently taken into account in resource allocation in Scotland. One focus of the review undertaken by NRAC was to assess whether the existing utilisation approach should be replaced with an epidemiological approach[4] or a TTD approach. Different methods were explored and NRAC argued that although the age-gender adjustment of the allocation formula does not account for remaining TTD, the MLC component would adjust for any deprivation-related effects and would so adjust for differences in life expectancy that are due to socio-economic components (Bishop et al., 2006).

NRAC's conclusion was that TTD was the least re-distributive of all alternative methods compared and therefore likely to underestimate variations in costs among Health Boards. For the TTD approach, NRAC found obstacles, especially in determining how close to death residents in each health board area were. The review concluded that these results were due to the omission of additional explanatory variables such as deprivation to explain differences in costs at different times before death. The review found that the current MLC adjustment (after age-gender adjustment) was highly correlated with life expectancy and in turn with TTD. NRAC concluded that through the current Arbuthnott index, which can be used as a proxy for HC need, a large proportion of the variation between health boards due to TTD is reflected. NRAC recommended that further research into HC needs that are related to TTD, age and resource allocation was required as TTD studies were at an early stage and recommended more empirical applications.

[4] An epidemiological approach would require detailed data on the morbidity of the entire population. This would also require linkage of morbidity data to subsequent utilisation of HC services at a patient level. After available data was reviewed by NRAC, it was concluded that implementing a formula based on a comprehensive epidemiological approach was not something that could be achieved within the time scale of the Committee's work (Bishop et al, 2006).

It has to be noted here that the studies NRAC based their recommendations and conclusions on are mostly preliminary studies (Graham and Normand, 2001, Lowe, 2005) that show scope for an improvement in methods, relating to both the sample used and also the econometric modelling techniques employed. Further 'room for improvement' is also found in the costing methods these studies have used. A detailed review of both studies is provided in Chapter 3.

2.5 Costs for long-term care

Apart from costs for acute inpatient care, which had been shown to be the main contributing sector to the entire costs for the NHS and other NHS costs, the LTC sector is another sector that would be expected to be heavily affected by a shift towards a higher proportion of elderly people.

The provision of LTC in Scotland does not fall within the remit of the NHS but is mainly the responsibility of Scottish local authorities (Councils). Costs for LTC are therefore not part of the Costs Book. Unlike hospital care, LTC can be provided in a variety of settings. Care can either be provided in care homes or in peoples' own homes. A wide range of financial sources provide payments to fund LTC. Local authorities receive funding through grants from the Scottish and the UK Government. Council tax and user charges also contribute towards financing LTC (Scottish Executive, 2006)

In care homes, user charges amount to 37% of total care home fees. In 2002, the Scottish Parliament introduced Free Personal and Nursing Care (FPNC), following recommendations from the Royal Commission on long-term care for people over the age of 65 either living in care homes or in their own homes (Bell and Bowes, 2006).

However, this does not include subsidies for hotel and accommodation charges, hence the rather substantial contribution that comes from user charges.

Care for people living in their own homes is also funded by a number of sources. Again, a proportion of care provided is funded privately. Estimates on private spending for home care are very difficult to obtain and subject to great uncertainty, according to the 'Review of Free Personal and Nursing Care in Scotland' (Scottish Government, 2008). A further share comes from local authorities and the main financial contribution comes from the Department for Work and Pensions (DWP). An additional component of LTC that is supported by local authorities is Housing Support (Scottish Government, 2008).

As pointed out earlier, spending on LTC is not published in the NHS Costs Book. Rough estimates can only be obtained at an aggregate level by summarising costs of each of the services that are most likely involved in providing LTC. This means that cost data for LTC is not available at an individual level. It will therefore be very difficult to relate costs to personal characteristics, such as gender, age and health status measures etc. This is further complicated by the fact that no patient level data are available, which would provide information on length of stay in care homes or the duration during which care was provided in peoples' homes, the level of care received etc. As a consequence, any cost estimates obtained using aggregate data are unlikely to be reliable. Without reliable data, it will however be very difficult to assess the impact that population ageing might have on the demand for LTC in Scotland.

LTC and its organisation differ substantially from HC. Ideally, primary care services, hospital care and LTC would all be considered in a study looking at population ageing and related social costs, especially as a shift between hospital care and LTC might be observed.

Given these data constraints, this thesis concentrates on the most expensive HC sector, namely hospital care. Limitations arising from not including other HC sectors, especially LTC are discussed in Chapter 7 of this thesis.

2.6 Measuring resource utilisation in Scotland

Information on resource use, which will serve as the basis to measure HC expenditure, needs to be available over a sufficiently long observational period during which death for a substantial part of the sample can be observed. Ideally data would be in a panel format, which means unobserved heterogeneity between patients can be controlled for, so that multiple observations per individual can be treated as dependent observations.

Scotland has the advantage of maintaining very comprehensive hospital episode statistics to measure resource use of acute inpatient and day care. These are known as the Scottish Morbidity Records 01 (SMR01) data and are held by the Information Services Division (ISD) of NHS Scotland. SMR01 records exist in computerised format since 1968 with approximately 1 million records generated per year (Scottish Public Health Observatory, 2010). Care episodes that are excluded from SMR01 are obstetric and psychiatric specialties. Geriatric long stay episodes were part of SMR01 until 1997. Since LTC does not fall within the remit of the NHS anymore, as outlined in Section 2.5, these records were excluded from SMR01.

2.6.1 Record linkage

Scotland also has the advantage of having a very good data linkage system, allowing SMR01 records to be linked to survey data. Linkage of medical records in Scotland goes back to the late 1960s and is undertaken by ISD using probability matching (Fischbacher et al., 2007). Probability matching allows for imperfections of the data

compared to an exact matching approach, which could miss up to 15% of true links. Linkage is usually undertaken on a number of core items: surname, initial, year, month and day of birth with a discrepancy rate of up to 3% in pairs of records belonging to the same individual. Probability matching is done by assigning probability weights (every time an item of identification is the same in two records, the probability that these two records belong to the same person is increased and vice versa) (Kendrick and Clarke, 1993).

2.6.2 Survey data

The inclusion of that part of the population, which is not observed in resource use data, e.g. that part of the population without any hospitalisations, can only be achieved through the utilisation of survey based data. The SMR01 datasets have been routinely linked to death records from the GROS. This link provides information on hospital episodes (positive costs) for individuals with a death record. However, it does not provide information on individuals with a death record, who never utilised hospital services. SMR01-GROS linked data also gives information on individuals without a death record, who incurred costs. It does not however provide any information on individual characteristics for those without a death record, who did not incur any costs. Linkage to a survey based dataset can provide information on individual characteristics for these people.

Therefore, administrative data does not seem to be sufficient to capture all subgroups of a population that are to be included in a TTD study. A population based approach that also includes individuals without positive HC expenditure requires a separate survey based dataset, where individuals can be observed regardless of incurring HC costs or having a death record. Exploiting the fact that SMR01 can also be linked to a number of other data sets this thesis makes use of two survey based datasets, the Renfrew/Paisley study (as one of the Midspan studies) (Hart et al., 2005) and the Scottish Longitudinal Study (SLS) (Hattersley and Boyle, 2007), which represents a 5.3% sample of the

Scottish Census. These two datasets are introduced and described in more detail in Chapters 5 and 6.

A further advantage of having longitudinal survey based data is that a number of explanatory variables can be exploited, some of which have not previously been included in an analysis of the association between TTD, population ageing and HC expenditure. These are health status measures, health behaviour and health risk variables. They constitute important individual characteristics, which are not routinely collected in resource use data. The ability to capture time trends and possible improvements in medical technology that could have influenced costs is also supported by the analysis of a comprehensive longitudinal linked dataset.

3 LITERATURE REVIEW

3.1 Introduction

This chapter summarises and critiques the seminal contributions to the literature in terms of population ageing and its effect on HC expenditure, thereby providing a) the motivation for this thesis and b) the justification for methods employed in this thesis. Early contributions to the research field are also reviewed. A review of the literature was carried out in MEDLINE after developing a search strategy (Appendix I). In addition, reference lists of studies that were identified from the search were scanned and the 'Web of Knowledge' database was used for citation searching. Language restrictions were imposed to include English studies only and the database was searched for studies published between 1950 and 2009.

This chapter outlines the underlying assumptions of why an ageing population is expected to cause a steep rise in HC costs. Following on from this, recent contributions to the literature are presented that also take into account other factors than population ageing that might impact on HC expenditures, namely the time immediately before an individuals' death, which tends to be characterised by aggressive and expensive treatments/therapies.

The review of the literature focuses on these TTD studies and specifically on the methods that have been employed to analyse the relationship between population ageing, TTD and HC expenditure, which are shown to vary widely. Issues of particular interest are the distinction between a macroeconomic and a microeconomic approach, the sample that is analysed and its representativeness (survivors versus decedents and individuals with and without zero cost observations), the HC sector (primary care, hospital care, LTC) and the different costing methods that have been used.

Furthermore, recurring methodological issues such as the appropriate econometric modelling framework, the problem of endogeneity of TTD and the inclusion of surviving sample members with an unknown TTD are discussed. Different methods that were employed in the literature to calculate the amount of future HC expenditure under different modelling scenarios are explained in order to inform HC expenditure projection for Scotland in Chapter 6. The review concludes with a detailed summary of the status quo of TTD studies in Scotland and an outline of how TTD is currently acknowledged in policy. Finally, data requirements and data availability to undertake a TTD study in Scotland are described.

Focussing on research that used micro-econometric analysis this chapter proceeds with outlining and critically assessing these studies in terms of their methodological differences which can lead to varying and sometimes conflicting results. Special attention is paid to differences in

• the econometric modelling framework and sample selection

• the HC sector that has been used in the analysis and its associated costs, the costing method and the choice of an appropriate estimator for HC expenditure,

• the inclusion of survivors in TTD studies

Sections 3.4 to 3.7 review and summarise the literature under these aspects and present the main contributions. Gaps in some of these methods are highlighted. These deserve further methodological investigation and have motivated the empirical analyses undertaken in this thesis, which are presented in Chapters 4, 5 and 6.

3.1.1 Pioneering research from the 1950's

Generally, as age increases, health deteriorates. Chronic diseases develop and require medical attention and the number of contacts with HC services usually increases, therefore HC spending varies with age.

The first research to investigate the relationship between population ageing and HC expenditure was undertaken by Abel-Smith and Titmuss in 1956. When forecasting future expenditure needs the authors assumed that demographic change would be the only factor influencing the cost of the National Health Service (NHS) and that other factors, such as incidence and type of disease and type and quality of treatment would remain unchanged. The authors estimated future HC expenditure combining population projections from the Registrar-General with Census data on the proportion of the population in hospital by sex and age (Abel-Smith and Titmuss, 1956).

This research presents very early work to quantify the impact that demographic change is expected to have on HC expenditure. The data included to answer their question are limited in a sense that it is aggregated data on only two variables which are expected to solve a rather comprehensive problem. This early research also shows its limitations in econometric techniques, which were less developed in the 1950s compared with more recent research. The assumptions Abel-Smith and Titmuss (1956) made about the unchanged incidence, the character of diseases, and the quality and quantity of treatments would also need to be reconsidered.

However this has been an important contribution and certainly pioneering work in this field which provoked and encouraged a growing research area in decades to come. Since the 1950s a wide range of studies was undertaken and published that employed new and improved methods to try and explain the impact that an ageing population has on HC expenditure. The following sections provide a comprehensive and critical review

of these studies and summarise improvements that were made in terms of methodology and econometric modelling techniques.

3.2 Morbidity scenarios

Research that was undertaken in order to explain the impact that population ageing might have on HC expenditure is usually motivated by one of the three different/conflicting assumptions (see Sections 3.2.1 to 3.2.3 below) about how morbidity as the main driver of HC demand and expenditure will develop in the future. Given that life expectancy is improving in general in most countries, the central question is that of quality of life (health status) in which these additional years of life will be spent. In contrast to Abel-Smith and Titmus (1956), this is based on the assumption that the type and incidence of disease would change over time. Changing disease pattern cause changes in the demographic composition of a population and due to increased longevity a higher proportion of elderly people will be present. This is mainly caused by a reduction in, for instance, cardio-vascular disease, so that people live longer but might be at risk of developing other morbidities, such as cancer.

However, evidence that a higher proportion of the elderly population causes an inevitable increase in HC expenditure is not as clear cut. The central question is whether any additional years of life will be spent in good or bad health, i.e. will an 80 year old person in 20 years time be more or less healthy than an 80 year old person now? In other words, how many of the additional years of life will be spent in good health and how many in bad health? If people, due to medical advances, experience shorter and/or less severe spells of illness towards the end of life this will have an impact on the amount of HC resources required to treat them. A measure commonly used to describe this relationship is healthy life expectancy, i.e. the number of years a person can expect

to live in good health. The difference between life expectancy and healthy life expectancy gives the number of years a person can expect to live in poor health. The three main concepts that had been put forward in order to describe the pattern of how life expectancy and healthy life expectancy could develop are 1) the expansion of morbidity concept, 2) the compression of morbidity concept and 3) a concept assuming a dynamic equilibrium. A detailed presentation of each of these scenarios is provided below.

3.2.1 The expansion of morbidity hypothesis

The expansion of morbidity concept was put forward by Gruenberg (1977) who assumed that additional years of life gained would be spent in poor health. Gruenberg (1977) argued that an increase in life expectancy was mainly achieved through improved medical technology, which serves to extend the lives of individuals with disabilities and diseases, but the underlying epidemiology of degenerative diseases would remain unchanged (Gruenberg, 1977). His failure of success hypothesis claims that individuals surviving to older ages would have increased levels of diseases and disabilities. With life expectancy increasing faster than healthy life expectancy, individuals would consequently spend more time in a state of ill health.

A similar assumption has also been put forward by Olshansky and colleagues (1991). Although the authors agreed generally with Fries' argument of a natural limit to longevity, they argue that even minor improvements in mortality for the elderly would still lead to increased morbidity due to people surviving longer with non-fatal chronic diseases (Olshansky et al, 1991).

3.2.2 The compression of morbidity hypothesis

A contrasting concept is that of the compression of morbidity which has been described by Fries (1980) and assumes both an absolute increase in life expectancy and also an increase in the number of years that are spent free of illness and disease. The age at

which illnesses occur (age at onset) and the progression of diseases are delayed through changes in lifestyle that modify risk factors for mortality. Increases in life expectancy are mainly achieved through improvements in the underlying epidemiology of diseases. Healthy life expectancy increases faster than life expectancy and the absolute number of years spent in ill-health decreases. Another assumption Fries made was that any increases in life expectancy must slow down over time as human longevity approaches a natural limit (Fries, 1980).

3.2.3 The dynamic equilibrium hypothesis

A third concept, the dynamic equilibrium, puts forward a ‘midway solution’ between the compression and expansion of morbidity hypotheses. It assumes a delay in the progression from less severe states of illnesses to more severe states. The number of years lived with an illness and the number of years lived with less severe illnesses would increase simultaneously and so result in an average increase in the number of years spent in a state of moderate illness. However, the level of care required during this period may decrease (Manton, 1982). An increase in life expectancy would therefore lead to an increase in disease prevalence, but this would mainly be caused by an increase in prevalence of less severe or less disabling diseases.

These three concepts can only be mutually exclusive in theory. In practice it seems more likely that factors such as delayed onset, delayed progression and increasing survival with severe illnesses that support either of these concepts would act together.

3.2.4 Evidence for morbidity scenarios

Which scenario will unfold over the next decades remains an issue that has not been resolved entirely and may also vary between countries (Williams, 2005). More recent research that has reviewed studies from different developed countries that have assessed how their demographics have changed over time suggested that although it is still not established, evidence seems to point in the direction of people living longer than

they had previously with less disabling diseases or functional limitations (Christensen et al., 2009). Further evidence that supports the ‘compression of morbidity’ concept as the scenario that might unfold in the future has been summarised by Payne and colleagues (2007).

3.2.5 Evidence for morbidity scenarios in Scotland

Findings from Christensen et al (2009) suggested that countries where the disparity in lifespan between population sub-groups is low are those that tend to have the longest life expectancies. Evidence from Scotland, published by the Healthy Life Expectancy Measurement in Scotland Steering Group showed that although increases in healthy life expectancy at age 65 had been similar to increases in life expectancy in absolute terms and larger in relative terms, there were significant differences between socio-economic groups (Clark et al, 2004).

On average this research found that remaining life expectancy for a 65 year old man was 14.8 years, of which on average 11.5 years will be spent in good or fairly good health. For a 65 year old woman mean life expectancy was 17.9 years, 13.4 of which will be spent in good or fairly good health. The report concluded that for people aged 65 and older healthy life expectancy is increasing at the same rate as life expectancy, so that the proportion of years spent in ill health has remained the same over the last 20 years.

The report also showed that healthy life expectancy at birth in the most affluent areas was almost identical to average life expectancy (0.3 years less), whereas in the most deprived quintile healthy life expectancy at birth was up to 17.7 years less than average life expectancy. Differences in healthy life expectancy by socio-economic status were also more pronounced in areas that experienced lower life expectancies and also having a higher level of morbidity whilst people were alive (Clark et al, 2004).

3.3 The cost of dying –TTD as predictor for HC expenditure

Based on the assumption of a compression of morbidity, there is a growing body of literature that takes into account factors other than population ageing to explain and estimate future HC spending. Accounting for changing disease pattern over time, these studies have tried to disentangle the effects that other factors than demographic changes might have on future HC expenditure. Among the most researched factors is remaining TTD. This is based on the experience that individuals near death might receive very expensive and aggressive treatments in order to prevent death. This implies that older people are more expensive not because they are older but because they tend to be closer to death compared to younger people. One study suggested that decedents, who made up 6% of the analysed sample accounted for 28% of total Medicare expenditure and that the intensity of HC utilisation increased as people approached death (Lubitz and Prihoda, 1984).

Accounting for remaining TTD will change the predicted effects of purely demographic changes, i.e. population ageing. If population ageing was the result of increased life expectancy, then the expectation would be that the age profiles of HC expenditure move downwards for those age groups for which mortality is improving. This would imply that HC expenditures could even decline (in theory).

In the 1980s, Fuchs (1984) established that cross-sectional differences in HC expenditures by age overestimated the changes that would result from an ageing population. Using Medicare data he found that HC spending is more a function of TTD than it is of age and that the reason why expenditure increased with age in cross-sectional data was the increasing proportion of people near death. Grouping people as survivors or decedents Fuchs showed that after adjusting for age and sex differences in the survivor group, most of the age-related increase in expenditure could be eliminated.

This study was one of the first to show that TTD may be a better predictor for HC expenditure than age (Fuchs, 1984).

A number of more recent studies followed that considered TTD in addition to age and how this affects HC expenditure employing an array of methods. The most influential work that provided evidence against the relatively simplistic methods of relating population ageing to HC expenditure was undertaken by Zweifel and colleagues (1999). In their seminal study the authors argued that population ageing could not be made responsible for increasing HC costs, an argument that has since entered the literature as the 'red herring' argument (Zweifel et al., 1999). The authors claimed that accounting for remaining TTD will significantly change the effect that demographic changes of the population will have on HC expenditure and if there was a significant association between TTD and HC expenditure, population ageing *per se* could not be the main cost driver. Zweifel et al (1999) found that the positive relationship between age and HC expenditure can be completely attributed to the fact that mortality increases with increasing age. The association between age and HC costs therefore seems to reflect a possibly stronger relationship between remaining TTD and HC expenditure, which Zweifel and colleagues found to be a much better predictor of acute HC costs than population ageing *per se.*

As more elderly people are at their end of life it has previously been assumed that age is driving HC expenditure. But if age alone would be made responsible for HC spending other aspects, such as treatment intensity at the end of life, age-related rationing and advances in medical technology over time would be ignored.

The conclusion reached by Zweifel and colleagues (1999) is a very strong one as it implies that demographic changes do not matter in terms of their contribution to HC expenditure. This research motivated a number of other national studies, some of which came to the conclusion that age is still an important factor associated with HC

expenditure, but accounting for TTD reduces the magnitude of the effect age had on HC costs (Seshamani and Gray, 2004a, Seshamani and Gray, 2004b, Moorin and Holman, 2008, McGrail et al., 2000). In addition to initiating further research in this area, Zweifel et al (1999) also provoked criticism among researchers (Salas and Raftery, 2001, Seshamani and Gray, 2004b) some of which is discussed in detail in the following sections.

This thesis highlights that the methods that have been used to analyse the relationship between population ageing, death and HC expenditure in different national studies vary greatly, which may hinder our ability to draw definite conclusions. The aim of the following sections is to provide a comprehensive description of these methods, concentrating on the following distinctions: a) studies that used descriptive analyses to explain the relationship between population ageing, HC expenditure and TTD, b) studies that used more advanced econometric techniques to explain this association.

An additional level at which a distinction between methods can be made is whether researchers have chosen a macroeconomic approach, using aggregate country level data or whether a microeconomic approach, using individual level data was employed.

Concentrating on research that used econometric techniques to analyse individual level data, this thesis will then proceed to outline further distinctions in methods that have been used within a microeconomic framework.

3.3.1 Descriptive analyses of the cost of dying and the cost of ageing

There are a number of studies which have undertaken descriptive analyses of the cost of dying and the cost of ageing, some of which have used a sample consisting of decedents only and have split these into different age groups. Costs for each age group were then plotted against TTD and HC expenditure was compared for a given TTD (last year of life) across different age groups (Batljan and Lagergren, 2004). Other methods

included the calculation of days spent in hospital by age group during the last year of life (Henderson et al., 1990).

Other descriptive studies have also included surviving sample members and generally compare HC costs incurred by a group of decedents over a particular time period (calendar year) with those costs incurred by a group of surviving sample members of the same age group. Results are then presented as, so-called decedents/survivor ratios. For instance, Roos et al (1987) split their sample into survivors and decedents for their projection period and made expenditure projections for each of the sub-samples. Combining the two separate projections, the authors concluded that hospital utilisation would increase by 64% between 1976-2000 compared to an increase of 73% if the standard method of cost projection was to be used (Roos et al., 1987). The standard method employed by the authors was based on the projected growth in the number of the elderly population by the year 2000, whereas the alternative projecting method, which produced a lower growth rate for HC utilisation, was based on the projected number of decedents and survivors in the year 2000. The authors estimated age-specific death rates and utilisation rates were obtained for survivors and decedents. The authors then applied utilisation rates without a decedent/survivor distinction to the projected number of the population in 2000 (standard method) and with a decedent/survivor distinction (alternative method) (Roos et al., 1987).

Another study undertaken in British Columbia, Canada by McGrail and colleagues (2000) also compared expenditures for survivors with expenditures for decedents. Costs for nursing and social care as well as acute medical care were analysed utilising data from the British Columbia Linked Health Data (McGrail et al., 2000). The authors calculated costs for hospital care for the last 6 months of life using per diem costs and multiply these by length of stay (LOS). Their comparison group consisted of survivors in the same age range over a 6 month period (McGrail et al., 2000). This research found costs for acute care to rise with increasing age, but concluded that TTD was a stronger

predictor for HC costs and additional costs of dying would fall with age. Contrasting results were found for the use of LTC, where costs increased with increasing age, but the additional costs of dying also increased with age (McGrail et al., 2000). The authors highlighted implications of these different findings for different HC settings.

Further research that has employed a descriptive analysis used a cohort study from Germany, which represented ten percent (stratified by age and gender) of all individuals insured by a German sickness fund (Busse et al., 2002). Instead of estimating HC expenditure, the authors compared the number of days that survivors and decedents spent in hospital, stratified by age and sex. For decedents they analysed the last three years of life and survivors were only included if they were observed to be at least three years away from death. For individuals in their last year of life the average number of days spent in hospital was found to be highest for ages between 55 and 64 years. Beyond this age the mean number of hospital days was found to decrease, whereas for the survivor group a steady increase in the mean number of hospital days was observed (Busse et al., 2002). The highest ratio of hospital days was found to be between decedents in their last year of life and survivors at age 44. The authors therefore concluded that the most costly patients were people who died young. This conclusion requires, however, that LOS is linearly related to costs, a concept that might not prove entirely correct given that a hospital stay is characterised by a fixed and a variable cost component.

The age groups studied by Busse and colleagues were more encompassing than the age ranges that have been used in other analyses, which may make direct comparison with studies that mostly include individuals aged 65 and older difficult. Findings from Busse et al (2002) are however in line with findings from other research, confirming the ‘red herring’ argument.

3.3.2 Macro-level analysis

Yet another distinction that can be made in terms of the methodology used to explain how the changing age structure might impact on HC expenditure is that between using aggregate country level data and using individual micro-level data. Macroeconomic data can be used to make comparisons across different countries. Many studies that have utilised a macro-economic approach have not included TTD, but have rather analysed the effect of the age structure of the population on HC spending.

Utilising cross-sectional data from 19 member countries of the Organisation for Economic Co-operation and Development (OECD) in 1987, Gerdtham *et al* (1992) analysed the effect that the age structure in addition to other factors, such as the Gross Domestic Product (GDP) had on HC expenditure (Gerdtham et al., 1992). The authors found no significant effect of age on HC spending and identified the GDP to be the biggest influencing factor (Gerdtham et al., 1992).

In a study by O'Connell (1996), country specific age variables were used to analyse the effects that ageing had on HC expenditure in a number of OECD countries (O'Connell, 1996). This study used data from 21 OECD countries for the period 1975 to 1990 and found the effect that the age structure had on HC spending to vary between countries. The age structure influenced HC spending significantly in a number of countries with a varying magnitude. The author acknowledged that less aggregated data would contribute to a better understanding of how exactly age influences HC expenditure (O'Connell, 1996). This is however difficult to achieve with country-level data as opposed to individual level data. It is also difficult to determine with this analysis approach, how unobserved country-specific effects impact on HC expenditure and the share of the Gross Domestic Product (GDP) devoted to HC expenditure.

Another study that analysed data on population ageing in OECD and UN countries is that of Anderson and Hussey (2000). They examine the correlation between the proportion of GDP spent on HC for people aged 65 and over and the proportion of the population in that age group (Anderson and Hussey, 2000). Their estimated correlation coefficient suggested very little correlation between these two variables and the authors proceeded to conclude that factors other than ageing might be far better predictors for HC expenditure (Anderson and Hussey, 2000).

Issues arising from using aggregate country level data are that these data might not be comparable between countries. It could also be argued that there might be a weak theoretical basis for using aggregate data to explain which factors exactly determine HC expenditure. Individual population characteristics can not be modelled using a macro-economic approach which makes it difficult to draw conclusions on the association between HC expenditure and population characteristics. As most macro-economic studies conclude, the age structure seems to have a negligible impact on HC expenditure. These studies also suggest that 'other' factors might be more important in explaining HC spending. However, using aggregate country-level data it is not possible to determine what these 'other' factors are. Another limitation of employing a macro-economic approach, using aggregate data is that these are averages over extreme values, and do not provide results for these extreme observations. In addition the quality of the data would be expected to vary greatly between countries.

Including TTD as well as age, Colombier and Weber (2011) did not compare different countries but used Switzerland as an empirical example and analysed aggregate country-level data to prove that when using individual-level data in regression analyses, the effect that TTD has on HC costs towards the end of life might be overestimated. The authors argued that applying econometric regression techniques would suffer from bias, firstly because population ageing in the past has not been as pronounced as it is expected to be over the next decades. The authors further argued that econometric

estimations might suffer from ‘expectation bias’. This could be caused since cost estimates for the end of life are based on *ex post* data. Colombier and Weber (2011) claimed that decedents should only be treated differently from survivors if physicians expect them to die, which is unknown until individuals are very close to death (Colombier and Weber, 2011). According to the authors, rather than using the number of deceased people as a proxy for an estimate of the cost of dying, it would therefore be more appropriate to use the number of people, who are terminally ill. Colombier and Weber (2011) concluded that mortality only plays a minor role when it comes to future developments of HC expenditure and pointed out limitations of the ‘red herring’ argument.

Despite the criticism that was raised by Colombier and Weber (2011), a microeconomic approach allows estimation of costs on an individual level which has the advantage of being able to capture differences in characteristics on an individual level rather than an aggregate level and so to account for individual characteristics. Individual level analysis also offers means to include explanatory factors that were measured on an individual level such as health status and health behaviour. Data availability could be perceived to be an issue here, however many countries now have administrative data available that facilitate a micro-level analysis. Scotland in particular has the advantage of having available excellent data linkage systems which provide a rich source of survey and administrative data, combing health data and additional baseline individual characteristics.

Focussing on research that used micro-econometric analyses this chapter proceeds with outlining and critically assessing these studies in terms of their methodological differences which can lead to varying and sometimes conflicting results. Special attention is paid to the following issues:

• the choice of an appropriate estimator for HC expenditure (Section 3.4)

• the econometric modelling framework (Section 3.5)

• the HC sector that has been analysed and costing methods employed (Section 3.6)

• the inclusion of survivors in TTD studies (Section 3.7)

• the approach employed in order to project future HC expenditure (Section 3.8)

• methods that have been employed to model the association between TTD, age and HC expenditure using Scottish data (Section 3.9).

Methodological issues arising from the literature have motivated the empirical analyses undertaken in this thesis, which are presented in Chapters 4, 5 and 6.

3.4 Estimators for HC expenditure

Knowledge about the characteristics of HC expenditure data and appropriate estimators informs any subsequent discussion on how to estimate HC costs accounting for TTD, age and other explanatory variables. In a recent paper Basu and Manning (2009) concluded that there was no universally optimal estimator for HC expenditure data and outlined important methodological limitations that alternative estimators had (Basu and Manning, 2009). However, the following paragraphs provide a summary of available methods, discussing their advantages and limitations.

Typical characteristics of HC expenditure data are: a mass point at zero, a non-normal distribution with long, heavy right hand tails and excess kurtosis (Deb et al., 2006). This distribution is typically observed because very few patients are usually responsible for a high proportion of costs, whereas the majority of patients tend to incur costs at the lower end of the scale. Mean HC costs are typically larger than median costs. Cost data are

further characterised by being non-negative and heteroscedastic[5], i.e. having a non-constant variance. And finally, the relationship between costs as the dependent variable and a set of regressors may not be linear. The choice of an appropriate estimator for HC expenditure is frequently discussed in the literature (Manning and Mullahy, 2001, Briggs et al., 2005, Hill and Miller, 2009). Discussion mainly revolves around the transformation of cost data versus the importance of being able to derive the arithmetic mean of cost estimates on the original monetary scale.

A number of approaches exist to model cost data. First, cost data can be estimated using Ordinary Least Squares (OLS). OLS offers the advantage of being easy to implement and cost estimates are obtained on the original monetary scale. OLS has however disadvantages as it can produce negative predictions, which would be meaningless when dealing with cost data. It also assumes a linear relationship between the cost variable and the regressors; unless fractional polynomials or cubic splines were used in the analysis, where a curvi-linear relationship would be assumed. Due to the presence of heteroscedasticity, the classical assumptions for OLS are violated. The resulting coefficients will be unbiased, but estimates will be inefficient, i.e. OLS can not be the best linear unbiased estimator (BLUE) when heteroscedasticity is present. The standard errors are usually underestimated and t-statistics are made too large. This is a problem in particular, when the dataset is small and in case of extreme observations.

Another approach would be to log transform the dependent cost variable and apply OLS. This transformation achieves a more normal distribution, increases robustness and improves precision. While log-transformation can solve the issue of skewness and reduce problems of heteroscedasticity and kurtosis, estimates can no longer be obtained on the original monetary scale and cumbersome re-transformation involving a smearing factor needs to be applied. Simple exponentiation of obtained estimates does

[5] Heteroscedasticity indicates that error terms do not come from the same probability distribution. It often occurs in cross-sectional data, where there are large differences in size between observations (Halcoussis, 2005)

not provide the arithmetic mean of costs but the geometric mean of costs. Log OLS models the arithmetic mean of log costs, which is the geometric mean. It has been shown that the log of the mean does not equal the mean of log (Glick et al., 2007). Another issue of using log OLS would be that the log of zero costs is not defined and an offset would need to be added. Any decision about what the offset should be would be arbitrary.

A third approach to estimate expenditure data is that of employing a Generalised Linear Model (GLM). GLMs are an extension of OLS and have the advantage of being able to specify a link function, which allows transformation of the mean of regressors rather than the mean of the cost variable, and a distributional family. For instance, GLM with a log link does not model the log of arithmetic mean costs, but the arithmetic mean of log costs. GLMs also allow for heteroscedasticity through a variance structure, which is defined through the distributional family and relates the variance to the mean (Glick et al., 2007).

An additional characteristic of HC expenditure data is the fact that there are usually a high number of observations in any one period without any HC utilisation. These are called ‘zero cost observations’. Single regression models including these zero costs will likely lead to problems in obtaining regression estimates. To overcome these problems, a two-part model can be employed (Mullahy, 1998). The first part estimates the probability of accessing HC (usually employing a probit or logistic model) in any given period and the following second part (cost estimation) predicts costs, conditional on having incurred positive costs. The second part can be estimated employing GLMs, as described above. Predictions from the first and the second part are then multiplied to obtain the expected costs for subgroups of patients (Glick et al., 2007).

Employing a two-part model has the advantage that the effects of individual characteristics on the probability of utilising HC services can be assessed in a first step.

This can be of special importance, when analysing multivariate models to explain the effects that age, TTD and also other factors, such as the socio-economic status, have on HC utilisation. Two-part models can unravel two things: what influences access and, given positive utilisation, what influences costs. Where there is no sample selection issue, a two-part model is preferred over a Heckman sample selection model. Given that all zero costs (times without hospitalisation) can be observed in the analyses of this thesis, the empirical analyses in Chapters 5 and 6 will utilise a two-part model.

Further, comprehensive reviews of statistical methods to analyse HC expenditure data are available here (Dodd et al., 2006, Mihaylova et al., 2011).

3.5 Micro-econometric models

Compared to purely descriptive analysis as described in Section 3.3.1, studies employing micro-econometric regression, some of which have already been introduced briefly, (Zweifel et al., 1999, Zweifel et al., 2004, Seshamani and Gray, 2004a, Seshamani and Gray, 2004b) take into account that the age profiles for HC expenditure are not constant over time. Especially over the last decade, a number of studies have developed empirical models employing individual level data to explain the relationship between TTD and HC expenditure when controlling for age and other explanatory factors. These more advanced models go beyond comparing costs for decedents and survivors. In particular the application of cross-sectional time-series models allows estimation of how HC expenditure develops and changes as individuals approach death.

Table 3.1 provides evidence on the main literature that is discussed throughout this chapter.

Table 3-1 Evidence from the literature

Author/ Country	Year(s) and Data	Age groups/ sample	HC sector	Dependent Variable	Method	Main Findings
Felder et al (2000) Switzerland	1985-1992 Deceased members of Swiss Sickness Fund	415 deceased individuals over 8 quarters N=3,300	All HC costs covered by sickness fund	HC expenditure for HC covered by insurance	OLS and log OLS of HC expenditure	HC expenditure increases with TTD, for retired individuals; HC expenditure decreases with age, low income individuals, as compared to high income individuals incur lower HC expenditure in the last months of life
McGrail et al (2000) Canada (British Columbia)	1987-1988 and 1994-1995 British Columbia Linked Health Data	65 years and older Matched sample of survivors and decedents	Medical care sector and social care sector	Costs of hospital care (service use multiplied by per diem rates)	Descriptive method	Costs for medical care rise with age for survivors and fall with age for decedents, Additional cost of dying falls with age, even when social care costs are included
Busse et al (2002) Germany	1989-1995 German sickness fund	N~70,000 (10% sample of sickness fund) Survivors and decedents	Acute inpatient care	n/a	Descriptive study of total number of hospital days	Hospital use for people, who die at 50 or later is directly proportional to number of years lived, no exponential rise in costs as longevity increases

Author/ Country	Year(s) and Data	Age groups/ sample	HC sector	Dependent Variable	Method	Main Findings
Serup-Hansen et al (2002) Denmark	1995 Prevention Register at Statistics Denmark	All ages Random sample of 1,011,000 individuals Survivors and decedents	Hospital use and primary care services	n/a	Descriptive study; Cohort component technique to project demographic changes	Age still has considerable impact on future HC expenditure; traditional projection method suggested 18.5% increase in costs between 1995 and 2020 and improved method suggested a 15.1% increase.
Lowe (2004) Scotland	1981-2004 SMR01 data linked with death records	65+ Sub sample for Ayrshire and Arran Health Board Region Decedents	Acute inpatient care	Per diem costs (aggregated to annual costs per patient)	Replication of Seshamani and Gray (2004b, 2004c) model Two part model	TTD in the last year of life has highly significant association with costs Age is a highly significant predictor for costs (age squared is highly significant and negative)
Seshamani and Gray (2004b, 2004c) England, Oxford Region	1970-1999 Oxford Record Linkage Study (ORLS)	65+ 106,000 in Oxfordshire Decedents, followed over 30 years	Acute inpatient care	Specialty specific costs	Two part model Heckman sample selection model as comparator	Heckman model: neither age nor TTD are significant predictors for hospital costs Two part model: age and TTD have a significant effect on quarterly costs as far as 15 years before death Tenfold increase in costs from 5 years to death until 1 year before death; 30% increase in costs from age 65 to age 85

Author/ Country	Year(s) and Data	Age groups/ sample	HC sector	Dependent Variable	Method	Main Findings
Stearns and Norton (2004) U.S.	1992-1998 Medicare Current Beneficiary Survey	66-99 years N=22,100 Decedents and survivors	HC expenditure as obtained from claims data	HC expenditure (inflated to 1998 $)	Two part model 1st part: logit 2nd part: OLS	TTD negatively correlated with HC expenditure and age, omitting TTD leads to overestimation of HC expenditure by 9% (for current population) to 15% (for projected population in 2020)
Breyer and Felder (2006) Germany	Swiss insurance claims data (1999) and population estimates from the German Statistical Office up until 2050	Ages 30-95 years N=91,327 4% decedents, 96% survivors 1999 by at least 42 months	All HC costs covered by sickness fund	HC expenditure for HC covered by insurance	Two part model of individual HC expenditure	Impact of medical progress is much larger than the impact of ageing; Overestimation of future HC expenditure when using a naïve model found to be small compared to other research (~4%)
Polder et al (2006) Netherlands	1998-1999 Health insurance data linked to data on home care and nursing home use and cause of death	N~2.1 million Survivors and decedents (~16,000)	All medical care costs including hospitals care, pharmaceutical, nursing home care and home care	n/a	Descriptive study	Costs for decedents were higher than for survivors; costs for people dying young were higher than for older decedents; costs highest for deaths from cancer; projection showed 10% decline in growth rate of future HC expenditure compared to conventional methods

Author/ Country	Year(s) and Data	Age groups/ sample	HC sector	Dependent Variable	Method	Main Findings
Werblow et al (2007) Switzerland	1999 insurance claims data (Swiss Sickness Fund)	30-95 years N= 62,120 57000 alive, 5000 deceased Decedents and survivors	HC expenditure by components: ambulatory care, nursing home care, home care, hospital inpatient care, hospital outpatient care, prescription drugs, other services	HC expenditure for HC covered by insurance	Two part model 2nd part GLM	Age effect on total HC expenditure negligible for survivors and deceased, TTD positively related to HC expenditure, same effect for LTC users, apart from acute care provided to LTC users, which is driven by age
Hakkinen et al (2008) Finland	1998 Individual level linked data from various sources (cause of death statistics, social insurance institution, hospital discharge register)	40% sample of Finnish population aged 65+ in 1997 (N=285,317), follow-up for death until 2002 Survivors and decedents	Decomposition of health care expenditure into long-term care and non long-term care components	Costs deflated from 2000 to 1998 prices	8 models, first: likelihood of being LTC patient, remaining models estimated separately for LTC and non-LTC Two-part model (logit/probit+ OLS)	Projection of HC expenditure is overestimated by 13% if a naïve model, excluding remaining TTD was used.
Moorin and Holman (2008)	1997-2000; Death records for Western Australia linked to hospital records	N= 13,783 Decedents only (up to 3 years prior to death)	Acute hospital inpatient care in the last 3 years before death	Inpatient hospital costs based on Australian DRGs	Comparison stratified by cause of death, Lorenz curves to detect variation in costs within strata	Increase in costs associated with TTD, but magnitude of increase inversely related to age; irrespective of age costs increase in last 5 months of life

Author/ Country	Year(s) and Data	Age groups/ sample	HC sector	Dependent Variable	Method	Main Findings
Shang and Goldman (2008) U.S.	1992-1999 Medicare Current beneficiary Survey	N= 83,412 Ages: 65+ Survivors and decedents	All HC costs in claims data	Total HC expenditure (include programme spending and out-of-pocket spending)	Proportional hazard model to predict life expectancy, comparison of predictive power of age and life expectancy in explaining HC expenditure, HC expenditure lagged by one year to mitigate endogeneity	Age has little predictive power for HC expenditure after controlling for life expectancy, introducing life expectancy in addition to age results in lower projections of future HC expenditure

3.5.1 Econometric modelling framework

The 'Red Herring'

Zweifel et al (1999) were the first to apply advanced regression modelling to analyse individual level costs for the last two years before death. In this study the authors employed a Heckman sample selection model (Zweifel et al., 1999), estimating a decedent's probability to utilise HC services in the first modelling part using probit regression. From the first modelling part the inverse Mills ratio λ[6] was calculated. The second part of the model estimated positive HC expenditures (log transformed to mitigate skewness of the data) using OLS regression. The second part included the same set of regressors as the first together with the inverse Mills ratio λ.

The modelling framework used by Zweifel and colleagues (ZFM model) had provoked some criticism, the first being raised by Salas and Raftery (2001), who showed weaknesses in the ZFM model. Their main criticism was concerned with the possible multicollinearity with the inverse Mills ratio in the second part of the model estimation (Salas and Raftery, 2001). The same point of criticism had later been raised by Seshamani and Gray (2004a, 2004b). The authors established that if a Heckman sample selection model was used in the first step of the model estimation, the second modelling part would only be identified if the inverse Mills ratio showed a non-linear relationship with the remaining regressors, i.e. the modelling needs an 'exclusion restriction' with an explanatory variable that is significant in the selection part, but not in the cost estimation part of the modelling (Seshamani and Gray, 2004b).

For their analyses Seshamani and Gray (2004a, 2004b and 2004c) used data from the Oxford Record Linkage Study (ORLS), which is a longitudinal dataset for hospital

[6] The inverse Mills ratio denotes the ratio between the probability density function and the cumulative distribution function. It is applied in regression analyses were there is selection bias as first suggested by Heckman in 1976 who suggested application of a two-part model to account for selection bias, estimating the inverse Mills ratio in the first part (probit) and using the estimated result in the second modelling part (Heckman, 1976).

episodes in Oxfordshire, England. The dataset included people who were aged 65 and over in 1970 and died during the follow-up period until 1999. In order to highlight issues of model selection, the first part of this study replicated the ZFM model as closely as possible, but with differences in the cost variable. Seshamani and Gray (2004b) analysed hospital costs for acute and inpatient care (weighted average per diem costs, specific to each specialty), whereas Zweifel et al (1999) had used HC costs that are covered by the sickness fund and consequently included additional costs from other HC sectors. Another difference in the regression model was the absence of an indicator variable for individuals' insurance status, which is very specific to the Swiss HC system, but is not relevant for the UK's National Health Service.

A replication of the ZFM model (Heckman sample selection model) with ORLS data revealed that neither age nor TTD had a significant effect on hospital costs, although an increase in the value of coefficients for TTD could be observed as individuals approached the end of life (Seshamani and Gray, 2004b). Overall, the size of the effect of TTD on costs was similar in both studies with differences found in quarters one and two before death. This might, however, be attributable to different numbers of quarters being analysed in the ZFM model (eight) and by Seshamani and Gray (2004b) (20). Furthermore, differences in findings in terms of the significance of TTD could be attributed partly to the different HC sectors analysed, although it seems surprising that hospital costs should not be strongly related to TTD and that other HC sectors, such as primary care or pharmaceutical prescriptions should be more closely associated with TTD.

In the second part of their study, Seshamani and Gray (2004b) employed an extended two-part model introducing additional measures (cause of death and social class) for the first modelling part. These variables however proved to be significant in both parts of the econometric model and could therefore not serve as an exclusion criterion. The authors subsequently posed the question of the appropriateness of a sample selection model as

zero costs were treated as missing values in the ZFM model, where in actual fact these were observed rather than unobserved. They argued that truncating the data in this way may misinform actual budgeting for HC expenditure (Seshamani and Gray, 2004b).

Further criticism of the ZFM was related to the fact that quarterly cost observations were treated as independent from each other, not allowing for correlation between observations coming from the same patient. Seshamani and Gray (2004b) therefore proposed clustering by patient to derive more accurate standard errors. Results of their updated model, employing a two-part model rather than a Heckman sample selection model, including zero cost observations for decedents and accounting for correlation between observations coming from the same individual did show that age as well as TTD had a significant effect on hospital costs, emphasising the importance of correct model selection and highlighting methodological issues that can severely affect results. If correlations between observations are not accounted for, this would usually under-estimate standard errors and could lead to invalid tests for statistical significance. Accounting for correlations though effectively decreases the sample size and reduces power, however, it provides a correct measure of the standard errors. Seshamani and Gray (2004b) concluded therefore that results obtained in the ZFM model could not be generalised when using alternative datasets.

Seshamani and Gray (2004a) later extended their analysis and applied a panel data framework to the ORLS, rather than a cross-sectional framework, so as to adequately account for prior hospitalisations. This study confirmed results from their previous analysis and also revealed that the effect of TTD overshadowed the effect that age has on costs (Seshamani and Gray, 2004a, Seshamani and Gray, 2004b).

The ‘red herring’ updated

In subsequent research, Zweifel et al (2004) updated their analysis to address the criticism that had been raised regarding their econometric modelling approach. The authors agreed that the second part of a Heckman selection model is only identified when λ can be specified as a non-linear function of the regressors, which was not the case in their first analysis in 1999. Fundamentally however the updated ZFM model confirmed the ‘red herring’ argument (Zweifel et al., 2004). This confirmation was reinforced by further research using the Swiss data (Werblow et al., 2007, Felder et al., 2010).

The research undertaken by Seshamani and Gray and Zweifel and colleagues can be regarded as the most influential in this area, however other national studies have been undertaken that also used econometric regression methods to test the impact that TTD had on HC expenditure towards the end of life and whether age *per se* remained a significant predictor. In a U.S. study, Stearns and Norton (2004) also focused on the justification of including TTD into a model of HC expenditure predictions. They argued that longevity was increasing, which in turn led to HC expenditure at the end of life being postponed into the future, i.e. to older ages. The authors therefore concluded that if TTD were omitted from a model estimating HC expenditure, biased estimates would be obtained for future HC expenditure (Stearns and Norton, 2004). Using data from the US Medicare Current Beneficiary Survey (MCBS) on survivors and decedents aged 66 to 99 for the period from 1992-1998, costs were estimated for the last eight quarters of life. The modelling framework used in this study also employed a two-part model, as done by Seshamani and Gray (2004a and 2004b). For their second modelling part, (the cost estimation), the authors used OLS regression, arguing that they were interested in predictions on a monetary scale rather than a log scale. However, using OLS regression neglects the skewed distribution and the other characteristic of HC expenditure data as outlined in Section 3.4.

A recent study from Finland used individual level linked data representing a 40% sample of the Finnish population aged 65 and over in 1997, followed up until 2002 (Hakkinen et al., 2008). The authors had linked data available from a number of sources, which included survivors as well as decedents. To prevent multicollinearity and endogeneity, costs were studied in one year and TTD was measured from the end of that year as a single explanatory variable (lagged). This also allowed inclusion of patients that survived until the end of the follow-up period. The authors decomposed costs into several components: LTC and non-LTC and estimated eight different models with the first one estimating the likelihood of being an LTC user. Estimating separate models they found that total expenditure for both LTC and HC rises with age, although the association is weaker when controlling for TTD (Hakkinen et al., 2008).

It could be argued here that by estimating separate models Hakkinen et al (2008) might be ignoring any substitutional or complementary pattern of HC resource use. This could potentially lead to an overestimation of the separately modelled effects and a systems approach such as 'Seemingly Unrelated Regression' (SUR) might have been a better estimator to capture potential simultaneous effects. The separate equations might be related through correlation in their error terms, i.e. decisions about accessing different HC services are not made independently from each other.

Very recent research has been carried out in the Netherlands which tests whether the 'red herring' argument holds for disease specific expenditures in the same way as it does for overall inpatient care costs or a variety of HC costs (Wong et al., 2011). Separate two-part models were run for different diseases (94 in total), and the results showed that the effect of TTD remained for most diseases and was strongest for patients with cancer. There were however varying degrees of influence of TTD and age on HC expenditure. Wong et al analysed separate datasets for different diseases, which means that patients, who were admitted for different diseases appear in different datasets with their respective costs allocated. The authors then estimated separate

Generalised Equation Estimation (GEE) models (Wong et al., 2011) to account for correlated observations, coming from the same patient.

One point of criticism that needs to be raised is that Wong and colleagues (2011) used different datasets for different morbidities. This would not take into account admissions for patients that suffer from multiple chronic conditions and whose hospital episodes would consequently appear in different datasets, ignoring that these observations are related as they come from the same patient. The impact and rise of multiple morbidities and their related costs is a very topical issue (Caughey et al., 2008, Aspin et al., 2010) and not controlling for it possibly underestimates the impact that co-morbidities might have on costs incurred. It could therefore be argued that any analysis should avoid splitting the data by disease area, something that will be taken into account in the empirical part of this thesis.

3.5.2 Sample selection

The selection of a sample to be analysed appears to be mainly driven by the availability of data to examine the effect that age and TTD have on HC expenditure. Table 3.2 shows four groups in any population/sample for any given period. It includes those who use HC services, those who do not utilise (or at least are not observed to utilise) HC services, and those who die and those who survive.

Most studies, because of the nature of their data, only consider a selection of the quadrants and not all four groups.

Table 3-2 Population groups

	HC utilisation	No HC utilisation
Decedents	Decedents who utilised HC services	Decedents who did not utilise HC services
Survivors	Survivors who utilised HC services	Survivors who did not utilise HC services

For example, in the initial ZFM model, only decedents' costs were analysed for periods with positive HC utilisation, excluding periods in which no utilisation could be observed. Zweifel *et al* (1999) acknowledged that the exclusion of deceased individuals, who did not incur costs in their last two years of life, may bias results: sick individuals, who are likely to incur higher costs, may be over-represented. They argued however that this bias would only be relevant if the inverse Mills ratio λ (which had been included to account for potential selection bias, which may have been caused by excluding zero cost observations), turned out to be significant in the second part of the model. If the sample selection test is non-significant though, Zweifel et al suggested that the exclusion of zero cost observations for decedents would not cause bias. Even if there was bias, the authors argued this would be corrected by including λ in the second part of the estimation.

Salas and Raftery (2001) on the other hand argued that selection bias could have been caused due to the exclusion of decedents with zero cost observations. To correctly inform budgeting procedures and resource allocation it appears important to include zero-cost observations and so to prevent selection bias. If the sample selection process is observed rather than unobserved, excluding zero costs results in missing data rather than a reflection of the underlying selection process. Seshamani and Gray (2004a, 2004b) later reinforced this criticism and proposed an updated model, which also included zero cost observations for decedents.

The exclusion of zero cost observations is a two-fold issue, which has not been made entirely clear in the above studies: Individuals will have periods in which they do not incur HC costs. Depending on the observational unit for TTD (years, quarters or months) these periods will need to be assigned zero costs. Another layer to this is that there will be individuals, who do not appear in resource use data at all, since they never accessed HC services (over their entire life, or over the observational period the administrative dataset spans). If these individuals are to be included in an estimation of costs incurred before death survey data is required to obtain demographic data. These are two different issues and both are informative and need to be taken into account. This thesis addresses this by using survey based datasets, which provide baseline characteristics for individuals who do not appear in resource use data, thus facilitating estimation of costs on a population level and avoiding sample selection and possible bias.

3.6 Health care sectors

Another factor that separates TTD studies in terms of their methodology is the HC sector that has been analysed in order to draw conclusions about the relationship between TTD, population ageing and costs. A much higher proportion of zero costs would be expected to be observed for acute inpatient care than for primary care, which is usually provided by General Practitioners (GP) who, in the case of the UK, control a large part of the access to hospital care. Huge variations would also be expected for the impact that age might have on expenditure for LTC and the impact it might have on expenditures for other HC services. Also the organisation of the provision, especially LTC, may influence any inference that can be made in terms of costs. For instance in Scotland, where LTC provision does not lie within the remit of the NHS, but is organised and provided by regional councils, costs are not borne by the NHS. This may only be a ‘spreadsheet exercise’ as costs have to be paid through public funds nevertheless, but it

is important to be aware of these distinctions when analysing expenditures for an ageing population in different institutional HC settings and different countries. Further differences in results might be attributed to the inherent differences between an insurance based HC system, as found in the U.S., where HC facilities are largely owned by the private sector and a publicly provided HC system funded through taxation, as found in the UK. Both systems create very different incentives for HC providers, which will impact on both, delivery and costs of HC.

Referral schemes in different HC systems will also have an impact on resource utilisation. The UK's GP gate-keeping system serves as a 'barrier' to accessing secondary care, a fact that will in all likelihood have consequences on the first part of a two-part model, where the probability of accessing HC services is estimated. GP's gate-keeping function will affect different HC sectors differently. Notably, different national referral schemes can not have been taken into account by researchers who have analysed aggregate country level data, something that could have affected results. This provides another argument for the analysis of individual level data within a HC setting, i.e. country. It might even provide justification for TTD studies to be undertaken for each country separately and tailored to their specific HC settings and other observable or unobservable characteristics of a) individuals within a country/ethnicity etc. and b) the HC system.

Zweifel et al (1999, 2004) utilised individual level data from Swiss sickness funds and therefore the included HC sectors and related costs were very comprehensive. The majority of other research however concentrates on the most expensive sector of HC provision; that of hospital care (Batljan and Lagergren, 2004, Busse et al., 2002, Culler et al., 1995, Graham and Normand, 2001, Henderson et al., 1990, Himsworth and Goldacre, 1999, Lowe, 2005, Moorin and Holman, 2008, Seshamani and Gray, 2004b, Wong et al., 2010, Wouterse et al., 2010, Wouterse et al., 2011, Wong et al., 2011).

A number of studies also analysed the effect that population ageing and TTD had on LTC (Riley and Lubitz, 2010, McGrail et al., 2000, Spillman and Lubitz, 2000, Schulz et al., 2004, Weaver et al., 2008, de Meijer et al., 2011). Results from studies analysing hospital care (see above) showed that TTD seemed to be an important predictor for HC costs and that the effect that age had on costs was reduced when TTD was accounted for. However this effect looked somewhat different for the LTC sector. McGrail et al (2000) reported costs for acute medical care to rise with increasing age for the survivor group, while costs seemed to decrease with increasing age for the deceased group. Costs for social and nursing care however were found to increase with age for both survivors and decedents. After adding the additional costs for social and nursing care to medical care costs, the authors still found decreasing total costs with age for decedents, but this decrease was much smaller than for acute medical costs alone (McGrail et al., 2000). In general, the authors supported the finding that TTD is a much stronger factor in determining HC costs.

O'Neill et al (2000) studied costs that were incurred in primary care (GP services) in a sample of nursing home residents and compared these to a sample living in the community, matched by age and sex. The authors found that among decedents, age was an insignificant predictor for GP costs, but TTD showed a significant association with costs. Although supporting conclusions drawn from Zweifel et al (1999) that TTD was a better predictor for HC expenditure than age (O'Neill et al., 2000), limitations of this study must be noted. The sample size was very small (N=52 for nursing home residents) and nine GP practices opted in to take part. It could be argued that this sample was not representative of the entire nursing home population in the UK and that sample selection bias might have been present. The small sample could also have had an effect on the power the statistical model possessed, rendering possible significant factors insignificant.

A number of studies that have analysed data from the U.S., i.e. the Medicare Current Beneficiary Survey (MCBS) have included total HC costs, which in this case encompassed costs for inpatient and outpatient care, costs for physicians, pharmaceuticals, home and hospice care. It also included – on top of the costs borne by the programme, cost that had to be paid out-of-pocket (Shang and Goldman, 2008, Hogan et al., 2001, Stearns and Norton, 2004). These studies have not necessarily undertaken separate analyses for these different cost components, but it should be noted that these are included in their overall costs that were estimated.

3.6.1 Costing methods

The choice of an appropriate costing method will mainly depend on the HC sector analysed. Costing methods differ between national studies, and the availability of alternative methods within a country makes this a very important methodological issue to consider.

For acute inpatient care, Busse et al (2002) used LOS as a proxy for HC expenditure (Busse et al., 2002). This would only provide meaningful results if the costing method chosen is based on per diem costs, i.e. the cost increases proportionally with LOS. Per diem costing neglects the fact that treatment intensity will vary with LOS and a proportion of costs incurred will be fixed and another proportion will vary with LOS.

The costing method used by Zweifel et al (1999 and 2004) was not explicitly explained, however as the authors used health insurance claims data, this will have been aggregated costs over a range of HC services including different methodologies of assigning a unit cost to a specific service (Zweifel et al., 1999, Zweifel et al., 2004). Hakkinen et al (2008) used the average cost per inpatient day specific to each DRG (NordDRG) (Hakkinen et al., 2008).

The analysis undertaken by Seshamani and Gray (2004a) employed expenditure data from the Department of Health, which were weighted average costs per inpatient day, specific to the specialty the patient was admitted to. These per diems were then aggregated to provide a yearly cost for each year before death. Per diem costs for inpatient care were also employed by Sato and Fushimi (2009), who analysed the impact of TTD, age, and LOS on HC expenditure (Sato and Fushimi, 2009). If per diem costs are employed and fixed and variable components of a hospital stay are not taken into account, it is likely that costs might be overestimated due to the assumption that the first day in hospital is as expensive as any subsequent day, which may not prove correct.

Generally, each costing approach will have advantages and disadvantages. Per diem costing doesn't account for the fixed and variable components of a hospital stay. In contrast a DRG or HRG costing approach is usually insensitive to small variations in LOS that do not exceed a trim point value.

The choice of an appropriate costing method therefore adds an important methodological angle to this research field. Varying results between national studies might be partially explained by varying costing methods. This thesis further highlights these issues in Chapter 4, by testing alternative methods of costing hospital episodes statistics, which uses the same HC sector and the same sample and still shows important differences. Operating across a variety of HC settings in different countries and costing methods as done in the literature presented above is very likely causing issues of results not being comparable between studies, something that should not be surprising.

3.7 Survivors in TTD studies

Another recurring issue in TTD studies is how to account for censoring and the resulting surviving part of the sample population. If the analysis of the relationship between ageing, TTD and HC expenditure is to aid resource planning and resource allocation at a population level, the sample ought to be representative of the population in question. The exclusion of survivors may lead to an overestimation of costs. If in any given year (or any other period) only costs for those individuals that will die during this period are considered, and costs for people who survive that period are neglected, estimated HC expenditure may not be a reflection of costs actually incurred by a population. If estimates based on decedents only were then to be used to project HC expenditure for future periods in order to obtain estimates of future HC demand, these projections may also be incorrect. The sample therefore ought to represent survivors as well as decedents in any given period.

As raised by Hakkinen et al (2008), the effect of age on HC expenditure may be different for survivors and decedents (Hakkinen *et al*, 2008, pg.170). It could be argued that there would be selection bias if only decedents were included. In addition, the inclusion of survivors increases the sample size and therefore the power for any econometric model. If there was HC rationing, depending on the survival prospect of individuals, this would result in a difference between survivors and decedents and should be accounted for in any analyses. One further reason that might distinguish survivors from decedents is the difference in treatments they will receive, which arises from advances in medical technology over time. Survivors live to experience medical care later than decedents, hence the chance for survivors to utilise more advanced therapies, pharmaceuticals and clinical knowledge.

In a longitudinal TTD study with an official study end, where death of participants can be observed, participants without an observed date of death (survivors) during the

observational period are typically right censored. Consequently, any HC costs that are observed at the end of the study are not necessarily HC costs at the end of life. The remaining TTD of survivors and therefore any HC expenditure incurred between the official end of the study and their death are unobserved (right censored). The length of time between entry into the study and in this case, death is unknown. Given entry at time 0 and observation at time t, all that is known is that the completed time in the study is of length T > t.

3.7.1 Addressing censoring of survivors

The issue of survivors' unknown TTD has been addressed by a variety of methods. A number of studies that have looked at the relationship between TTD, age and HC expenditure have done so by excluding survivors from their analysis (Zweifel et al., 1999, Felder et al., 2000, Moorin and Holman, 2008). It could be argued here that these studies have avoided the issue of survivors' censored TTD rather than addressed it adequately. Some studies that have included survivors have done so mainly for descriptive analysis, comparing decedents' with survivors' HC expenditure (Polder et al., 2006, McGrail et al., 2000, Busse et al., 2002).

For the analysis carried out using the ORLS, survivors were excluded due to the fact that there were very few individuals without a death record at the end of the observational period, most of which had migrated (Seshamani and Gray, 2004a; 2004b; 2004c).

Hakkinen et al (2008) estimated the relationship between TTD, age and HC expenditure for two groups of individuals: LTC and non-LTC individuals. Notably Hakkinen et al raised the issue that the effect of age on HC expenditure may be different for survivors and decedents. They note that their approach "is extended to include patients who survive to the end of the follow-up period, since concern has also been that the effect of age may be different for the survivors than it is for the deceased" (Hakkinen *et al*,

pg.170). Therefore survivors had been included by means of studying HC expenditure in an initial year (1998) and measuring TTD from the end of that year until 2002, observing decedent and survivor status until 2002. However, survivors were still censored at the end of follow-up and their TTD remained unknown.

An exploratory study undertaken in Scotland by Graham and Normand (2001) used Scottish Morbidity Records (SMR01) linked to death records from the GROS. Their data were split into separate datasets for decedents and for survivors. Further stratification of the cost data by age and sex facilitated comparison of effects that a changing age structure had on costs. Their results showed that acute HC costs for survivors increased with increasing age, whereas costs for decedents decreased with increasing age. This seems to confirm the concerns raised by Hakkinen et al (2008) above.

Stearns and Norton (2004) include dummies for quarters until censoring for survivors instead of quarters until death and analysed survivors alongside decedents. These quarter dummies were also interacted with age, analogous to interacting TTD with age. TTD and age interaction terms take account of the fact that TTD affects HC expenditure differently for different age groups. In their analysis the authors used MCBS data and specifically the ‘Cost and Use’ files for the years 1992 to 1998. Respondents aged between 66 and 99 years were included and costs observed at a quarter-person level.

Breyer and Felder (2006) assumed a constant TTD for all survivors in their study that analysed the impact on HC expenditure that population ageing could have in Germany. To do this they used a Swiss data set to obtain HC expenditure profiles stratified by gender and survival status, i.e. survivors vs. individuals in their last 4 years of life. In order to impute a TTD for survivors the authors set TTD as being one month greater than the entire observational period (Breyer and Felder, 2006). The authors compared a model with age as predictor for HC expenditure, a model also including TTD and a model accounting for a technology driven increase of costs (1% annually) and found

small differences between the 'age' and 'TTD' model, but a rather large impact that advances in medical technology would have.

Lastly, Wong *et al.* (2011) modelled decedents and survivors separately in order to deal with different age patterns between these groups. Although they included survivors in their sample, they excluded their TTD and only included a dummy variable for the year of admission to hospital. The authors then generate 'deceased/survivor' ratios for every specific disease they investigate for different age groups and found that TTD was a significant predictor for HC expenditure for most diseases and strongest for cancer (Wong et al., 2011).

Other studies that have included survivors have used a variety of methods, from simple descriptive analysis to interactions and separate regression analyses. This makes it difficult to draw comparative conclusions.[7]

In summary, various approaches have been employed to deal with the unknown TTD of survivors in a sample. Excluding them from the analysis could lead to an overestimation of costs, since at any given age, HC expenditure was found to be higher for decedents than it was for survivors (Graham and Normand, 2001, Hakkinen et al., 2008). Employing a constant TTD (acknowledging survivor status but adding a constant period beyond the censoring date) neglects individual characteristics of survivors. The approach of treating them as if they were deceased (using their censoring date as date of death, but accounting for survivor status) also carries the risk of not correctly estimating costs, since any observed costs for survivors can not be attributed to a particular period before death. This limited consistency and generalisability makes comparisons across the studies very difficult. It seems that an approach that could predict survivors remaining life time would add to solving this methodological issue.

[7] This is further complicated by those studies which despite obviously including survivors do not explicitly state how the unknown TTD for survivors is handled, see for example Pavlokova (2009)

Shang and Goldman (2008) realised these shortcomings and investigated a method that might rectify weaknesses from previous research. The authors investigated whether age or life expectancy drives HC expenditure and argued that for any HC expenditure forecasting exercise a prospective method should be employed based on a cohort that is alive at the time the research is undertaken. Based on data from the 1992-1999 MCBS the authors estimated hazard models to predict remaining life time and then used regression analysis to test the predictive power that life expectancy and/or age had on HC expenditure. Predicted life expectancy was based on demographic characteristics as well as health status simulating a survival curve for each individual. Simulation was repeated until the mortality rate was close to one and life expectancy was calculated as the area under the curve.

TTD for each individual was predicted using a random draw to determine an individual's death in the next period. If predicted mortality from the previous step was greater than the random draw that individual was predicted to die in the next period. The random draw process was repeated until every individual in the sample died. TTD was then calculated as the difference in years between entering the study, i.e. the interview date and the year of death. The authors found that predicted TTD had a much larger variance than predicted life expectancy. Actual TTD may contain information on unobserved characteristics, which could not be controlled for in estimations. The authors therefore judged predicted life expectancy to be a better predictor for HC expenditure. Shang and Goldman (2008) also compared the distribution of predicted TTD obtained from hazard models with the distribution of TTD obtained from life tables and found these to be very close. The distribution of predicted life expectancy obtained from hazard models however was found to be very different from the distribution of TTD.

Shang and Goldman's (2008) approach is extended in this thesis insofar that a comparison of the magnitude at which estimated costs differ, when employing alternative methods of correcting for survivors' unknown TTD is made. Results are also

expected to reveal differences in the association between costs and covariates and so reveal to what extent cost estimates are influenced by sample selection.

3.7.2 Endogeneity between HC expenditure and TTD

One frequently identified issue with TTD studies is the possible endogeneity between HC expenditure and TTD. Salas and Raftery (2001) were the first to raise this and based their discussion on results shown in Zweifel et al (1999), who had argued that age *per se* did not influence HC costs once TTD is controlled for. The authors argued that these results would hinge on the assumption that TTD was exogenous, i.e. HC expenditure had no effect on remaining life expectancy. This assumption may not hold and the reverse may seem more likely. Individuals seek medical care and medical interventions are aimed at prolonging and saving individuals' life. Therefore, Salas and Raftery (2001) argued that if HC was sought in any given period of observation, this must clearly affect an individual's health status in that period and might therefore also determine their remaining life expectancy. TTD would thereby be influenced by current and previous HC expenditure. Estimates might consequently be biased and inconsistent and standard errors will be incorrect (Salas and Raftery, 2001).

To rectify this econometric modelling weakness, the authors recommend that if TTD is not strongly exogenous, and lagged HC expenditure is uncorrelated with the error term, that lagged HC expenditure can 'Granger-cause'[8] TTD and may therefore be used as an instrumental variable (IV). This would require the lagged dependent variable (HC expenditure) to be orthogonal to the error term. This assumption could not hold however if unobserved time-invariant individual characteristics (disease etc) are likely to influence HC expenditure (lagged and non-lagged) (Salas and Raftery, 2001). To reduce the

[8] Granger causality is inferred when lagged values of a variable x have explanatory power in a regression of a variable y on lagged values of y and x. If lagged values of a variable x have no explanatory power for any of the variables in a system, then x would be viewed as weakly exogenous GREENE, W. (2008) *Econometric Analysis*, Pearson Prentice Hall.

problem of endogeneity, Zweifel et al (2004) adopted a quasi- instrumental variable (IV) approach that was suggested by Salas and Raftery (2001).

Stearns and Norton (2004) in their study also acknowledged the problem of endogeneity and suggested the application of a fixed effects model. This approach was based on their reasoning that endogeneity bias was mainly caused by correlations in the error terms between simultaneous equations. A fixed effects model should control for unobserved time-invariant characteristics and reduce correlations in the error terms. The authors also acknowledged methods of using lagged values etc, but did not employ these for their specific analyses (Stearns and Norton, 2004).

In an updated analysis, Felder *et al.* (2010) concentrated on the endogeneity problem and agreed with criticism that had been raised previously and rejected an exogeneity assumption of TTD and HC costs (Felder et al., 2010). Their most recent analysis of the 'red herring' hypothesis concentrated on testing instrumental variables that could purge TTD off its endogeneity. The authors used an extended dataset, including 60,000 individuals. Death was observed for some individuals (11%) from 2000-2006, and costs were observed from 1997 and 2006. Felder *et al*. (2010) used the first three years of observed HC expenditure (1997, 1998 and 1999) and TTD for the following three years (2000, 2001 and 2002) to calculate estimated TTD values for the years 2003-2006. These estimated values were then used to replace observed values for TTD to estimate HC expenditure for 2003, i.e. the authors used lagged (by three years) explanatory variables to explain more recent HC expenditure. They found that although the instrument failed the Hausman exogeneity test, TTD retained its explanatory power, leading the authors to conclude that even if it was not possible to entirely purge TTD of its endogeneity, the 'red herring' hypothesis could still be confirmed (Felder et al., 2010).

Shang and Goldman include life expectancy instead of TTD in their analysis (Shang and Goldman, 2008). The authors argued that this would solve the problem of endogeneity

to some extent as the predicted life expectancy in year *t* was based on demographics and health status in year *t* and was not correlated with HC expenditure after year *t*. Actual observed TTD however would not solve this problem (Shang and Goldman, 2008).

None of the above studies reached an entirely satisfying conclusion on how to account for the possible endogeneity between TTD and HC expenditure. And although attempts have been made it did not seem possible to purge TTD of its endogeneity. This thesis therefore assumes exogeneity of TTD throughout the analyses.

3.8 HC expenditure projections

To complement this review of the main contributions to the research field, the following section discusses those studies that have analysed population ageing and the impact this might have on future HC expenditure using a simplified approach by assuming constant age profiles for HC expenditure and studies that have used remaining TTD in addition to demographic changes in order to project future HC costs.

3.8.1 HC expenditure projections: constant age profiles

This simplified method to calculate the effect that changing demographics may have on future HC expenditure decomposes current HC expenditure into expenditure by age or age groups. Earlier research mainly looked at how much spending for HC varied by age group and found that per capita spending increased steadily with age for most HC sectors (Fisher, 1980). Fisher's research on population ageing and HC expenditure showed that a disproportionate amount of money was spent on providing HC to the elderly (Fisher, 1980). Fisher analysed three factors that constitute total expenditure on HC: the number of contacts with HC providers (number of hospital episodes, LOS), the

intensity of the contact (number of treatments), and the price of the service provided. Analysing different HC sectors, he found that for the sector of hospital care, elderly people had longer stays than younger individuals, but that the intensity of care was less. Fisher (1980) therefore concluded that volume, i.e. number of episodes and LOS were the dominant factors that caused the observed differences in HC spending by age groups. These results have led the author to predict an increasing financial burden for HC policy and financing, especially with the share of elderly people increasing and the share of younger people, who incur less costs decreasing.

Fisher's findings have partly been confirmed by further research undertaken in Sweden in the 1970s and 1980s (Gerdtham, 1993). In the absence of exact measures of HC utilisation by different age groups, researchers have reverted back to using age-specific number of bed days per capita. But this could lead to an overestimation of costs for the older age groups as their expenditure per bed day is lower on average compared to younger age groups (Gerdtham, 1993). Fisher (1980) had already pointed out that the intensity of care is less in older ages.

Other research involves the projection of HC expenditure in order to quantify the future demand of HC. Using the population numbers in each age group, expenditure was decomposed into expenditure per capita. To project HC expenditure into the future, current or historical HC expenditures are multiplied by the projected number of people in each age group. Current and projected HC expenditures can be compared and the difference is attributed to population ageing, i.e. the ageing effect. This method has been widely used (Dang et al., 2001, Jacobzone, 2000, Serup-Hansen et al., 2002).

Dang et al (2001) undertook a very comprehensive study including a number of countries and analysing HC and LTC. According to the authors' findings, expenditure on HC and LTC in a number of OECD countries are expected to increase from 6% of the GDP in 2000 to 9.3% of the GDP in 2050. Population ageing would be responsible for

55% of this increase (Dang et al., 2001). A slightly lower projection had been calculated in a study from the Economic Policy Committee in 2001, which analysed HC and LTC spending for European countries and predicted an increase from 6.6% in 2000 to 8.8% in 2050, which reflects an increase due to demographic changes of 33% (Economic Policy Committee, 2001).

This purely demographic method of extrapolating HC expenditure possesses a weakness that was pointed out earlier in this chapter: it assumes that any given age group is expected to consume the same amount of HC in the future as they are currently consuming. Under the compression of morbidity assumption, however, a downward shift of the age profiles of HC expenditure would be observed, i.e. HC expenditure might be observed to decrease over time at any given age. At the same time, if morbidity levels are reduced, reduced mortality rates at any given age can be observed as mortality is shifted to older ages, so that the demographic method might not be projecting HC expenditure correctly, since the mortality component is ignored. If remaining TTD as an indicator of an individual's health status is not accounted for, constant age-expenditure profiles are assumed.

Many researchers have raised the issue of an overestimation of future HC costs if constant age-expenditure profiles are assumed and have highlighted advantages of being able to capture changes in morbidity over time when employing econometric techniques of analysing the association of costs, TTD and demographic indicators and also using longitudinal data to do so (see Payne *et al*'s (2007) review of the TTD literature).

3.8.2 HC expenditure projections: accounting for TTD

In their descriptive analysis of the cost of dying and subsequent projection of HC costs, Serup-Hansen et al (2002) found that age still played an important role when estimating future HC expenditure. Using a random sample of the Danish population (19%) the

authors first used the cohort-component technique to project demographic changes. These data are generally available from national statistics in varying precision in terms of either providing projections for age groups or single years of age. Serup-Hansen and colleagues (2002) then employed two methods to project HC expenditure. The first, traditional method assumed that costs were a function of age and sex, whereas a second, improved method assumed costs to be a function of TTD as well (Serup-Hansen et al., 2002). Average costs per person, where calculated for each age and sex stratum, irrespective of TTD, i.e. irrespective of whether an individual had died. These costs were ultimately assigned to the projected population to obtain projected costs under the traditional approach. The improved method calculated costs in the same way, but separately for survivors and decedents and assigned obtained costs to projected population numbers in the future. The authors found HC expenditure to increase by 18.5% (1995-2020) using the traditional method, whereas an approach accounting for remaining TTD revealed a 15.1% increase in future HC expenditure (Serup-Hansen et al., 2002).

One further study that used extrapolation adjusting for TTD to calculate future costs was carried out in the Swedish region of Skane (Batljan and Lagergren, 2004). The authors argued that a simple demographic extrapolation to forecast future HC demand was based on the assumption that changes in the total number of individuals in a certain age group determined the extent of service need (Batljan and Lagergren, 2004). Their analysis was based on inpatient and outpatient care utilisation data and compared ratios for HC expenditure for different strata (age, sex, year before death). Results showed that less than 1% of their sample within their last year of life were responsible for about 11% of the total annual HC expenditure for inpatient care. Projecting HC expenditure the authors compared a simple extrapolation with their mortality adjusted demographic extrapolation and found these to be markedly lower (Batljan and Lagergren, 2004).

Seshamani and Gray (2004c) used age-specific per capita HC expenditure from the Department of Health and population projections by single year of age from the Government Actuary's Department, England (Seshamani and Gray, 2004c). These population numbers were stratified by age and sex group and also by remaining TTD. From their econometric model, the authors predicted yearly per capita HC expenditure for individuals aged 65 and older (their sample). They then multiplied these with projected population numbers in each sex, TTD and age groups and so obtained cost estimates for the years 2008-2026 under the TTD approach. Seshamani and Gray found that using this approach provided an annual growth rate of 0.40%, which was half the growth rate than that obtained from their comparison projection, which only analysed expenditure changes associated with increased life expectancy and did not account for TTD (Seshamani and Gray, 2004c).

Stearns and Norton (2004) found that the exclusion of remaining TTD from a cost prediction model led to higher cost estimates compared to a model that included TTD. They also explored the magnitude at which HC expenditure may be overestimated if TTD is not controlled for. Estimating two models, one including TTD quarter dummies and one, excluding these measures they found predictions for HC costs to be 9% higher for a model that did not include TTD using current life tables and 15% higher for projected life tables in 2020 (Stearns and Norton, 2004).

Breyer and Felder (2006) combined their utilisation data from Switzerland and population projections from Germany to estimate the demographic impact on HC expenditure until 2050. To do this, the model was calibrated to reflect German HC expenditures (Breyer and Felder, 2006). The authors projected costs under two assumptions, first a naïve method, where only the age structure changes and second, an extended method that takes account of higher costs in the last year of life. Breyer and Felder (2006) found that the first method projected a 23.9% increase in HC expenditure by 2050, whereas the second method only projected a 19.5% increase.

They found however that the increase in HC expenditure that would be due to advances in medical technology would outweigh the rather small effect that would be found when excluding the cost of dying (Breyer and Felder, 2006).

Slightly different results in terms of the magnitude of overestimation of costs if TTD was excluded from expenditure projections were found in a more recent study undertaken by Hakkinen et al in Finland (Hakkinen et al., 2008). The authors estimated a 13% lower projection for total expenditure (HC and LTC) when including TTD, compared to a model that does not include TTD. These results are in line with projection results from other studies, which consistently range from a 9-15 percent lower expected expenditure when TTD is incorporated as compared to analyses, which do not account for remaining life expectancy (Payne et al., 2007).

In general, HC expenditure projections that are based on the inclusion of TTD when HC estimates are obtained, are based on the assumption, that decedents and survivors are different and incur different costs in any period. It is also based on the fact that mortality rates change over time and fewer individuals are observed to die at any given age in the future.

3.9 Scottish studies

The research in Scotland that has investigated the relationship between population ageing, death and HC expenditure is limited and provides scope for a detailed analysis as undertaken in this thesis.

The first research undertaken in the West of Scotland analysed the pattern of hospital utilisation for an ageing cohort employing data from the Renfrew/Paisley study as one of the Midspan studies (Hanlon et al., 1998). The authors analysed baseline risk and

combined these data with subsequent hospital admission data over a follow-up period of 23 years. In their descriptive analysis they also examined acute hospital use before death and found that decedents had a higher number of hospital episodes. Hanlon et al (1998) detected an increasing demand for hospital services over time for the cohort analysed. 42% of all acute admissions for decedents were in the last 12 months of their life and 33% in the last six months (Hanlon et al., 1998).

Graham and Normand (2001) conducted an exploratory study using Scottish Morbidity Records (SMR01) linked to death records from the General Register Office for Scotland to investigate the variation of utilisation of acute hospital services by age, TTD and other explanatory factors (Graham and Normand, 2001). Their data were split into separate datasets for decedents and for survivors. Further stratification of the cost data by age and sex facilitated comparison of effects that a changing age structure had on costs. The dataset for decedents had information on people, who had died in 1999 and their hospital admissions for the 12 months preceding their death. The dataset for survivors included people, who did not have a death record, but had at least one episode of acute hospital care in 1999 and information for the last six months of 1998. Graham and Normand (2001) assumed that the rest of the population did not utilise HC during that period.

Analysing HC expenditure for decedents and survivors separately, Graham and Normand (2001) found that acute HC costs for survivors increased with increasing age, whereas costs for decedents decreased with increasing age. Graham and Normand (2001) also analysed variations in these patterns by different socio-economic groups and found significant differences in costs incurred by survivors or decedents between deprivation categories and by age group. Costs for hospital care were found to be significantly higher for decedents at younger ages that were living in the most affluent areas compared with decedents at younger ages from the most deprived areas. From the age of 75 however, people from more deprived areas became more expensive than

people from more affluent areas. The analysis of differences between health boards revealed significant differences in costs as well. Results from this study have not been published in peer-reviewed journals, and can only be found in their final report to the Chief Scientist Office (CSO) (Graham and Normand, 2001).

No detailed description of the statistical methods and/or econometric modelling used by Graham and Normand (2001) is provided in their CSO report, so no discussion about these methods can be made here. No information can be found on how zero cost observations have been dealt with. Although the report stated that decedents are less expensive than survivors it does not explicitly show how HC expenditure develops as people approach death. The costing method used, seems to be based on specialty specific costs, leaving scope for the introduction of more precise measures of costs that are based on disease classifications rather than the specialty patients were admitted to. Using specialty specific costs means that there is a set of costs for 50 specialities only. Compared to using costs that are disease and treatment specific this does not offer much variation. Although Graham and Normand (2001) provided some initial important results in this research field for Scotland, they also left scope for extensive future research in this area.

Other unpublished research that utilised Scottish data was undertaken by Murray Lowe in 2005 for the purpose of a MSc dissertation (Lowe, 2005). The author used a similar dataset to the one analysed by Graham and Normand but for a later time period and only analysed data for one Health Board region in Scotland, Ayrshire and Arran. Linking SMR01 data to death records the association between TTD, ageing and HC expenditure was estimated following the methodology employed by Seshamani and Gray (2004b). The sample population consisted of people, who were aged 65 and over at the beginning of 1981 and who subsequently died during the follow up period until the end of March 2004. Consequently, the sample only includes decedents with hospital

episodes between 1981 and 2004. HC expenditure was measured on a yearly basis and the last five years before death were analysed.

To account for differences in costs and utilisation by socio-economic status SIMD (Scottish Index of Multiple Deprivation) quintiles were used as one explanatory variable in regression modelling. The costing method employed to estimate HC expenditure was that of applying specialty specific per diem costs multiplied with individual episode LOS to derive a total cost per episode. These costs were then aggregated to obtain a yearly cost variable. The author acknowledged the potential problem of endogeneity of TTD but assumed exogeneity for the analysis. Including zero-cost observations for years without hospital utilisation, Lowe (2005) employed a two-part model to estimate HC expenditure, conditional on positive utilisation.

Results showed a significant association of age and TTD with HC expenditure. The author found a steady increase in costs as individuals approached death with costs being 78% higher for someone in their last year of life compared to an individual five years away from death. Although age at death also was a significant predictor for costs, the effect was less pronounced than that of TTD, with one additional year leading to an increase in costs by 4.45% (Lowe, 2005). Lowe also found significant effects on costs by socio-economic status, the health board of residence and the principal diagnosis.

Similar to Graham and Normand (2001), Lowe's (2005) study also leaves scope for further analysis. Although econometric modelling techniques used here are more advanced than those (apparently) used in Graham and Normand (2001), the author did not include the surviving part of a population. The costing method employed by Lowe (2005) uses specialty specific per diems. Although having the advantage of being very sensitive to small variations in LOS, per diem costing does not account for the nature of a hospital stay as explained earlier. Alternative costing methods could be explored in order to account for the fixed and variable cost components of a hospital stay. In the

absence of a survey based dataset that could have been linked to hospital admission records, the author also misses the opportunity to account for individual baseline characteristics that could prove important in explaining future HC expenditure.

3.9.1 Recognition of TTD in policy

In its second report ‘The future care of older people in Scotland’, the Range and Capacity Review Group for the Scottish Executive (Scottish Executive, 2006) emphasized the predictive power of TTD for future HC expenditure, based on published work from Seshamani and Gray (2004b). The researchers argued that if the assumption of improved levels of age-specific health holds, the impact that an ageing population might have on the demand and consequently the cost of acute HC services could be weakened to some extent. The authors also claimed that this pattern may look very different when the effect of an ageing population on the demand for social or long-term care were analysed and that the above research findings could not easily be applied to the LTC sector.

Based on published evidence from the UK and other countries, in his report for the HM Treasury in 2002, Derek Wanless acknowledged that the cost for acute care services is strongly related to TTD, regardless of age at death (HM and Treasury, 2002). This review took account of demographic changes in the UK by developing three different scenarios of population growth, life expectancy and morbidity. When modelling utilisation and costs of acute hospital care a split is made between people in their last year of life (decedents) and people not in their last year of life (survivors) in order to incorporate TTD.

3.10 Conclusion

There seems to be a general agreement in the literature as well as amongst policy makers that age alone does not drive HC expenditure. The association between age and HC costs seems to reflect a possibly stronger relationship between TTD and HC expenditure, which in turn seems to be a much better predictor of acute HC costs than population ageing *per se*.

Conflicting opinions exist on the extent to which future HC expenditure might be influenced by TTD, age and also other (supply side) determinants, such as technological advances in medical care. Most of these conflicting results seem to arise from applying different methods to estimate HC expenditure at the end of life. This includes the choice of the sample (survivors and/or decedents) and whether this is representative of the population, the HC sector that is analysed, the costing method employed for assigning unit costs to HC resources used and the econometric modelling techniques employed to estimate HC expenditure.

A conclusion that can be drawn from findings in the literature so far is that the inclusion of the additional factor TTD may provide a more accurate estimate for future HC expenditure. If remaining TTD is not accounted for, HC budgeting could be misinformed and as a consequence, future costs could be overestimated.

This thesis will add to the existing research by picking up on a selection of these issues and introducing methods that could add clarification. A thorough investigation of the existing limitations will help our understanding of factors that should be considered in this research area.

4 COMPARISON OF ALTERNATIVE COSTING METHODS FOR ACUTE INPATIENT CARE[9]

4.1 Introduction - valuing resource utilisation

In publicly funded health care systems (through taxation or national health insurance) such as the NHS in the UK, which are characterised by the absence of prices, costs are used to value resource utilisation. The estimation of the economic burden of disease in the absence of a 'gold standard', and in the presence of a multitude of alternatives, requires a decision about the most appropriate costing method. First and foremost the costing method should be guided by the research context. However, data availability or alternative choices may also play a role in the decision process. The variety of costing methods is especially apparent for hospital inpatient care, which has been shown to be the main contributor to the total cost of health care provision in many countries (OECD, 2010). For hospital inpatient care, costing can either be undertaken as per diem, per episode, per stay, or as case-mix costing. However, these alternative methods differ in data collection and costing methodology.

The aim of this chapter is to outline and compare alternative costing methods for acute inpatient care episodes in Scotland, highlighting advantages and disadvantages of alternative approaches. Five different costing methods are compared. To facilitate comparison and to guide the choice of an appropriate costing method for Chapters 5 and 6 that will analyse costs for acute inpatient care towards the end of life, regression analysis is employed to test differences between methods. The choice of the costing method may influence the inferences that can be made from the econometric modelling of costs. Assessing the marginal effect that explanatory variables have on estimated costs will provide valuable information beyond scale differences. Results from this

[9] This chapter is based on a published paper: Geue C et al (2011). Spoilt for choice: Implications of using alternative methods of costing hospital episode statistics. Health Econ. DOI: 10.1002/hec.1785

analysis of Scottish data will also highlight implications for other countries with a publicly funded health care system.

4.1.1 Relevant costs

Health care resource utilisation can be valued either from a societal perspective, including direct and indirect costs or from a payers' or insurers' perspective, including direct medical costs only. Direct costs represent resources that have been consumed by patients and can again be split into different categories. The first group of direct costs can be seen as costs that are incurred in order to provide the necessary services. These costs encompass all treatment costs and include costs for the hospital stay, diagnostic tests and pharmaceuticals, health care professionals' time, hospital rent and overheads. These direct costs have also been described as organising and operating costs (Drummond et al, 1987). The second group of direct costs include those that are borne by the patient or their families and include out-of-pocket payments for medical services and travel expenses that are related to the treatment process. Indirect medical costs occur in the form of production losses due to time out of work for either the patient or their family that is related to the treatment process (Drummond et al, 1987).

4.1.2 Bottom-up versus top-down costing

The analysis in this chapter will consider direct medical costs from a payer's (NHS) perspective which include costs that fall into the first category of direct costs described above. These costs can be measured using either bottom-up costing (micro-costing) or top-down costing. Bottom-up costing measures resource use at patient level after which a unit cost for each type of resource consumed can be calculated (Mugford et al., 1998). Top-down costing calculates a unit cost per patient by dividing total expenditure by a measure of volume (per diem, per episode or per case-mix). Top-down approaches usually emphasise national average costs, whereas bottom-up approaches are utilised to measure local variations in costs between different medical centres (Chapko et al.,

2009). A bottom-up approach to costing is employed for instance by the US Department of Veterans Affairs' Decision Support System. Although bottom-up or micro-costing usually provides greater precision in measuring costs it does have the disadvantage of being very complex and expensive to implement (Chapko et al., 2009). The decision whether to apply a top-down or bottom-up approach to costing will mainly be determined by the research question, the availability of data and financial resources.

The analysis in this chapter is presented as follows: Section 4.2 reviews costing methods for hospitalisation data. Section 4.3 describes the dataset that has been employed and details the econometric modelling. Results are presented in Section 4.4, followed by a summary and discussion of main findings in Section 4.5.

4.2 Review of costing methods

All costing methods that are explored in this chapter use a top-down approach. Five methods of deriving costs for hospital inpatient care are analysed, which generally differ in the unit at which resource utilisation is measured. Regression analysis is employed to test whether the choice of costing method influences any inferences that can be made from econometric modelling of costs.

The identified costing methods are based on three broad schemes, which differ in their underlying assumptions. A review of the literature on costing acute inpatient care, both in the UK and worldwide has identified Diagnosis Related Group (DRG) costing (or the respective national equivalent) (Lorgelly et al., 2010, Poole et al., 2010, Maheshwari et al., 2010, Anandan et al., 2009) and per diem costing, which is mainly used in economic evaluations, (Gray et al., 2001, Stewart et al., 2002, Ringborg et al., 2009, Harjola et al., 2009, Christensen and Munro, 2008, Liu et al., 2002, Miller et al., 2009, Walker et al.,

2003), as the two most commonly applied approaches. These can also be employed in combination, for example Hakkinen et al used the average cost per inpatient day specific to each DRG (NordDRG) (Hakkinen et al., 2008). As mentioned by Reinhardt (2006) Medicaid and private insurance payments to hospitals are also dominated by either flat fees per DRG or per diems (Reinhardt, 2006). Given the predominance of per diem and DRG-type costing, special emphasis is given to comparing these two methods.

Two further costing methods are introduced, which do not frequently feature in the literature, but for which costs are easily accessible in Scotland. The first, per episode costing, uses individual LOS and a variable/fixed cost split, assigning a fixed cost component per episode and a variable cost component per diem; while a final method explored here uses per episode costing based on national average LOS.

4.2.1 HRG based costing

Healthcare Resource Groups (HRGs) are similar to DRGs. DRGs were first developed in the U.S. in the early 1980's for Medicare to be used as a prospective payment system for hospitals. Since the 1990s HRGs have routinely been used to cost hospital activities in England (Street and Dawson, 2002). HRGs are a measure of case mix, presenting standard groupings for clinically similar treatments, which consume a common set of health care resources (The Health and Social Care Information Centre, 2010a). Each case-mix group or HRG provides the cost for each category of hospital inpatient (cases). The precision of an HRG depends on the level of detail when specifying the cases. Based on procedure, diagnosis, LOS, complications, co-morbidity, discharge method, age and gender, each patient record can be grouped in an HRG and reflects one finished consultant episode (FCE) (Street and Dawson, 2002). Australia and many European countries have developed similar grouping systems, which are based on the Health Care Financing Administration (HCFA) system introduced in the U.S., but have been modified substantially to meet local requirements (Schreyogg et al., 2006).

Two methods that employ HRG costing are presented. The first (method 1) uses the English tariff to cost hospital episodes, while a second approach (method 2) utilises the national tariff for Scotland. This last approach provides a means to test the implications of one country 'borrowing' another country's data/methods in the absence of its own. Although the NHS in the UK is funded centrally through taxation, the NHS in England, Scotland, Wales and Northern Ireland are managed separately, resulting in differences in the development of HRGs and the collection of financial data.

HRGs based on the English Tariff (method 1)

The English tariff provides cost data for elective and non-elective hospital episodes and an additional per diem cost for very long stays that exceed the so called 'trim- point', which marks the expected LOS for each HRG. Information on respective trim- point values is available for both, elective and non-elective admissions. Employing a top-down approach; a hospital's annual financial returns data are cascaded down to treatment services, specialties and finally HRGs to derive a cost (Street et al., 2007). Compared to a bottom-up approach, which might be more preferable, this approach circumvents the issue of underestimating costs as it is more likely to cover all key input variables to care (Mugford et al., 1998). Estimated costs are reported as a national schedule of reference costs (The Health and Social Care Information Centre, 2010b) and are also aggregated by hospital to provide the reference cost index[10] (Street and Dawson, 2002).

HRGs based on the Scottish National Tariff (SNT) (method 2)

In Scotland, HRG based tariffs have recently been developed for cross boundary flows between health boards for acute inpatient care and day cases, that is where patients reside in one health board area, but are treated in another (ISD, 2010). The Scottish National Tariff (SNT) has been designed to better reflect differences in case-mix

[10] Equal to a weighted average of all HRG costs in each hospital relative to the national average.

complexity. To develop the SNT, the SNT project group had exploited English reference costs. Cost data from the Scottish Costs Book was used to derive a unit cost per HRG. The SNT is therefore a direct representation of national average costs, as published on the ‘Costs Book’, but distributed over hospital activity data. In Scotland, costs for inpatient hospital episodes are not available on an HRG level, only at specialty level. The SNT project group has therefore developed an algorithm that allows the estimation of costs at the more specific HRG level. This approach involved deriving relative cost weights utilising English costs, and applying those weights to the Scottish cost basis. This was done under the assumption that the resource differential between any two procedures was the same in Scotland and England (ISD, 2010). Calculated costs were converted into a tariff, adjusted for pay and price factors and published as the SNT.

Notably the derived SNT does not provide information on extra daily costs if a hospital stay exceeds a trim point and will therefore give less weight to individual LOS.

This method is an example of one country using information and data from another country in the absence of own sufficient data and also represents a variation of procedures used elsewhere. Denmark and Germany for instance do not calculate average prices for each DRG, but calculate cost weights to define a ratio between treatment episodes. Only the price for the DRG with a cost weight of one is negotiated and prices for the remaining DRGs are calculated by applying the respective cost weights (Schreyogg et al., 2006).

4.2.2 Per diem costing (method 3)

Per diem costing is frequently used in costing studies, especially in economic evaluations. Per diem costs might be available as either disease specific per diem costs, where the average daily cost for treatments in a certain disease area is provided, or as average per diem costs over all categories of patients or diseases. In Scotland per diem costs are available on a specialty level. To derive specialty specific per diems,

information on the total costs incurred by a specific specialty and the number of patients treated are routinely collected by ISD and then used to assign a per diem cost to a specialty level. Total costs are direct costs per case and include all medical and dental costs, costs for nursing, pharmacy, allied health professionals, theatre and laboratory costs. When per diem costs are applied to cost acute inpatient stays, the published per diem cost is multiplied with individual LOS in order to derive costs per episode.

In general, a per diem costing approach assumes that the cost for the first day in hospital is equal to the cost of every subsequent day, thus neglects the split between 'hotelling costs' and 'medical costs' and consequently places a very high weight on LOS. This might lead to an overestimation of costs for longer hospital episodes and a possible underestimation of costs for shorter hospital stays.

4.2.3 Episode costing

There are two variations of this method, both utilise cost data available at an episode level with costs specific to specialty and hospital of treatment. One approach (method 4) takes account of individual LOS and has been developed by researchers from ISD to review the resource allocation formula in Scotland (Bishop et al., 2006). This is a novel approach, and has not previously been applied in costing exercises. It distinguishes between a fixed and a variable cost component. The second variation (method 5) neglects information on individual LOS and applies a cost per episode based on national average LOS without distinction between fixed and variable costs.

Episode costing- Individual LOS and fixed/variable cost split (method 4)

This approach has been used in the latest review of resource allocation in Scotland. Its novelty is the distinction between fixed and variable costs, which is based on the assumption that some proportion of costs (fixed costs) is the same for all patients

treated in a specialty, regardless of their LOS (for example medical, theatre and laboratory costs).

Variable costs, however, are assumed to be related to and vary proportionally with LOS (nursing costs, linen costs etc). Variable costs are assigned to each bed day and fixed costs to each episode. Using fixed treatment costs and variable LOS costs are aimed at providing a more transparent and accurate costing of hospital episodes (Bishop et al., 2006). To derive a percentage split between fixed and variable costs per episode, national average specialty costs were split into a fixed and variable component. This method generates a cost per episode based on individual LOS and can so account for small variations in LOS as well as the fixed and variable components of a hospital episode.

Internationally, this has also been estimated with clinical cost functions, for instance by the U.S. Department of Veteran Affairs. To estimate the cost of a hospital stay, researchers regress costs on characteristics of the hospital stay. Coefficients obtained from the regression model are then applied to hospital stays providing an estimated cost of each stay (U.S. Department of Veteran Affairs, 2011).

Episode costing- national average LOS (method 5)

This costing method also uses national average specialty costs per episode, but does not distinguish between fixed and variable costs, nor does it take into account individual LOS information. The rationale for the inclusion of this costing method is that if a representative sample were used to estimate costs, national averages should provide similar results to those obtained from more elaborate costing methods (cf. method 4). However, this assumption may not hold for a number of reasons: (a) the empirical sample is not representative of the population, (b) using historic hospital episodes with longer stays in previous decades and costs that are for more recent periods will not produce comparable results.

4.3 Methods

4.3.1 Data

The analysis in this chapter uses longitudinal data based on a large cohort study undertaken in the 1970s in the West of Scotland. The Renfrew/Paisley study, one of the Midspan studies, covers a total period of 35 years, and includes baseline survey data linked to subsequent acute hospital admissions (SMR01). The initial survey took place from 1972-1976 and includes men and women from the towns of Renfrew and Paisley, aged between 45 and 64 years at the time of study entry. Participants were asked to complete a questionnaire and invited to attend for a screening examination at clinics. Computer linkage was established for SMR01 from 1972 onwards, and study members have been followed up either until death or the end of the study period, currently December 2007 (Hart et al., 2005).

This longitudinal cohort study will also be utilised in the subsequent empirical chapter (Chapter 5) which estimates the impact of population ageing and remaining TTD on expenditure for acute inpatient care. Further particulars and characteristics of this survey data will be explained in detail in this subsequent chapter.

Hospital episode statistics (Scottish Morbidity Records, SMR01) have episode-based patient records that relate to all acute inpatient and day cases. Care episodes that are excluded from SMR01 are obstetric and psychiatric specialties. Geriatric long stay episodes were part of SMR01 until 1997 and due to this inconsistency and the nature of the care episodes, have been excluded from the analysis. The data that are collected to describe each episode include demographic information, episode management details and general clinical information. Diagnoses are recorded using ICD10 codes (previously ICD9) while procedures performed are recorded using OPCS-4 codes (ISD Data Dictionary, 2009). A more detailed description of the SMR01 dataset will be given in the following chapter.

116 observations were excluded as they showed very high costs due to very long stays mainly incurred in the specialty areas ‘Geriatric Assessment’ and ‘Orthopaedics’, which can not be classified as acute episodes. After taking account of missing observations for explanatory variables and missing cost variables (as the dependent variable) for any of the five analysed costing methods, regression models are run for 45,634 stays, coming from 10,415 individuals for the time period between 1980 and 2007. All regression models are run utilising the same sample.

4.3.2 Implementation of costing methods

Hospital stays can consist of multiple episodes. In Scotland, an entire hospital stay is conventionally called a ‘Continuous Inpatient Stay’ (CIS) and lasts from admission to hospital until discharge. Discharge can be from the same or a different hospital if the patient was transferred. A CIS is an uninterrupted period of time a patient spends as an inpatient in hospital. The patient can change consultants, specialty, significant facility and/or hospital during a CIS (ISD Data Dictionary, 2011). The different costing methods that are presented here have different levels at which their respective costs are available. For costing methods 4 and 5 costs are published on an episode level. For costing method 3 costs are available as daily costs, which then need to be multiplied with individual LOS information to obtain a cost for the entire episode. Methods 1 and 2 however require the entire hospital stay (CIS) to be summarised for any costing exercise. In order to facilitate comparison of costing methods, a common denominator needs to be chosen. This common denominator is a CIS and 2006/07 was used as the cost reference year, as the dataset provides information on hospitalisation until 2007 at which point the dataset was censored.

The following paragraphs describe in detail how a cost per CIS has been obtained for each of the costing methods using both formulae and also flowcharts to visualise the process of how costs build up to a cost per CIS.

Assigning HRG based costs (English and Scottish Tariff) (methods 1 and 2)

Notably ISD only recently added an HRG code to their routinely collected SMR01 data, as such this variable was not available from the data set that is used here and had to be added. The HRGv3.5 Grouper software available from the Health and Social Care Information Centre (IC) in England was used to assign an HRG to every patient record (IC, 2010c). This software first carries out a validation check on the required data input fields and then assigns an HRG code based on diagnosis (ICD10), procedure performed (OPCS4), gender, age, LOS and the discharge method using a complex mapping algorithm. Each episode can have multiple diagnoses and procedure codes. Each procedure and diagnosis gets assigned a hierarchical level during the grouping process, which is associated with its resource consequences. These hierarchies provide a comparison tool and diagnoses and procedures are separately ranked in the order of their complexity (IC, 2011). If more than one procedure has been recorded for an episode of care, the HRG grouper selects the dominant procedure using the ranking.

Because the HRGv3.5 Grouper software requires the diagnosis to be in the most recent version format, i.e. ICD 10, earlier admissions (pre 1992) with ICD9 codes had to be converted into ICD10 codes. This was done using a look-up file (New Zealand Health Information Service, 2010). As noted earlier, admissions with a historic ICD8 code had to be discarded from further analysis, since no conversion algorithm between ICD8 and ICD10 exists.

After an HRG code is assigned to every episode, episodes that form a CIS need to be converted so that the dominant episode is selected by simultaneously taking into account any other ‘non-dominant’ episodes within this CIS. The ‘Episode to Spell Converter’ software (IC, 2010c) utilises information on the date of admission for the first episode of a CIS, the date of discharge of the last episode within that CIS, the episode

order, episode LOS and the HRG, and so selects the dominant HRG within each CIS, which then gets a tariff assigned to it.

The procedure of applying the 'HRGv3.5 Grouper' and the 'Episode to Spell Converter' software was carried out for both the English tariff (Department of Health, 2010), and the Scottish National Tariff (ISD, 2010). Information on the type of admission was used to distinguish between tariffs for elective and non-elective admissions, while LOS information guided the decision about assigning extra per diem costs. Information on extra per diem costs however was not available for the SNT. Equation (4.1) and Figure (4.1) detail the calculation of costs per CIS when LOS exceeds the trim point. Equation (4.2) and Figure (4.2) show how costs are calculated when LOS is less than or equal to the trim point.

Both equations and figures are valid when using HRG costing based on the English Tariff, whereas Equation (4.1) and Figure (4.1) can not be applied in the context of costs for the SNT due to unavailable trim point information. The SNT can therefore be seen as a simplified version of the English tariff.

$$C_{CIS} = TAR^{E}_{hrg} + (PD_{hrg} * (LOS_{CIS} - trim_{hrg})) \quad \text{Equation (4.1)}$$

$$C_{CIS} = TAR^{S}_{hrg} \quad \text{Equation (4.2)}$$

Where C_{CIS} is the cost per CIS, TAR^{E}_{hrg} and TAR^{S}_{hrg} are published tariffs for each HRG respectively (that is the dominant HRG in the CIS), LOS_{CIS} is the LOS for that CIS, $trim_{hrg}$ is the specified trim point for each HRG, and PD_{hrg} is the per diem cost for each HRG.

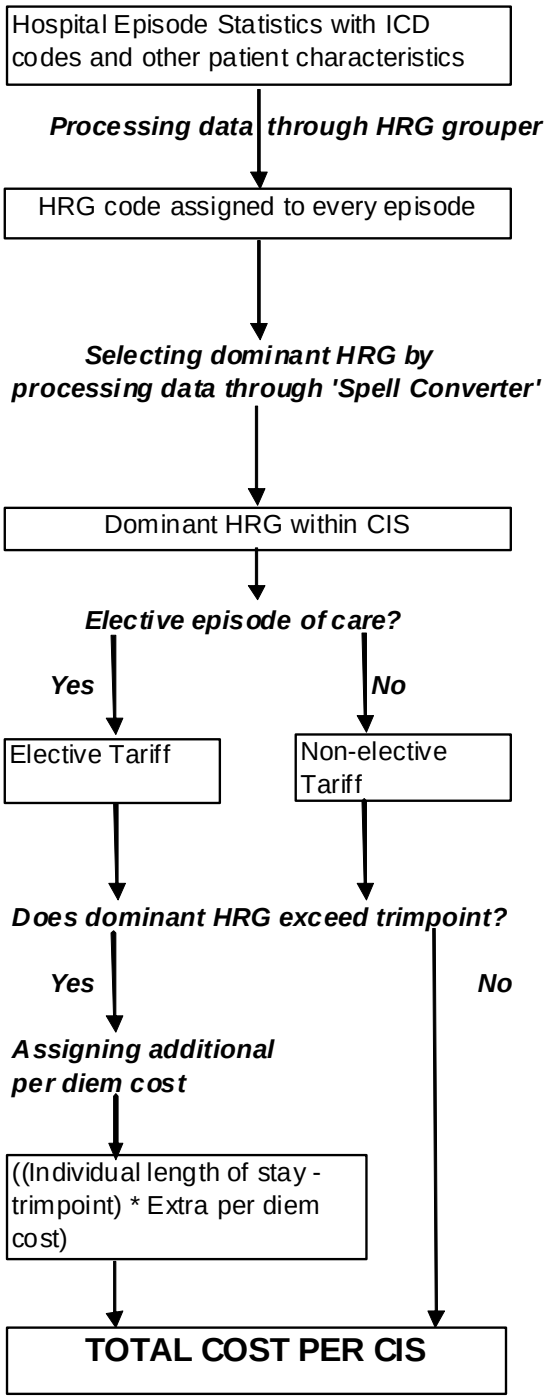

Figure 4-1 Deriving a cost per CIS using the English Tariff based on HRGs (method 1)

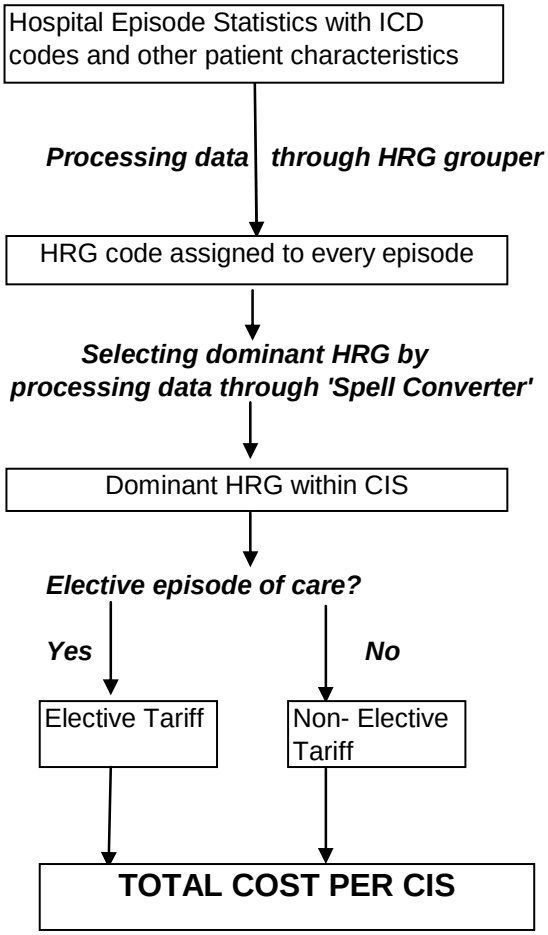

Figure 4-2 Deriving a cost per CIS using the SNT based on HRGs (method 2)

Assigning per diem costs (method 3)

This method assigns costs based on hospital and specialty codes. Scottish health services costs ('Costs Book') are the only source of published cost information for Scotland. They are based on Scottish Financial Returns data provided by each of the 14 health boards.

Per diem costs were extracted from the 'Costs Book' and multiplied with the individual LOS to derive a cost per episode. In order to derive costs per CIS, costs for each

episode that belonged to a CIS, were summed over the entire CIS. Equation (4.3) and Figure (4.3) show how a cost per CIS was derived for this method.

$$C_{CIS} = \sum_{e=1}^{x} C_{ei} + (LOS_{ei} * PD_{hs})$$

Equation (4.3)

Where C_{ei} is the cost per episode *e* for patient *i,* LOS_{ei} is each episodes LOS for patient *i* and PD_{hs} is the per diem cost, both specialty and hospital specific.

The hospital code served as one matching criterion, so that hospital codes that have ceased to exist, either because the hospital no longer exists or because hospitals have merged, were either replaced with the code of the hospital they now belong to or were discarded from hospital/specialty specific cost merging.

Per diem costing, as well as the two following costing methods 4 and 5, also rely on the specialty as the second identifying entity and therefore require the specialty group/name to match those provided in the ‘Costs Book’ and particularly ‘R040’, which is one part of the Scottish Financial Returns data. Specialties provided in SMR01 data are on a more devolved level than those for which costs are provided in the ‘Costs Book’. Specialties therefore had to be re-categorised. A list of specialty groups and specialties can be found in Appendix II.

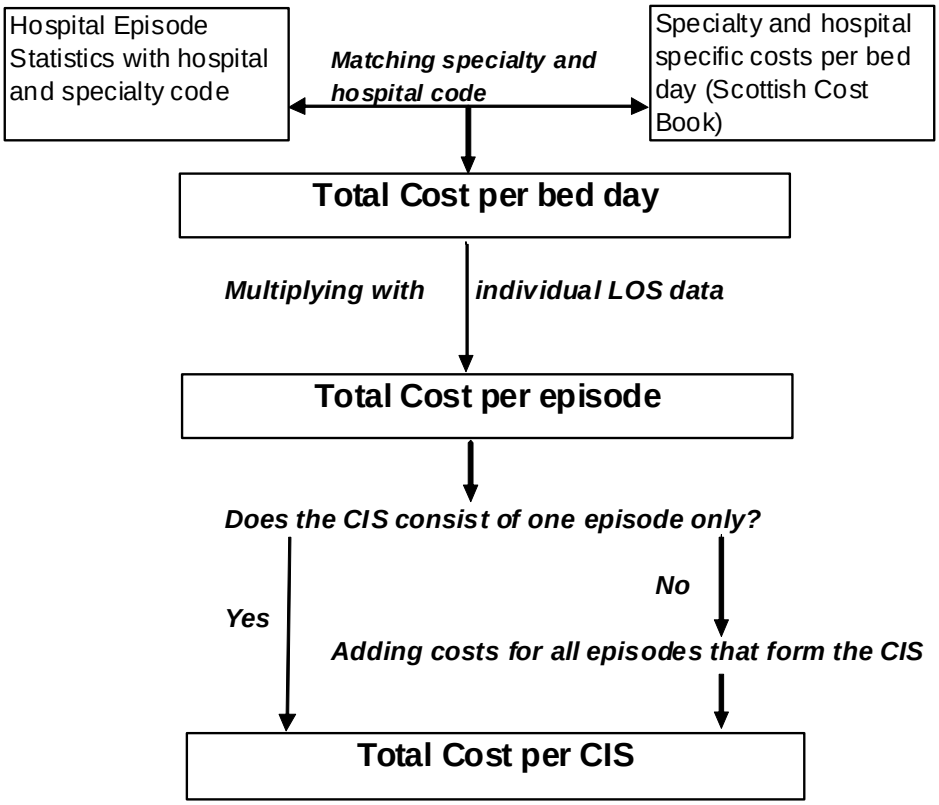

Figure 4-3 Deriving a cost per CIS using per diem costing (method 3)

Assigning costs per episode– individual (method 4) and average LOS (method 5)

For both, methods 4 and 5, costs were assigned on an episode level and were obtained from the 'Costs Book'. Similar to per diem costs, episode costs are also specialty and hospital specific and the matching has been done using these two qualifiers.

The percentage split for method 4, which had been used to assign a fixed and variable cost component was derived from regression analysis that was originally undertaken by researchers in ISD using 2004-2005 cost data. In order to derive the respective percentage splits for each of the specialties, average LOS for each specialty was regressed on 'total gross cost per episode'. The value of the resulting constant term is

used as the fixed cost component and the value of the coefficient as the variable cost component. ISD focused their analysis on four main specialties: General Medicine (55.5% fixed, 44.5% variable), General Surgery (66.7% fixed, 33.3% variable), Gynaecology (71.8% fixed, 28.2% variable) and Obstetrics (60% fixed, 40% variable). Regression results from these specialties were used by ISD to calculate the percentage split for the remaining specialties. A list of the latest percentage splits for each specialty can be found in Appendix III.

After costs were assigned to each episode utilising the percentage split provided by researchers from ISD, it was checked whether the CIS consisted of more than one episode. If this was the case, the cost of the most expensive episode within each CIS was selected. In order to also take account of any remaining less expensive episodes within that CIS, their variable cost component was added to the cost of the most expensive episode. Equation (4.4) and Figure (4.4) provide details on how costs per CIS were estimated for method 4.

$$C_{CIS} = \sum_{e=1}^{x} (C_{vare} * LOS_e) + C_{fixe} \qquad \text{Equation (4.4)}$$

Where C_{vare} is the variable cost per episode *e*, C_{fixe} is the fixed cost per episode, and LOS_e is the LOS for each episode.

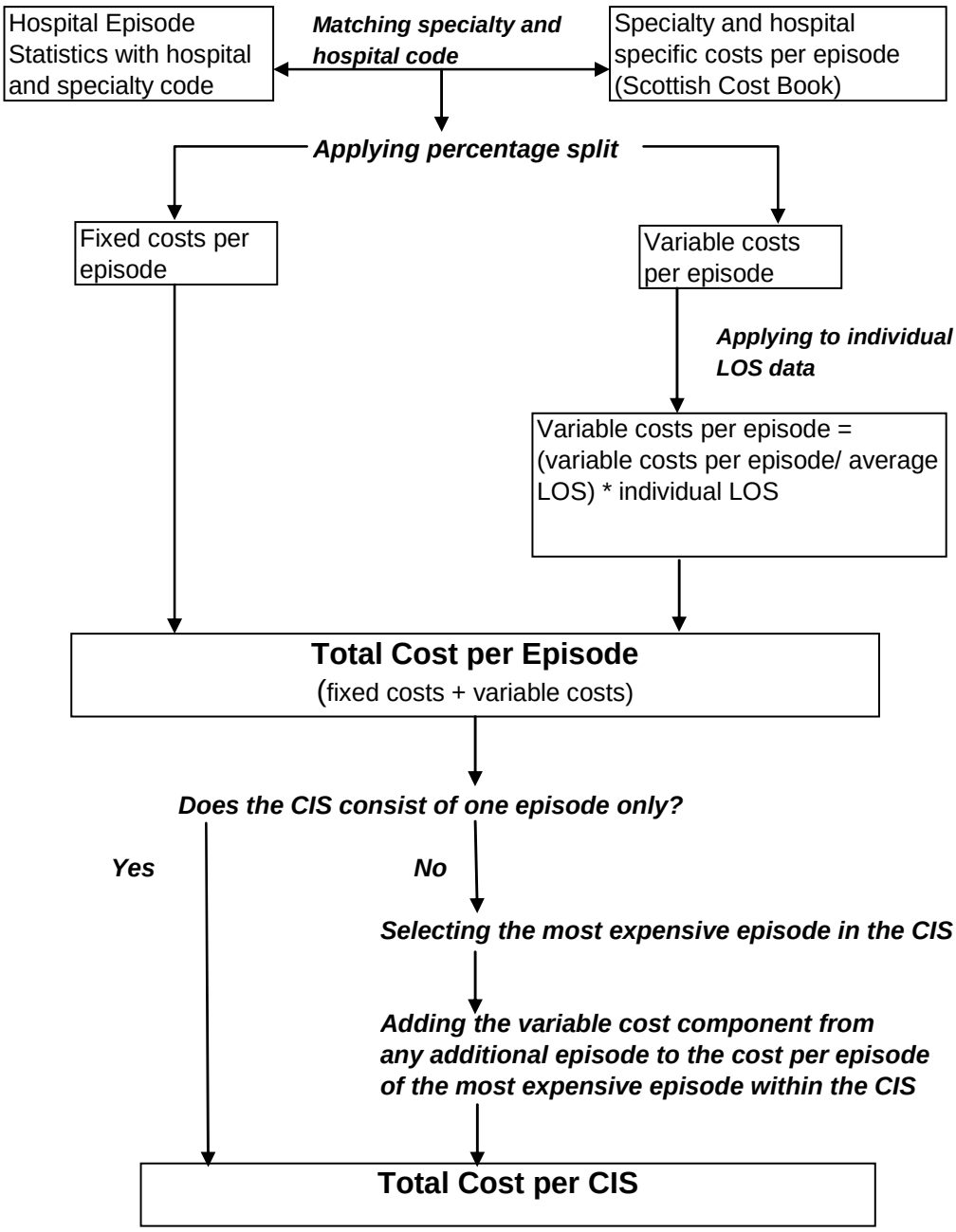

Figure 4-4 Deriving a cost per CIS using per episode costing – individual LOS and a variable and fixed cost split (method 4)

Costing method 5 does not take into account individual LOS or a split between fixed and variable costs. Costs for each episode belonging to a CIS are summed over the entire CIS. Equation (4.5) and Figure (4.5) provide guidance on how costs employing method 5 build up.

$$C_{CIS} = \sum_{e=1}^{x} NPE_{hs}$$

Equation (4.5)

Where NPE_{hs} is the net cost per episode. These costs are specialty and hospital specific.

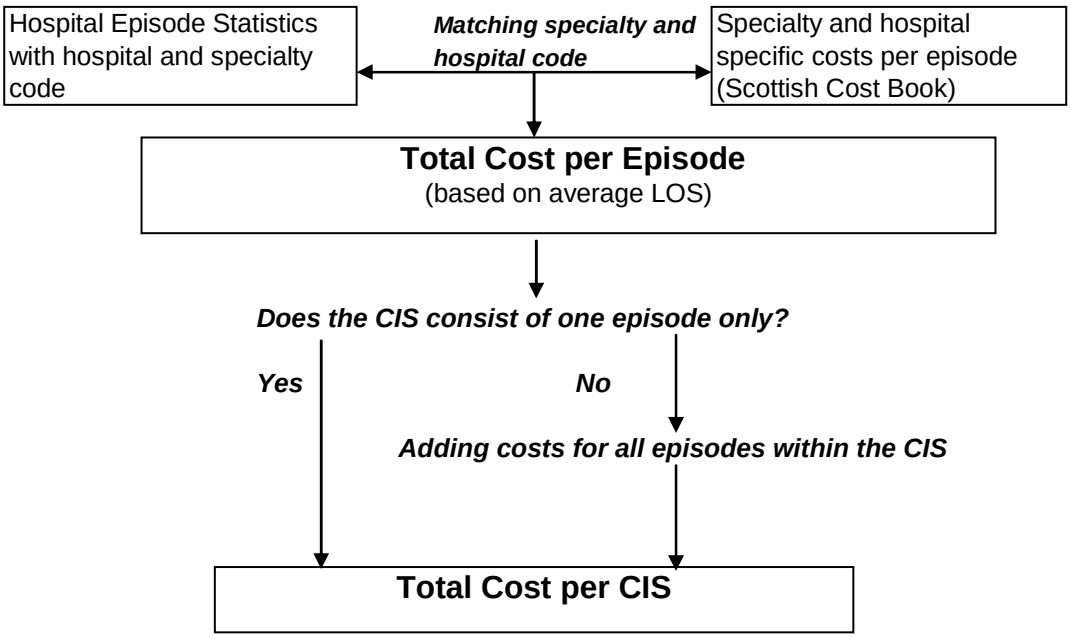

Figure 4-5 Deriving a cost per CIS using per episode costing- average LOS (method 5)

4.3.3 Regression modelling

Generalised Linear Models to estimate HC expenditure

STATA10/SE was used as the statistical package for the analysis throughout Chapters 4 and 5. GLMs are an extension of OLS and have been widely used to estimate HC expenditure data. As introduced in Section 3.4, GLMs offer a number of advantages over OLS or log OLS. They are estimated by specifying a distributional family and a link function. The distributional family that is specified corresponds to a distribution that reflects the mean-variance relationship. For instance if Gauss is chosen as the distributional family (as would be the case for OLS) a constant variance would be assumed. A gamma family would assume that the variance is proportional to the square of the mean (see Table 4.1 for commonly applied distributions and link functions).

Conventionally, a Gamma distribution is chosen to model cost data as it offers means to account for heteroscedasticity and places less weight on very high costs (Dodd et al., 2006). A misspecification of the distributional family would lead to less efficient estimates, but would not lead to a loss in consistency if the link function and covariates are specified correctly (Glick et al., 2007).

The link function in GLMs specifies the relationship between the mean and the linear predictor of the covariates. The link function specifies how the mean on the untransformed scale is related to the linear predictor and allows transformation of the mean of regressors rather than the mean of the cost variable. If an identity link is specified the assumption is that the mean equals the linear predictor (as would be the case for OLS). If a log link is specified the log of the arithmetic mean costs is modelled (Equation (4.6)).

$$(\ln (E(y/x))= X\beta) \qquad \text{Equation (4.6)}$$

Contrary to modelling log OLS, GLM with a log link models the log of the arithmetic mean and not the arithmetic mean of log costs (Equation 4.7).

$$(E(\ln(y)/x=X\beta) \qquad \text{Equation (4.7)}$$

A miss-specified link function could cause biased results. Commonly used link functions and distributional families are shown in Table 4.1 below.

Table 4-1 Commonly used distributional families and link functions

Distribution	
Gauss	Constant Variance
Gamma	Variance proportional to the square of the mean
Poisson	Variance proportional to the mean
Inverse Gaussian/Wald	Variance proportional to the cube of the mean
Link Function	
Identity	$g(u)=x_i\beta_i$
Square Root	$g(u)=(x_i\beta_i)^2$
Log	$g(u)=\exp(x_i\beta_i)$
Reciprocal	$g(u)=1/(x_i\beta_i)$

In order to specify the correct distributional family and link function, diagnostic tests need to be performed. This is not always easy to implement as family and link function need to be determined simultaneously, i.e. the specification of the link function is tested given the distributional family and vice versa. The recommended distribution can be derived from the coefficients obtained after executing the modified Park test (Glick et al., 2007). The test is run after GLM regression and predicts the square of the residuals as a

function of the log of the predictions through using a GLM with a log link and Gamma distribution. A coefficient of 0 indicates a Gaussian distribution, a coefficient of 1 a Poisson distribution, 2 indicates that the data follow a Gamma distribution, and 3 indicates an inverse Gaussian or Wald distribution. However, other considerations in addition to the comparison of results from diagnostic tests should be taken into account when deciding on the appropriate distribution. For instance when modelling costs that can take non-integer values, a Poisson distribution would not be appropriate.

No single test is available to identify an appropriate link function. The Pregibon link test can be employed to check linearity (Pregibon, 1980). The Hosmer and Lemeshow test and the Pearson correlation test both check for systematic bias in fit on the original scale of estimation (Hosmer and Lemeshow, 2000; Pearson and Please 1975). Ideally all three tests will provide insignificant p-values. In this study a user written STATA programme ‘glmdiagnostic.do’ (Glick, 2008) has been employed, which conducts the modified Park test, the Pearson correlation test, the Pregibon link test and the modified Hosmer and Lemeshow test simultaneously. The do file can easily be implemented and a number of link function-family combinations can be tested, observing how p-values change. The combination with the highest p-values is chosen as the best fit for the data as this does not reject the null hypothesis of being the correct specification for the data that are analysed.

In addition to being able to specify a distribution and a link function, GLMs also have the advantage over log OLS of being able to include zero cost observations. However if there is a substantial proportion of individuals that have incurred zero costs during the observational period for which costs are estimated, the application of a two-part model is more appropriate. As outlined in the review of econometric modelling techniques in Chapter 3, the common procedure is to estimate a two-part rather than a Heckman sample selection model when the zero costs are observed rather than unobserved.

Model specification

The cost of a CIS is estimated using a GLM clustered on patient identifier. A series of five regressions with cost as the dependent variable are run in order to highlight the influence that different costing methods have. Following conventions for determining the appropriate distribution and link function, diagnostic tests are performed using the user written programme 'glmdiagnostic' as described above (Glick, 2008). Variations in the recommended distributional family and link functions could be observed between costing methods and to facilitate comparison of results and interpretation of coefficients, a Gamma distribution with a log link is chosen as the most commonly used combination for analysing HC expenditure data (Dodd et al., 2006). In addition, the results of the correctly specified model are also reported in sensitivity analysis.

Explanatory variables

The magnitude of the effect that a set of a-priori identified regressors has on costs when using different costing methods is assessed. Cost per CIS is regressed on age at admission, gender, socio-economic status, and the time period of admission, which is represented in four categories (Table 4.2). Socio-economic status is measured on a scale from one to seven, using the Carstairs-Morris deprivation categories (Carstairs and Morris, 1991), with 1 representing the most affluent postcode sectors and 7 representing the most deprived. The underlying assumption is that the expected value of HC expenditure (HCE) is a function of these explanatory variables.

$$E[HCE] = g(x\beta) \qquad \text{Equation (4.8)}$$

with $x\beta$ representing the linear predictor for HCE.

The following equation provides details on the linear predictor.

$$E[HCE] = \alpha + \beta_1 A + \beta_2 S + \sum_{d=3}^{7} \mu_d D_d + \sum_{t=2}^{4} \gamma_t T_t + u_i \qquad \text{Equation (4.9)}$$

Where *A* is age at admission for patient *i, S* is patient's gender, *D* is the deprivation category, *T* is a time period dummy and u_i represents the error term.

Sensitivity analysis

As a first sensitivity test, OLS regression as a special case of GLM was performed (a GLM with a Gauss family and the identity link is equivalent to an OLS). Even though the assumption of normality and homoscedasticity might be violated, OLS provides a consistent estimator of mean arithmetic costs on the raw scale, thus allowing convenient comparison of results.

Further sensitivity analysis was carried out by re-running regressions with their recommended distributional family and link function as suggested by the goodness of fit tests. In order to test the magnitude of the effect that explanatory variables have on cost estimates when using different distributions and link functions, the linear predictor was calculated after the regression analysis. In order to facilitate comparison between costing methods and their respective distributions and link functions, the linear predictor was re-transformed to obtain estimates on the raw, monetary scale. Equations 4.10 to 4.12 show the appropriate re-transformations for the different link functions used in the analysis that had been applied to the linear predictor.

Retransformation for log link:

$$g(u) = \exp(\beta x) \qquad \text{Equation (4.10)}$$

Retransformation for power link -0.7:

$$g(u) = \frac{1}{\beta x^{\frac{1}{0.7}}}$$ Equation (4.11)

Retransformation for power link -1:

$$g(u) = \frac{1}{\beta x}$$ Equation (4.12)

In order to obtain the re-transformed linear predictor of costs, all but the explanatory variable of interest (in this instance the socio-economic status) are held constant. Categories for socio-economic status are varied to show the impact on costs for the same cost variable, but different distributions and link functions. Changes in the re-transformed linear predictor provide a measure of the relative effect of the explanatory variable of interest. The remaining explanatory variables are held constant at the following values:

• Age at admission: 70 years

• Gender: male

• Period: period 3 (admissions between 1994 and 2000).

4.4 Results

4.4.1 Descriptive results

Table 4.2 shows descriptive results relating to a total number of 45,634 CISs, coming from 10,415 individuals. Mean age at admission was 72.2 years [SD 7.4]. A higher proportion of admissions for females could be observed (57.3%). Most admissions were observed between 1993 and 2000 with 39.1% of all admissions to hospital falling into this period. The highest proportion of admissions could be observed for deprivation category 5 (36%).

Table 4-2 Sample characteristics

Variable Name	Mean (SD) or Frequency (%)
Age at admission	72.2 (7.4)
Male	4,450 (42.7)
Female	5,965 (57.3)
Deprivation Category 1*	693 (6.7)
Deprivation Category 2**	0 (0)
Deprivation Category 3	1,428 (13.7)
Deprivation Category 4	2,315 (22.2)
Deprivation Category 5	3,754 (36.0)
Deprivation Category 6	1,803 (17.3)
Deprivation Category 7	422 (4.1)
Admissions in 1980-1986	2,338 (5.1)
Admissions in 1987-1993	9,890 (21.7)
Admissions in 1994-2000	17,830 (39.1)
Admissions in 2001-2007	15,576 (34.1)

45,634 admissions, relating to 10,415 sample members; * Most affluent area;
**No observations for deprivation category 2

4.4.2 Cost estimates

Average cost estimates that are calculated using HRGs with the English tariff (method 1) are lowest (£1,993), followed by the approach which employs HRGs and the SNT (method 2) (£2,378). As expected, episode costing with national average LOS information produces similarly low mean costs (£2,478) and has the lowest variance (SD=£1,460). The total cost for acute inpatient care between 1980 and 2007, using 2006/2007 as the reference year for costs and for the sample analysed in this paper (N=10,415), ranges from £91,200,000 for HRG based costing using the English tariff to £137,000,000 using per diem costing.

Table 4.3 presents mean HC expenditure, their standard deviation and the 95% CI over the entire observational period and for specific time periods for all 5 costing methods. Costs that are mainly driven by LOS, through the application of a per diem costing approach (methods 3 and 4), are higher on average (£3,002 and £2,764) than costs derived using any of the alternative methods that place less weight on LOS. The standard deviations of these costing approaches are also higher than for other cost variables (£4,505 and £3,181), suggesting substantial variation in individual LOS.

The early decline is most likely due to a decrease in LOS on average over time. This is most evident in methods that rely heavily on individual LOS (methods 3 and 4). While the subsequent increase is possibly driven by the ageing cohort, which may experience more expensive chronic conditions that require longer stays.

Table 4-3 Mean costs per CIS in £ (2006/07)-different cost variables and periods

Variable	Mean	SD	95% Conf. Interval
All Years			
Method 1	1993	2043	1974, 2012
Method 2	2378	2039	2359, 2397
Method 3	3002	4505	2960, 3043
Method 4	2764	3181	2735, 2793
Method 5	2478	1460	2464, 2491
1980-1986			
Method 1	2200	2101	2114, 2285
Method 2	2239	1325	2185, 2293
Method 3	4027	4632	3939, 4215
Method 4	3420	3372	3283, 3557
Method 5	2599	1991	2518, 2679
1987-1993			
Method 1	1927	1994	1887, 1966
Method 2	2249	1939	2210 2287
Method 3	3415	4480	3327, 3504
Method 4	2912	3056	2853, 2973
Method 5	2278	1307	2252, 2304
1994-2000			
Method 1	1898	1984	1869, 1928
Method 2	2381	2088	2350, 2411
Method 3	2757	4278	2694, 2820
Method 4	2624	3002	2580, 2668
Method 5	2461	1453	2439, 2482
2001-2007			
Method 1	2113	2122	2080, 2146
Method 2	2479	2127	2446, 2513
Method 3	2867	4712	2793, 2941
Method 4	2730	3406	2677, 2784
Method 5	2606	1450	2583, 2629

Method 1: Costs per CIS, based on HRGs (English Tariff)
Method 2: Costs per CIS, based on HRGs (Scottish National Tariff)
Method 3: Costs per CIS, based on specialty and hospital specific per diem costs
Method 4: Costs per CIS, based on specialty and hospital specific episode costs, individual LOS
Method 5: Costs per CIS, based on specialty and hospital specific episode costs, national average LOS

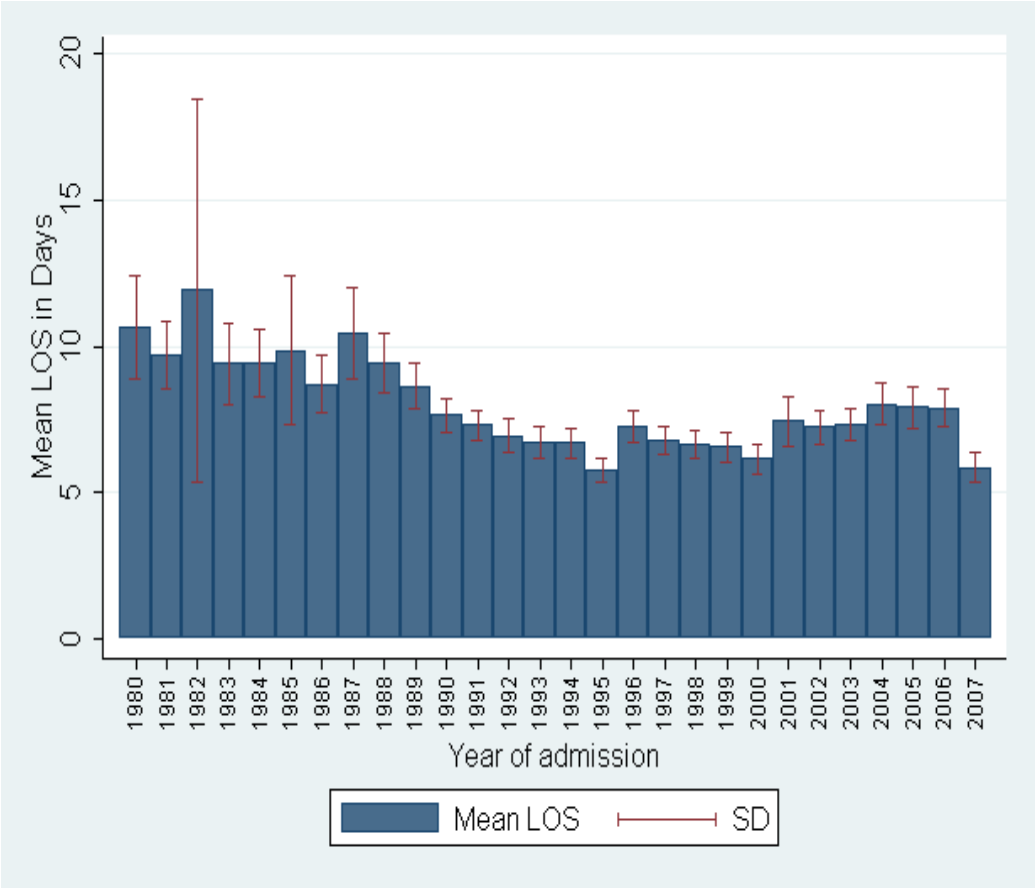

Figure 4-6 Distribution of LOS by year of admission

Figure 4.6 shows the distribution of mean LOS for each year of admission with the 95% CIs. On average, mean LOS was observed to have decreased over time. In the 1980s mean LOS had a value of about 10 days. SDs seemed to be wider during this period indicating more variation around mean LOS. For more recent periods mean LOS was observed to be lower on average compared to more historic periods (~7 days) and SDs seem to be much tighter. The subsequent increase in LOS from the year 2001 might be explained with the ageing process of the cohort, requiring longer stays on average.

Figure 4.7 shows the distribution of mean costs per CIS over time with the 95% CI for all five costing methods. Costs were generally higher on average in the earliest periods. Costing methods, that rely heavily on individual LOS information (methods 3 and 4 and to a lesser extend method 1) show higher costs on average and especially for more

historic periods. Average costs for these methods can also be observed to have wider CIs. Very little variation over time can be observed for method 2 (SNT). Average costs obtained employing this method also show very tight CIs. Differences between methods have become less marked with tighter CIs for more recent years.

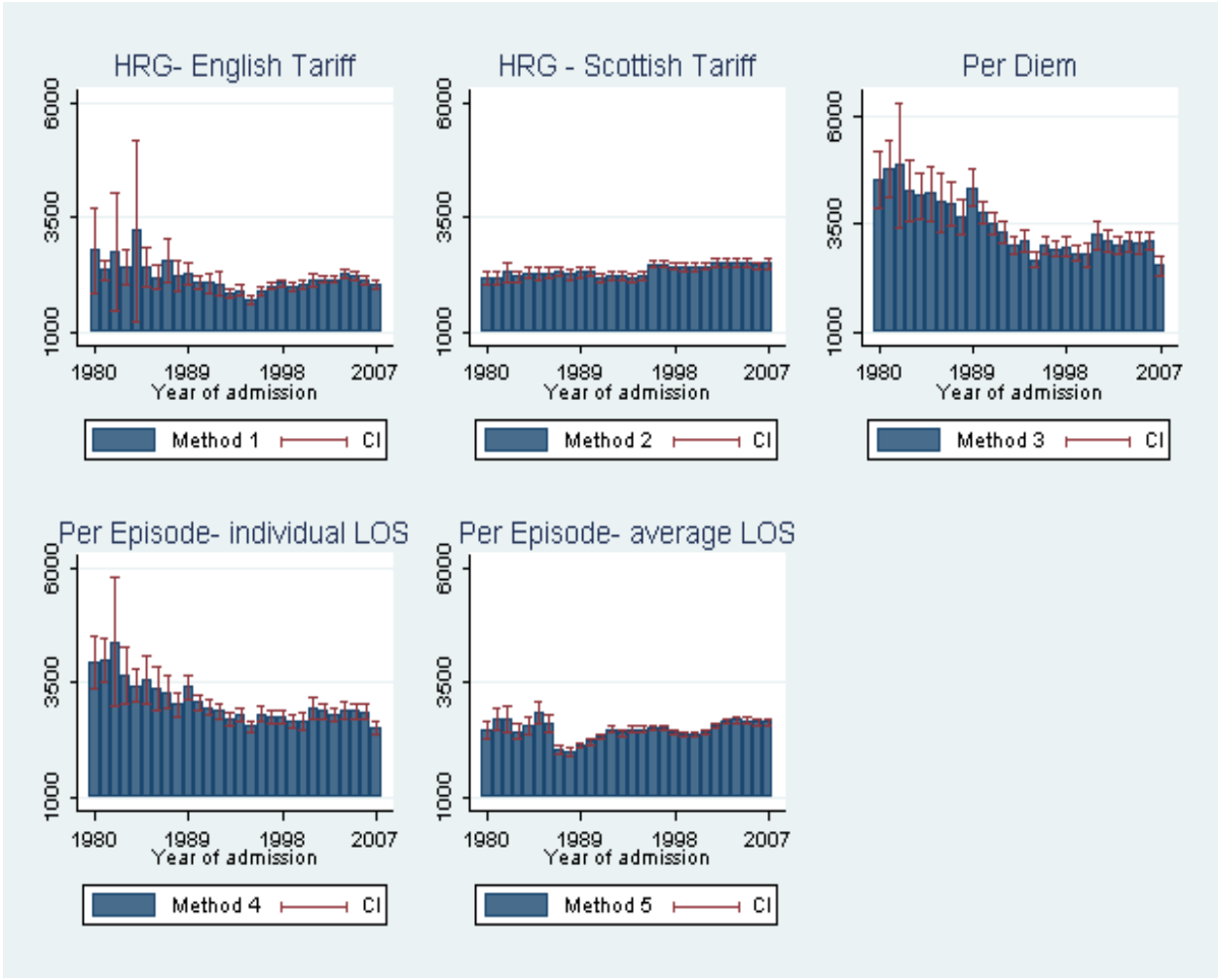

Figure 4-7 Distribution of mean costs per CIS over time

In addition it was tested how the socio-economic status impacts on LOS on average. This was done since LOS is one major component that is used in the process of deriving the different costing methods and individuals' socio-economic status is hypothesised to influence LOS. Figure 4.8 shows the distribution of LOS over deprivation categories and an increase in mean LOS is observed as individuals become more deprived.

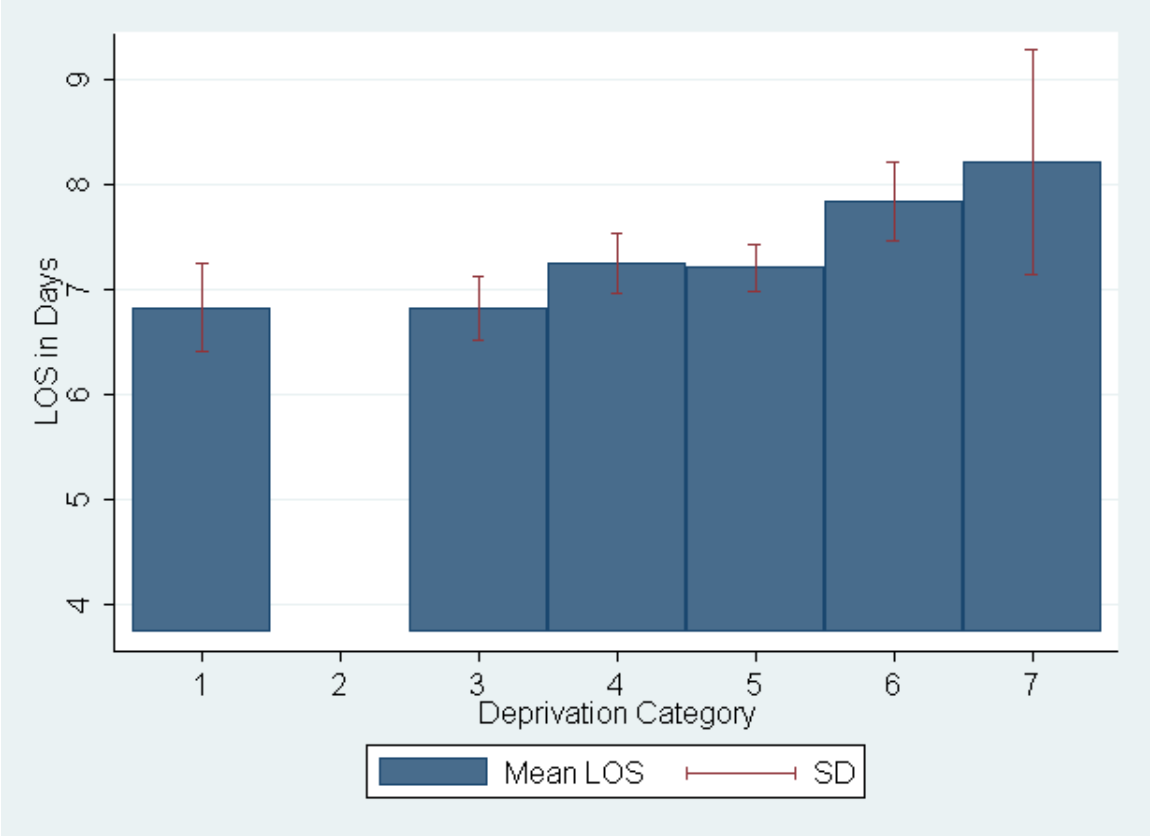

Figure 4-8 Distribution of LOS by socio-economic status

A test, whether these differences were statistically significant showed that individuals living in deprivation categories 6 and 7 have significantly longer stays at hospital compared to individuals living in the most affluent areas (deprivation category 1) (p=0.002). The size of this effect is on average one day for individuals from deprivation category 6 compared to individuals from category 1, and on average 1.4 days for individuals living in the most deprived postcode areas (category 7).

4.4.3 GLM regression results

Results for GLM regression analyses are shown in Table 4.4. The coefficients presented here have been re-transformed and are shown as cost ratios. They are presented with their associated standard errors (in parentheses) and their 95% CI. AIC and BIC goodness of fit measures are presented at the bottom of Table 4.4; they show similar values for all five costing methods.

GLM regression results show, that the association between age at admission and cost is highly significant and positive for all costing methods. Costs increase between 0.5 percent (method 5) and 2.3 percent (method 3) for each additional year.

Males are found to incur significantly lower costs than females. These differences range from 18% when applying per diem costing (method 3) to 2% for episode based costing using national average LOS (method 5). Socio-economic status has a small and generally non-significant effect on costs across most methods. The only two methods which are found to report a significant association with socio-economic status were HRG based costing applying the SNT (method 2) and episode based costing using national average LOS (method 5); the regression coefficients suggest that people living in more deprived postcode areas are less costly. For example, the size of the effect for method 5 would suggest that people living in the most deprived postcode areas incurred costs that were 5% lower than costs for people living in the most affluent postcode areas. A joint hypothesis test, performed after estimation, rejects the hypothesis that a regression model excluding deprivation category indicators is correctly specified compared to a model including these measures for costing methods 2 and 5. The respective p-values for these tests are presented in Table 4.4.

The indicator variables representing the period of admission show an increasing significant negative association with costs for later admissions compared to the very early years for costing methods 1 to 4. In general this suggests lower costs for more recent periods compared to the most historic period (1980-1986). The size of the effect was found to be largest for costing method 3, which used per diem costing. Here, costs were found to be about 55% lower in the most recent period (2001-2007) than in the most historic period (1980-1986). Compared to costing methods 1 to 4, a decreasing negative association of the period of admission with costs could be observed for costing method 5.

Table 4-4 Regression results - GLM

Costing Method	Method 1	95%CI	Method 2	95%CI	Method 3	95%CI	Method 4	95%CI	Method 5	95%CI
Age at admission	1.022***	1.019, 1.024	1.017***	1.015, 1.019	1.023***	1.019, 1.026	1.018***	1.015, 1.020	1.005***	1.004, 1.007
	(0.001)		(0.001)		(0.001)		(0.001)		(0.0009)	
Gender	0.893***	0.870, 0.918	0.940***	0.918, 0.961	0.822***	0.791, 0.854	0.873***	0.849, 0.899	0.980*	0.961, 1.002
(male=1)	(0.013)		(0.011)		(0.019)		(0.014)		(0.010)	
Deprivation	0.966	0.911, 1.031	0.936**	0.889, 0.991	0.996	0.917, 1.092	1.010	0.949, 1.081	1.007	0.966, 1.047
Category 3	(0.031)		(0.027)		(0.044)		(0.033)		(0.020)	
Deprivation	0.991	0.939, 1.053	0.978	0.932, 1.033	1.001	0.925, 1.093	1.005	0.947, 1.072	0.975	0.940, 1.015
Category 4	(0.029)		(0.026)		(0.042)		(0.031)		(0.019)	
Deprivation	0.978	0.928, 1.034	0.948**	0.904, 0.997	0.983	0.913, 1.064	0.992	0.938, 1.051	0.976	0.941, 1.009
Category 5	(0.027)		(0.024)		(0.039)		(0.029)		(0.017)	
Deprivation	1.016	0.958, 1.077	0.984	0.933, 1.038	1.021	0.940, 1.111	1.010	0.949, 1.075	0.952**	0.916, 0.990
Category 6	(0.030)		(0.027)		(0.042)		(0.031)		(0.019)	
Deprivation	1.038	0.958, 1.129	1.000	0.932, 1.080	0.972	0.867, 1.097	0.969	0.890, 1.060	0.951*	0.902, 1.002
Category 7	(0.042)		(0.037)		(0.060)		(0.044)		(0.026)	

Table 4.4 continued

Costing Method	Method 1	95%CI	Method 2	95%CI	Method 3	95%CI	Method 4	95%CI	Method 5	95%CI
Period 2	0.758***	0.727, 0.802	0.901***	0.865, 0.938	0.730***	0.682, 0.779	0.750***	0.717, 0.800	0.839***	0.808, 0.881
(1987-1993)	(0.027)		(0.022)		(0.036)		(0.030)		(0.023)	
Period 3	0.641***	0.631, 0.704	0.861***	0.834, 0.911	0.501***	0.479, 0.558	0.599***	0.582, 0.657	0.882***	0.844, 0.926
(1994-2000)	(0.030)		(0.023)		(0.040)		(0.032)		(0.025)	
Period 4	0.637***	0.625, 0.709	0.827***	0.795, 0.882	0.456***	0.438, 0.523	0.563***	0.548, 0.630	0.909***	0.863, 0.957
(2001-2007)	(0.034)		(0.027)		(0.047)		(0.037)		(0.027)	
Constant	593***	500, 697	829***	717, 955	1081***	834, 1339	1219***	996, 1433	1948***	1674, 2155
	(0.083)		(0.072)		(0.119)		(0.091)		(0.064)	
Observations	45,634		45,634		45,634		45,634		45,634	
AIC	17.17369		17.53766		17.97354		17.82953		17.62603	
BIC	-458792		-464713		-430255		-458372		-478756	
Joint Test for Deprivation	p=0.207		p=0.012		p=0.823		p=0.845		p=0.023	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Deprivation category 1 (most affluent) serves as the reference category, no observations for deprivation category 2 in the sample; Period 1 (1980-1986) serves as the reference category

4.4.4 OLS regression results (sensitivity analysis)

OLS regression results are presented in Table 4.5, with their associated standard errors (in parentheses) and their 95% CI. Operating on the raw scale, coefficients can be interpreted in monetary terms. Overall, OLS regression results reveal a similar association between costs and explanatory variables in terms of sign and significance as GLM regression results.

The association between age at admission and costs is highly significant and positive for all costing methods. However, the size of the effect is small and ranges from an additional £13.97 to £70.25 for every additional year of age at admission. The smallest effect can be observed for the costing method that uses episode costing based on national average LOS (method 5) and the largest effect is found for per diem costing (method 3).

Male patients are found to incur significantly lower costs than females across all costing methods, again with the magnitude being largest for per diem costing (method 3) with £575.20 and smallest with £50.16 (although only marginally significant) for episode costing using average LOS (method 5).

Overall the effect of socio-economic status on costs is small and mostly non-significant. A significant negative effect of socio-economic status could be observed for method 5, episode based costing using national average LOS and HRG based costing using the SNT (method 2). For costing method 5, individuals living in the most deprived and second most deprived postcode areas seem to incur ~£120.00 less on average than individuals living in the most affluent postcode areas. These findings imply that lower mean costs are incurred by people living in more deprived areas compared to people from more affluent areas, after adjustment for age, sex and period of admission.

The time period of admission has a consistent negative and significant association with costs across costing methods. The magnitude of the effect is generally smallest for episode based costing using national average LOS (method 5) with cost estimates being between £237.00 lower for the most recent period (2001-2007) and £413.90 lower for the period ranging from 1987-1993, both compared to the most historic time period (1980-1986). The period of admission was observed to have the largest effect on costs for per diem costing (method 3), ranging from estimates being £2,678 lower in the most recent period (2001-2007) compared to the most historic period (1980-1986) and £1,082 lower for the period spanning the years 1987-1993 compared to the most historic period.

Similar to results obtained from GLM regression modelling, method 5 was observed to be the only costing method to produce reversed effects of the period of admission. While for the remaining four methods an effect could be observed that had lower costs that increased in their magnitude over time, method 5 produced cost estimates that moved in the opposite direction, i.e. the magnitude of the effect, although still negative, that time had on costs decreased over time. While costs incurred in period 4 (2001-2007) were £237.00 lower than in period 1 (1980-1986), they were £413.90 lower in period 2 (1987-1993).

Table 4-5 Regression results- OLS

Costing Method	Method 1	95%CI	Method 2	95%CI	Method 3	95%CI	Method 4	95%CI	Method 5	95%CI
Age at admission	44.40***	39.54, 49.26	39.36***	34.61, 44.10	70.25***	59.79, 80.72	50.41***	42.90, 57.91	13.97***	9.501, 18.44
	(2.48)		(2.42)		(5.34)		(3.83)		(2.28)	
Gender	-229.0***	-280.2, 177.9	-152.8***	-206.1 , -99.55	-575.2***	-683.1, 467.3	-374.8***	-451.2, 298.5	-50.16*	-100.7, 0.395
(male=1)	(26.08)		(27.18)		(55.03)		(38.95)		(25.79)	
Deprivation	-60.44	-184.0, 63.08	-154.6**	-286.9, 22.25	7.847	-245.8, 261.5	36.03	-143.1, 215.2	13.12	-88.40, 114.6
Category 3	(63.01)		(67.51)		(129.4)		(91.40)		(51.79)	
Deprivation	-18.72	-135.2, 97.76	-53.17	-180.4 , 74.09	3.711	-241.0, 248.4	15.06	-155.8, 185.9	-57.80	-154.6, 39.00
Category 4	(59.42)		(64.92)		(124.8)		(87.18)		(49.38)	
Deprivation	-51.15	-160.4, 58.11	-133.7**	-253.4, 14.06	-60.41	-285.5, 164.7	-29.36	-187.8, 129.1	-64.68	-152.9, 23.52
Category 5	(55.74)		(61.06)		(114.8)		(80.82)		(45.00)	
Deprivation	16.69	-104.0, 137.4	-45.93	-177.2, 85.30	17.03	-229.7, 263.7	8.885	-164.4, 182.2	-120.9**	-217.9, -23.88
Category 6	(61.58)		(66.95)		(125.9)		(88.43)		(49.49)	
Deprivation	73.01	-91.25, 237.3	9.427	-169.1, 187.9	-90.32	-428.8, 248.1	-78.04	-312.4, 156.3	-120.5*	-248.8, 7.805
Category 7	(83.80)		(91.06)		(172.7)		(119.5)		(65.44)	

Table 4.5 continued

Costing Method	Method 1	95%CI	Method 2	95%CI	Method 3	95%CI	Method 4	95%CI	Method 5	95%CI
Period 2	-563.5***	-671.6, 455.4	-247.0***	-338.5, 155.4	-1,082***	-1,331, 832.4	-843.5***	-1,022, 665.3	-413.9***	-521.8, -305.9
(1987-1993)	(55.16)		(46.72)		(127.2)		(90.90)		(55.08)	
Period 3	-830.3***	-948.1, 712.5	-326.6***	-427.0, 226.2	-2,119***	-2,384, 1,853	-1,404***	-1,595, -1,213	-307.4***	-423.7, -191.1
(1994-2000)	(60.09)		(51.22)		(135.5)		(97.50)		(59.34)	
Period 4	-843.4***	-977.5, 709.3	-427.7***	-548.2, 307.1	-2,380***	-2,678, 2,083	-1,564***	-1,777, -1,351	-237.0***	-365.4, -108.5
(2001-2007)	(68.41)		(61.51)		(151.6)		(108.8)		(65.53)	
Constant	-511.2***	-847.6, 174.8	-120.3	-455.8, 215.2	-175.1	-910.0, 559.8	376.4	-151.8, 904.5	1,791***	1,474, 2,107
	(171.6)		(171.2)		(374.9)		(269.4)		(161.5)	
Observations	45,634		45,634		45,634		45,634		45,634	
R squared	0.021		0.016		0.018		0.015		0.011	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Deprivation category 1 (most affluent) serves as the reference category, no observations for deprivation category 2 in the sample; Period 1 (1980-1986) serves as the reference category

4.4.5 Results for sensitivity analysis using the recommended distributional family and link function

Cost estimates obtained after GLM regression using the recommended distributional family and link functions are presented in Table 4.6. These represent the re-transformed linear predictors as detailed in Section 4.3.3. Cost estimates revealed a negligible difference between results obtained when using Gamma as the distributional family and a log link function (as presented in Table 4.4) compared to using the distribution and link function that were recommended through the goodness of fit tests provided in 'glmdiagnostic.do'. The difference in cost estimates when varying the deprivation category was very small for costing method 1, where results only varied by £2.00 (for deprivation category 6) to £24.00 (for deprivation category 3). Similar, very small variations in costs estimates were found for the remaining costing methods. However, comparing cost estimates between costing methods, differences are substantially larger, ranging from £906.00 for deprivation category 3 to £661.00 for deprivation category 7, when comparing costing method 1 with method 5.

Table 4-6 Cost estimates in £: Comparison of recommended family and link function with Gamma and log link (cf. Table 4.4)

Costing Method	1	1	2	2	3	3	4	4	5	5
Distribution	Gamma	Gamma	Poisson	Gamma	Poisson	Gamma	Gamma	Gamma	Poisson	Gamma
Link function	Power -1	log	Log	log	Log	log	Power -0.7	log	log	log
Deprivation Category 3	1547	1523	2023	2017	2156	2140	2233	2212	2422	2429
Deprivation Category 4	1574	1563	2112	2109	2156	2150	2222	2200	2355	2359
Deprivation Category 5	1554	1539	2041	2040	2109	2108	2192	2168	2348	2353
Deprivation Category 6	1594	1596	2117	2115	2163	2185	2219	2206	2295	2298
Deprivation Category 7	1630	1634	2167	2156	2085	2085	2154	2121	2295	2295

Cost estimates for covariance matrix: Gender=male, age at admission=70, time period of admission=3

4.5 Discussion

The effects of five different costing methods, based on three main approaches, for costing hospital episodes have been considered in this chapter. The first two methods were based on disease classification (HRGs); the third utilised information based on per diem costs. The final two methods derived specialty specific costs on an episode level using individual LOS plus a variable and fixed cost component split, and national average LOS without a cost split.

The initial research question was: How do different methods to cost inpatient hospital stays affect cost estimates and what marginal effect do various explanatory variables have?

Descriptive analysis revealed substantial differences in the scale of mean costs. Mean costs that include an element of individual LOS were higher on average with a greater variance. Using average LOS information produced the lowest mean cost with the smallest variance. The differences between mean costs however were found to narrow over time, which can be partly explained by decreasing LOS over time as shown in Figure 4.6 in Section 4.4.1.

A further focus of this analysis was to assess whether alternative costing methods influence the magnitude of the effect a set of regressors has on costs. It was found that the costing method does have a substantial influence on the predictions observed. Results obtained when employing episode based costing using national average LOS seemed to differ consistently from results produced by alternative costing methods, especially in terms of the association between socio-economic status and costs and also in terms of a reversed effect that the time period of admission had on costs. The main difference between this method (method 5) and the four alternative methods is that it does not take account of individual LOS. An effect of socio-economic status on costs, which would be in line with previous research that suggests that ‘the poor cost more’ (Cookson and Laudicella, 2011), was not observed to the extent that was expected. A possible explanation for this might be that any effect that was present was modified by including LOS into the calculation of the cost variable. This is based on the assumption that individuals from more deprived postcode areas tend to have longer hospital stays on average, often due to a lack of care or support in their own homes, they may also delay seeking care until their condition is serious, thereby requiring a longer stay. Using this data it can not be confirmed when individuals seek medical care, however, it could be shown that individuals living in more deprived areas required longer hospital stays on average compared to individuals from the most affluent areas (see Figure 4.8).

Both sensitivity analyses, using OLS regression, as a special case of GLMs and using the recommended distributional family and link function, confirmed that the choice of the econometric modelling framework has a negligible impact on cost estimates. A much more substantial impact was observed in the actual costing method. This could easily be observed by comparing GLM regression results across different costing methods. This chapter has therefore laid important foundations by testing for such differences and found them to be negligible.

It is recognised here that the costing approach is mainly determined by the research question, but this chapter highlights important issues that arise from the application of alternative methods. A comparison of HRG and per diem costing as the two most commonly used methods revealed substantial scale differences and some difference in the size of the effects that regressors have on costs. Studies that employ a per diem costing approach neglect the nature of a hospital stay, which is characterised by fixed costs being independent of LOS and variable costs varying with LOS. Although general conclusions in terms of sub group analysis, i.e. males are less costly than females, do not seem to be influenced by the type of costing, the magnitude of the effect is.

The application of the HRG costing method (method 1) is therefore recommended for the analysis of costs in Chapters 5 and 6. This costing method is disease specific; it incorporates a fixed and variable cost approach through the application of a trim point payment, and also allows adequate costing of hospital stays that involve more than one episode.

5 EMPIRICAL ANALYSIS – RENFREW/PAISLEY STUDY

5.1 Introduction

The empirical analysis in this chapter will add to the understanding of the association between population ageing, TTD and costs, mainly through the inclusion of previously unconsidered explanatory variables, such as health status and health risks at baseline. The analysis will make use of a survey based longitudinal dataset, which was introduced in the previous chapter.

5.1.1 Rationale for including survivors

If the analysis of the relationship between ageing, TTD and HC expenditure is to aid resource planning and resource allocation on a population level, the sample ought to include the surviving part of the population. The review of the literature in Chapter 3 explained reasons for the inclusion of the surviving part of the sample into a model that estimates HC costs as people approach death. Issues of applying varying approaches to account for survivors' unknown TTD were discussed and a summary of the main methods that were employed elsewhere was presented.

The literature review concluded that this issue has to date not been addressed to a satisfactory extent in regression analysis. If right censoring of survivors is not correctly accounted for, cost estimates may be incorrect. For example, if the censoring date were used as the date of death, costs that are observed are assigned to the incorrect year, or quarter before death and results might be misleading. Costs observed in the last quarter before censoring are not costs in the last quarter of life. To account for survivor status in regression analyses researchers have reverted back to including an indicator variable. However, this does not correct cost observations.

To guide future research, the analysis presented in this chapter aims to correct for limitations arising from varying methods through the implementation of an approach which could rectify problems of not adequately dealing with survivors' right censoring. In a recent study Shang and Goldman (2008) have used survival analysis to predict the effect of life expectancy on HC expenditure. Their approach is extended here. As the authors used a cohort consisting of survivors only, they were not able to compare the magnitude at which estimated costs might differ, when employing alternative methods of correcting for survivors' unknown TTD.

The analysis (and data) presented in this chapter allows an in-depth examination of this issue, specifically this chapter estimates costs for the following scenarios:

a) Inclusion of decedents only (scenario A),

b) Inclusion of survivors only, using the censoring date as date of death (scenario B)

c) Inclusion of decedents and survivors, using the censoring date as date of death for survivors (scenario C),

d) Inclusion of decedents and survivors, using an imputed date of death for survivors (extended approach) (scenario D)

A comparison of results from scenarios A, C and D provides insight into the magnitude of any over- or under-estimation of costs at the end of life produced in previous research. Results will also highlight differences in the size and significance of the effect that included covariates have on costs, thus reveal to what extent estimates are determined by sample selection. Estimation results obtained for scenario B add further information in terms of singling out the 'pure' survivor effect. This adds to the understanding and interpretation of results from scenarios C and D, where survivors are included, but two different approaches are used to do so.

The Renfrew/Paisley sample offers the advantage of having a very high number of study participants for which death could be observed over the study period. This facilitates means to test differences in estimated costs at the end of life when using the censoring date as the date of death for a sub-sample for which death could subsequently be observed. These results can be compared to cost estimates obtained when using the actual date of death for this sub-sample. This approach is novel and provides useful information on the magnitude of the difference in costs under two different methods.

In addition, the nature of the data allows consideration of further bias in the form of omitted variables. Little is known about the role of previously omitted covariates such as baseline health status and health risks on future hospital costs. An understanding of this is important as it provides guidance on how important such characteristics are for the estimation of future HC costs.

The remainder of this chapter is structured as follows. A detailed description of the utilised linked dataset is given in Section 5.2. This section also provides a detailed explanation of the comprehensive data manipulation and an account of how acute hospital care costs have been derived and assigned to episodes of inpatient care. Section 5.3 provides results for sample characteristics and the descriptive analysis of costs. Methods employed to predict survivors' TTD are described in Section 5.4 and results for these analyses are presented in Section 5.5. Econometric methods used to estimate HC expenditure at the end of life are described in Section 5.6 and Section 5.7 presents results. Section 5.8 provides a presentation of a method to validate the method of including survivors through survival analysis and the chapter concludes with a final discussion of the main findings and limitations in Section 5.9.

5.2 Methods - data description

5.2.1 The Renfrew/Paisley Study (Midspan)

Midspan is the name used for a series of surveys on occupational and general population health carried out in the West of Scotland. It included almost 30,000 people and started in the 1960s. The Midspan studies include three separate original studies, and one study undertaken 20 years after the original studies including the offspring of participants in one of the main studies.

The Renfrew/Paisley study, as one of the Midspan studies, is a longitudinal study based on a large cohort. It was carried out between 1972 and 1976 in the towns of Renfrew and Paisley and covers a total observational period of 35 years (the current censoring date is 31st December 2007)[11]. It includes men and women, who were aged between 45 and 64 years at the time of study entry. The total dataset includes 15,402 individuals 7,049 of which are men and 8,353 of which are women. The Renfrew /Paisley study is the third largest study of its kind in the world. Remarkably, it is the only study in the UK of its time to include women. It studies a location which still includes a high proportion of socio-economically disadvantaged people.

The data recorded from the Renfrew/Paisley study can be grouped into four areas: questionnaire data, clinical measurements, derived data and follow-up data. Study members were asked to complete a questionnaire, which collected information on participants' sex, marital status, occupation, smoking habits, bronchitis and angina. Participants were also invited to attend screening examinations at clinics, which were set up specifically for the study. Clinical data were collected on height, weight, respiratory function (Forced Expiratory Volume (FEV) in 1 second; % predicted FEV1)[12],

[11] See http://www.gla.ac.uk/researchinstitutes/healthwellbeing/midspan/

[12] Derived by dividing actual FEV1 (in litres) through expected FEV1 value, where the expected value is derived from a healthy subset with similar characteristics

systolic and diastolic blood pressure and cholesterol. A chest x-ray was also performed. Data that were subsequently derived includes the age at screening, the 1981 Carstairs deprivation category (based on postcode information from 1972-1976, with category 1 representing the most affluent postcode sectors and category 7 the most deprived ones), the Body-Mass-Index (BMI) and the Rose Angina classification.

Computer linkage exists with SMR01 and individuals were followed up in terms of hospital use and death until December 2007. This provides a rich data set of hospitalisations for a wide range of causes. Indirect follow-up of mortality was established at the time of the study with the General Register Office Scotland (GROS) (Hart et al., 2005).

A total of 23 participants (0.15%) have been lost to follow-up and consequently there is no information on their utilisation of hospital services. These observations were deleted from the dataset. For people, who have left the UK (N=121; 0.78%) there is no information on their use of HC services or on their date of death after they had embarked. These observations have therefore also been discarded from the analysis. 1,565 individuals (10.16%) from the Renfrew/Paisley study had never accessed acute hospital care until their death or censoring of the study. These will remain part of the sample, but without any resource use data.

The Renfrew/Paisley study provides very important baseline characteristics for individuals, allowing the inclusion of previously omitted explanatory variables and therefore adding to the understanding of the association between population ageing, HC expenditure and TTD. It is however based on a small sample of the Scottish population from a very confined area in the West of Scotland and therefore may not be representative of Scotland.

5.2.2 Scottish Morbidity Records 01 (SMR01)

SMR01 has episode-based patient records that relate to all acute inpatient and day cases. Every record in SMR01 data reflects one episode of care. An SMR01 record is generated every time a patient completes an episode of inpatient or day case care. Completion of an episode includes discharge home, transfer to another consultant in either, the same or a different hospital, a change of specialty under either the same or a different consultant, or death. The data that are collected to describe each episode include clinical (diagnoses and procedures) and non-clinical (demographic information, episode management details) information. Diagnoses are recorded using the International Classification of Disease- ICD-10 (previously ICD-9 and ICD-8) while procedures performed while hospitalised are recorded using the 'Office of Population, Censuses and Surveys Classification of Surgical Operations and Procedures' - 4th revision (OPCS-4, previously OPCS-3)) (ISD Data Dictionary, 2009).

SMR01 records have been computerised since 1968 (Scottish Public Health Observatory, 2010). Linked SMR01-Renfrew/Paisley data reach back to the 1970s, which has resulted in the allocation of different ICD coding schemes; specifically observations in the dataset have ICD8, ICD9 or ICD10 codes. Admissions with ICD9 codes (pre 1992) have been converted into ICD10 codes using a look-up file (New Zealand Health Information Service, 2010). Very early hospitalisations (pre 1981) with an ICD8 code for disease classification cannot readily be converted into ICD10 codes, as there is no available conversion algorithm between these two.

The episode information also included the specialty the patient was treated at. Length of stay (LOS) information is recorded in days with LOS being zero for day cases. After an informal discussion with ISD and their confirmation, one day is added to each of these admissions to facilitate inclusion of these episodes in the cost analysis. However this also means that day cases are treated as inpatient stays and receive the same cost as an inpatient stay of one day.

5.2.3 Linked SMR01- Renfrew/Paisley data

SMR01 records for the Renfrew/Paisley sample consist of 98,262 completed hospital episodes that relate to 13,693 Renfrew/Paisley study members[13]. Data cleaning was carried out as a first step of the data manipulation process. To reduce measurement error, the SMR01 data was checked for data entry anomalies. An initial check of the data for duplicates in terms of patient identifier, date of admission, date of discharge and specialty revealed 107 episodes to be duplicates. To avoid potential double-counting of hospital episodes, these have been deleted from the dataset. The data were further screened for overlapping episodes for individual patients, which have occurred in the same specialty setting. For episodes that overlapped by ten days or more (N=26), those episodes with the shorter LOS have been deleted from the dataset. Further checks revealed episodes that were completely nested within another episode for the same patient and the same specialty. Nested episodes (N=7) were also deleted from the SMR01 dataset. 115 episodes were deleted as these related to individuals that had embarked.

Merging of the SMR01 and the Renfrew/Paisley datasets resulted in 99,572 observations that relate to 15,258 sample members. For individuals without any hospital records (N=1,565) data from the Renfrew/Paisley study provides their baseline characteristics.

Further checks have been carried out after linkage of the two data files and four admissions were detected after the observed death of a sample member. LOS for these admissions was one day and they were deleted from the dataset. Geriatric long stay episodes were only part of SMR01 until 1997. Due to this inconsistency and the nature of the care episodes, six individuals who only had geriatric long stay episodes were discarded from the analysis and a further 540 admissions were also excluded from the

[13] Note that 1,565 sample members do not have a resource use record and therefore do not appear in SMR01 data.

analysis. This provides a final dataset of 99,028 episode observations, relating to 15,252 sample members. Figure 5.1 shows a flowchart of how the analysis sample was derived, looking at both the number of hospital episodes and the number of sample members these episodes relate to.

Observations are episode based, i.e. each row in the dataset represents one hospital episode. Individuals who accessed hospital services can have several episodes of care. These episodes can either be unrelated, single hospital episodes, where the patient is discharged home, and at some point in the future, is admitted again, or they can form an entire hospital stay, where the patient is transferred within or between hospitals. Multiple episodes that form an entire stay are called continuous inpatient stays (CISs). A CIS lasts from admission to hospital until discharge (from the same or a different hospital if the patient was transferred) or death. In order to highlight all episodes that form a CIS for a patient, transfers were marked as follows: if the admission date of an episode is equal to the discharge date of the previous episode these episodes classify as belonging to a CIS. The discharge date for the last episode within a CIS and the admission date of the first episode within a CIS are used to calculate the total LOS for that CIS.

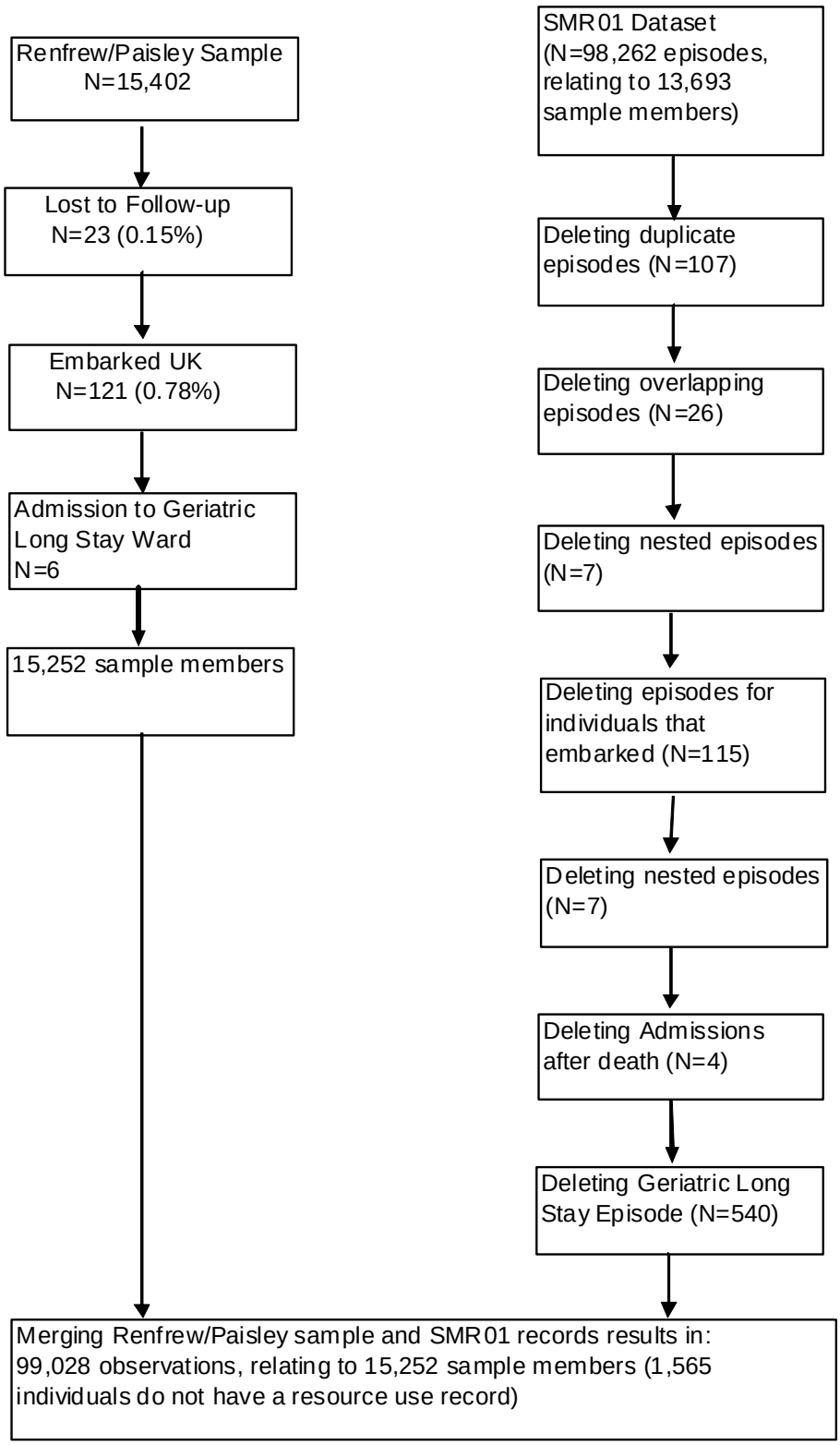

Figure 5-1 Sample set-up

5.2.4 Quarterly cost assignment

The initial set up of the data was a flat file. Every sample member appeared in the dataset either once or several times, depending on the number of hospital episodes that were observed. Sample members without any hospital records only appeared once in the dataset. The panel is in long format with each row representing one single hospital episode (or no episodes). In its original set up the panel was unbalanced and rows (episodes) did not represent a certain time point or period. The data also did not include any information on periods in which no costs were incurred, i.e. periods without a SMR01 record. As the interest of this study lies in the estimation of quarterly costs as people approach death the data needed to be manipulated so that each row represented one quarter (90 days) before death. Measuring costs in quarters instead of years will facilitate analysis for a very defined and narrow time period. Costs could then be assigned to the quarter in which they were incurred and quarters without a cost observation could be filled with zeros.

The initial exploration of the data showed that costs increased markedly in the last two quarters of life. Exploratory regression analysis determined when TTD became an insignificant predictor for costs. It was therefore decided to analyse the last three years of life, measured in quarters (i.e. 12). Each sample member therefore has 12 rows of data, unless they could not be observed for 12 quarters because they died within three years of entering the study. These sample members contribute the maximum number of quarters they could be observed for and are represented by the respective number of rows in the dataset, e.g. a sample member who died two years after entering the study have eight rows of data. 416 sample members contribute less than 12 quarters. Sample members may have had several individual hospital stays (CIS) during one quarter. Costs for these CISs were aggregated so that one row represents one quarter with all incurred costs assigned to it.

A variable that indicates when the last 12 quarters (or less) of life start for each individual patient was generated by subtracting 1,080 days from the date of death. It was assumed that one quarter equals 90 days. If this date was smaller than the date at which individuals entered the study, i.e. individuals have not been in the sample for the entire 12 quarters this date was replaced with the date of study entry, so to mark the maximum period patients were observed for. Admissions that took place out with the 12 quarters before death were discarded from any further analysis.

Each hospital stay (CIS) was then assigned to a particular quarter before death. This was done separately for the admission and discharge date as a CIS can span more than one quarter. The quarter before death into which a CIS fell was first determined by the date of admission. It was then ascertained whether the CIS only belonged to one particular quarter before death or whether it lasted to span more than just one quarter. A marker for each CIS that lasted for more than one quarter was generated. 90.6% of all admissions only span one quarter (<=90 days) and 9.0% lasted between 91 and 180 days. A check to confirm that the admission quarter was always greater than the discharge quarter was also performed. If a CIS lasted for more than one quarter, the assigned costs were split accordingly. This was done by dividing costs by the respective number of quarters. Costs were split evenly across quarters.

Once all costs were assigned to the quarter before death in which they were incurred, using the date of admission as starting point for any cost incurrence, the next step was to add up all costs incurred in each quarter, and so obtain total quarterly costs.

The dataset was then expanded to 12 rows for each individual, or less if sample members could not be observed for 12 quarters. The resulting dataset was not perfectly balanced due to individuals dying within three years of entering the study. It provides the exact number of rows needed for each individual determined by how many quarters they

had completed in the sample before dying (between 1 and 12) and also determined by the number of quarters before death that were analysed (12).

Following the construction of the panel data set, quarters without any hospitalisation were assigned zero costs. If costs were split over two quarters these were equally shared between quarters. This seemed reasonable as the proportion of hospitalisations, where this could be observed was judged to be minimal.

Finally, deletion of episodes before 1980 was carried out, since these had ICD-8 codes assigned, for which no conversion algorithm was available. After taking account of missing information for the dependent variable, and deprivation category, the following samples were analysed: scenario A: 127,982 observation quarters, relating to 11,579 sample members; scenario B: 38,910 observation quarters relating to 3,281 sample members; scenario C: 166,892 observation quarters, relating to 14,860 sample members, and scenario D: 141,420 observation quarters, relating to 13,686 sample members.

5.2.5 Costs

Following recommendations based on results obtained from the analysis of alternative costing methods, as outlined in Chapter 4, this empirical analysis uses HRG based costing applying the English Tariff. This costing method has been chosen for the following advantages it possesses: it is disease and procedure specific and incorporates a fixed and variable cost component, thereby avoiding the assumption that the first day in hospital incurs the same cost as each subsequent day. It also allows adequate costing of hospital stays that involve more than one episode. The costing method followed the steps described fully in Section 4.3.2.

5.3 Results - sample characteristics

5.3.1 Descriptive statistics

The characteristics of the sample are presented in Table 5.1 for the entire sample and by survivor status at the end of the observational period. A total number of 14,860 participants were analysed descriptively, a number that varied in regression analysis according to the sample scenario analysed. 22.1% of the sample population did not have a death record at the end of the study period (N=3,281).

The proportion of females in the survivor group is significantly higher than in the decedent group ($p<0.01$). 10% of the sample population never accessed hospital care, a proportion that does not differ by survival status ($p=0.63$). A higher proportion of individuals living in the most affluent postcode areas could be found in the survivor group, with 8.3% in deprivation category 1, compared to 5.9% in the decedent group. 15.1% of survivors were observed in deprivation category 3, compared to 13.1% in the decedent group. The differences between survivors and decedents in terms of their socio-economic status was highly significant ($p<0.01$).

A higher proportion of the sample population (55.1%) was observed to have a BMI above 25, which is the threshold to being overweight. A higher proportion of individuals with an increased BMI can be observed in the decedent group (55.9%) than in the survivor group (52.2%). This difference is highly statistically significant ($p<0.01$). Individuals' SBP measured at baseline is above a normal reading of 140mmHg for 60.8% of the sample population. A significantly higher share of decedents have a SBP above what is regarded as normal (>140mmHg).

No significant differences between survivors and decedents could be found for two of the health risk and health status measures. The share of the population with a healthy cholesterol level (<6.2mmol/L) in both groups is about 54%. Another non-significant difference between groups can be found for the proxy measure that was used to capture physical activity, i.e. the number of minutes spent each day walking to and from work. In both groups, about 74% spent ten minutes or more walking.

A higher proportion of smokers (66.9%) than non-smokers was found in the entire sample population. Significantly more smokers were present in the decedents group compared to the survivors group and a significantly higher share of decedents have a very low % predicted FEV1 reading (<70%).

The mean age at study entry was 55.3 years (SD= 5.5) for decedents. Survivors were younger when they entered the study with a mean age of 50.7 years (SD= 4.3). Survivors were on average ten years older at censoring than decedents at death (84.1 years [SD=4.4] and 74.2 years [SD=9.3] respectively). This could have been partly caused by the fact that survivors were on average five years younger than decedents at the time they entered the study. The distribution of age across the seven age categories, which are used in regression analyses throughout this chapter, is presented to aid interpretation of regression results. The average number of hospital episodes was observed to be 6.3 [SD=6.9] for the survivor group and 7.4 [SD=7.5] for the decedent group. This difference was found to be highly significant ($p<0.01$).

Table 5-1 Sample characteristics

VARIABLE	FREQUENCY (%) Sample N=14,860 (100%)	FREQUENCY (%) Decedents N= 11,579 (77.9%)	FREQUENCY (%) Survivors N=3,281 (22.1%)	Differences between survivors and decedents (t-test; chi2 test) p-value
Male	6,840 (46%)	5,711 (49.3%)	1,129 (34.4%)	
Female	8,020 (54%)	5,868 (50.7%)	2,152 (65.6%)	p<0.01
Age category at death < 65 years	1,901 (12.8%)	1,901 (16.4%)	0	
Age category at death 65-69 years	1,655 (11.1%)	1,655 (14.3%)	0	
Age category at death 70-74 years	2,098 (14.1%)	2,098 (18.1%)	0	
Age category at death 75-79 years	2,819 (19%)	2,344 (20.2%)	475 (14.5%)	
Age category at death 80-84 years	3,453 (23.2%)	1,988 (17.2%)	1,465 (44.7%)	
Age category at death 85-89 years	2,033 (13.7%)	1,125 (9.7%)	908 (27.7%)	
Age category at death >= 90 years	901 (6.1%)	468 (4%)	433 (13.2%)	Overall p<0.01
Number of HC users	13,300 (89.5%)	2,929 (89.3%)	10,371(89.6%)	
Number of non-users	1,560 (10.5%)	352 (10.7%)	1,208 (10.4%)	p=0.63
Deprivation Category 1	948 (6.4%)	677 (5.9%)	271 (8.3%)	
Deprivation Category 3	2,008 (13.5%)	1,514 (13.1%)	494 (15.1%)	
Deprivation Category 4	3,234 (21.8%)	2,465 (21.3%)	769 (23.4%)	
Deprivation Category 5	5,381 (36.2%)	4,221 (36.5%)	1,160 (35.4%)	
Deprivation Category 6	2,674 (18.0%)	2,193 (18.9%)	481 (14.7%)	
Deprivation Category 7	615 (4.1%)	509 (4.4%)	106 (3.2%)	Overall p<0.01
BMI <= 25	6,670 (44.9%)	5,103 (44.1%)	1,567 (47.8%)	
BMI > 25	8,190 (55.1%)	6,476 (55.9%)	1,714 (52.2%)	p<0.01
Syst. Blood Pressure <140mmHg	5,824 (39.2%)	4,183 (36.1%)	1,641 (50.0%)	
Syst. Blood Pressure >=140mmHg	9,036 (60.8%)	7,396 (63.9%)	1,640 (50.0%)	p<0.01
Cholesterol < 6.2mmol/L	7,991 (53.8%)	6,219 (53.7%)	1,772 (54.0%)	
Cholesterol > = 6.2mmol/L	6,869 (46.2%)	5,360 (46.3%)	1,509 (46.0%)	p=0.76
Walking >= 10 min	11,058 (74.4%)	8,635 (74.6%)	2,423 (73.9%)	
Walking < 10 min	3,802 (25.6%)	2,944 (25.4%)	858 (26.1%)	p=0.41
Smoker	9,939 (66.9%)	8,130 (70.2%)	1,809 (55.1%)	
Non-Smoker	4,921 (33.1%)	3,449 (29.8%)	1,472 (44.9%)	p<0.01
FEV in 1 sec <70%	2,532 (17.0%)	2,255 (19.5%)	277 (8.4%)	
FEV in 1 sec >= 70%	12,328 (83.0%)	9,324 (80.5%)	3,004 (91.6%)	p<0.01
	MEAN (SD)	**MEAN (SD)**	**MEAN (SD)**	
Age at death or Censoring	n/a	74.2 (9.3)	84.1 (4.4)	p<0.01
Age at study entry	54.3 (5.6)	55.3 (5.5)	50.7 (4.3)	p<0.01
Number of Hospital Episodes	6.5 (7.1)	6.3 (6.9)	7.4 (7.5)	p<0.01

*No observations for deprivation category 2

5.4 Methods – Inclusion of survivors

5.4.1 Censoring date

Under scenario C, the surviving part of the sample is censored at the date when hospital use could be observed last (31st December 2007). Their date of death is assumed to be at censoring. Consequently, quarters observed before death start on that date and count back to the 12th quarter before censoring (death). Each survivor therefore, has exactly the same observational period that is declared to be their last 12 quarters of life (1st January 2005 until 31st December 2007).

Estimates from a regression model using this approach are compared with the new approach of employing survival analysis (scenario D), which is detailed below. A comparison is also made with estimates obtained from the approach of analysing a sample of decedents only (scenario A). To complement this analysis and to add to the understanding of the impact that different sample scenarios have on estimated costs at the end of life, regression results are also obtained for the surviving part of the sample only (scenario B).

5.4.2 Survival analysis to predict additional life time after censoring

The proposed novel approach in this thesis in order to include survivors in a TTD study is based on the projection of remaining lifetime to aid assignment of observed costs to the correct period before death. The survival function is denoted as:

$$S(t)=1-F(t) \qquad \text{Equation (5.1)}$$

Where F(t) is the failure function and *t* is the time elapsed since state 0 (study entry)

Survival analysis allows for the survival time to be estimated indirectly via a 'hazard rate', which reflects the chance of making a transition at each defined time period given survival up to that point (Equation 5.2) (Cleves et al, 2008).

$$h(t)=f(t)/S(t) \qquad \text{Equation (5.2)}$$

with f(t) representing the probability density function, the probability of failing at time t and S(t) representing the survival function, i.e. the probability of surviving to at least time t.

This analysis uses the density function in survival analysis for that part of the sample that is uncensored, i.e. for which failure can be observed, and the survival function for that part of the sample that is censored, i.e. for which it is only known that they survived until at least time *t*.

Regression analysis is undertaken in order to estimate the hazard of failing (dying) using a parametric modelling approach. A Gompertz distribution of the hazard of dying is assumed. A Gompertz distribution has been used extensively by researchers to model mortality data and is suitable for modelling hazard rates that increase or decrease exponentially, with the shape parameter 'gamma' providing information on whether the hazard increases (positive gamma) or decreases (negative gamma) with time (Cleves et al, 2008). Alternative distributions were explored (Weibull, exponential), but were not found to perform better than a Gompertz distribution.

Using a Gompertz regression, time until failure (death) is predicted using the following covariates: age at study entry, gender, and the socio-economic status (measured on a scale from one to seven, using the Carstairs deprivation score) (Carstairs and Morris, 1991). Age is assumed to be the main predictor for death. Males are known to have a shorter life expectancy than females. In Scotland the socio-economic status, amongst others, has been shown to be a predictor for life expectancy (Popham et al., 2010).

Other variables representing health risks and health status measures that were available from the Renfrew/Paisley data, such as smoking status, SBP and BMI were considered in exploratory survival analysis. However, given that the survival analysis in this present chapter is to inform the method of using survival analysis in order to predict TTD for the SLS sample (representative sample of the Scottish population), and these measures are not available from the SLS, a decision was made in favour of consistency.

The coefficients obtained from the Gompertz regression are utilised to calculate the linear predictor of time until failure for each surviving participant using their respective covariate values. Based on these results the probability of surviving each year after study entry can be calculated using the respective survival function for a Gompertz distribution (Equation 5.3). This is extended up to *t*=100 with the probability of survival becoming infinitesimal.

$$S(t) = \exp\{ -\exp(\lambda_j)\gamma^{-1}(\exp(\gamma * t_j) - 1)\} \quad \text{Equation (5.3)}$$

Where: λ_j = linear predictor; γ = Ancillary or shape parameter; t= time period indicator.

In order to obtain a value for survivors' additional predicted years of life, the area under the survival curve resulting from the Gompertz regression is calculated for that part of the curve that is beyond the censoring date.

The area under the curve is calculated by applying the trapezoid rule, where the region of interest is divided into trapezium shaped segments, with each segment representing one year (Equation 5.4). Adding up values for each of the segments beyond censoring provides a prediction of the number of additional years of life for survivors.

$$T = (H[n+1] + H) / 2 * (Y[n+1] - Y) \quad \text{Equation (5.4)}$$

Where T= trapezoid segment; H=hazard; Y=years after study entry

Predicted additional years of life are converted into quarters (i.e. additional quarters of life) and added to the observed censored quarters before the end of the study. For example, if the predicted remaining life expectancy was four quarters, what was to be the last quarter of life when using the censoring date as the death date, becomes the fifth quarter before death. This ensures that survivors' incurred costs are estimated for the 'correct' quarter before death. Another adjustment that is made is the correction of the age at death, which is the sum of the age at censoring plus additional years of life, obtained from the application of the trapezoid rule.

The application of this method means that even though cost observations for survivors can be re-classified, there are missing cost observations for the period between censoring and predicted death, since there is only information on resource utilisation up until the 31st December 2007. This also means that survivors are still effectively right censored, however, it allows the surviving part of the sample to be included in the analysis with their adjusted remaining quarters before death instead of making the assumption that sample members have either died at the censoring date, or have a constant TTD.

5.5 Results - survival analysis

Kaplan-Meier survival estimates for males and females are shown in Figure 5.2. The probability of survival for males is lower at any given point compared to the probability of survival for females.

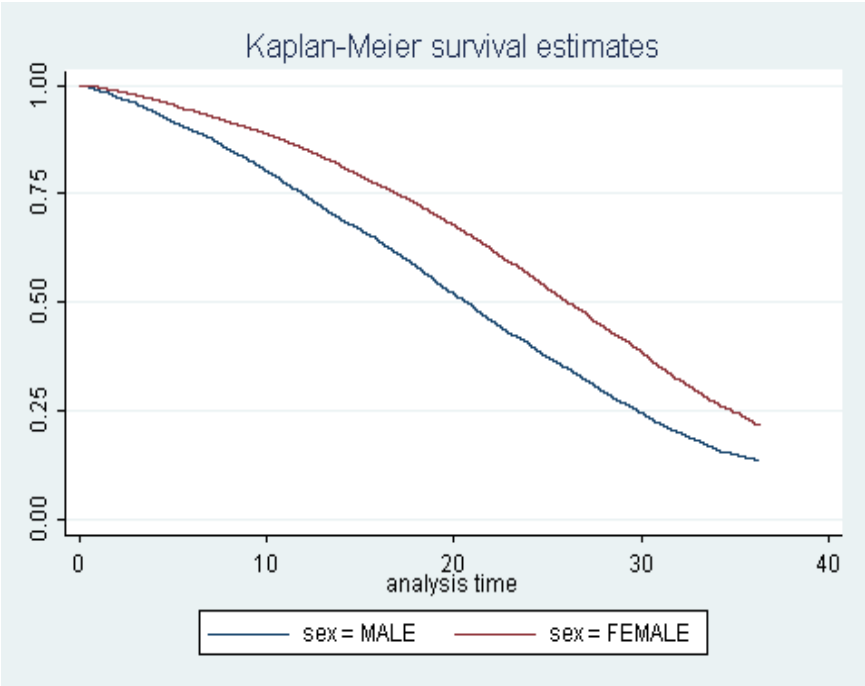

Figure 5-2 Kaplan-Meier SE by gender

Figure 5.3 shows the Kaplan-Meier survival estimates for different deprivation categories. Differences in the probability of survival can be observed with individuals living in more affluent areas having a higher probability of survival at any given point in time than individuals living in more deprived areas.

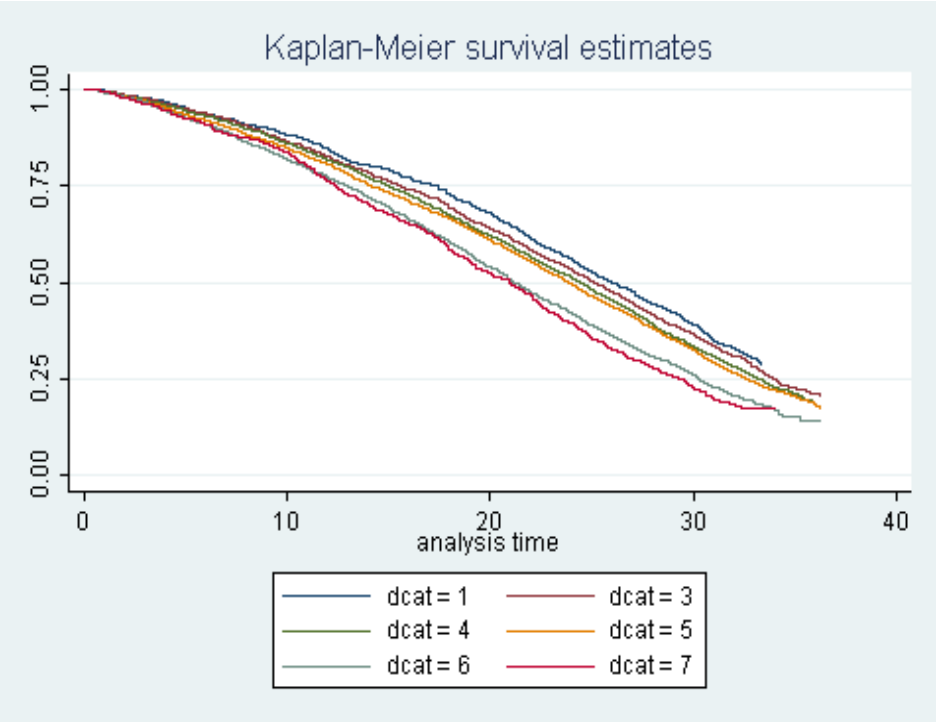

Figure 5-3 Kaplan-Meier SE by socio-economic status

Regression results for the survival analysis using a Gompertz distribution undertaken for the entire sample population to aid prediction of survivors' TTD are shown in Table 5.2. Coefficients are presented as hazard ratios. All explanatory variables for time until failure (death) have a highly significant impact and also show the expected sign.

Table 5-2 Results- Gompertz Regression

Variable	Hazard Ratio	Standard Error
Gender	1.638***	(.031)
Age at Study Entry	1.100***	(.002)
Deprivation Category=3	1.172***	(.054)
Deprivation Category=4	1.226***	(.053)
Deprivation Category=5	1.314***	(.054)
Deprivation Category=6	1.148***	(.065)
Deprivation Category=7	1.733***	(.101)
Gamma	.081***	(.001)
No. of subjects	14,868	
No. of failures	11,587	

*** p<0.01; Deprivation Category 1 serves as the reference category, no observations for deprivation category 2

On average, male individuals show a risk of dying that is 63.8% higher than that of female participants. Each additional year of age at study entry increased the risk of dying by 10%. Individuals living in more deprived areas compared to the most affluent area also have a higher risk of dying with the size of the effect increasing as socio-economic status decreases. Individuals living in the most deprived areas (deprivation category = 7) show a risk of dying that is on average 73.3% higher than the risk of those individuals living in the most affluent areas (deprivation category 1). One possible explanation might be the issue of access to HC services and a higher risk of mortality for less affluent areas could serve as a further explanation (Popham et al., 2010).

The ancillary parameter ‘gamma’ is positive, confirming an exponentially increasing hazard of dying as time progresses. Figure 5.4 shows the resulting survival curve. The censoring point is at 33 years, marked by the shaded area representing the average follow-up time with recruitment into the study being between 1972 and 1976 and the study end being in 2007.

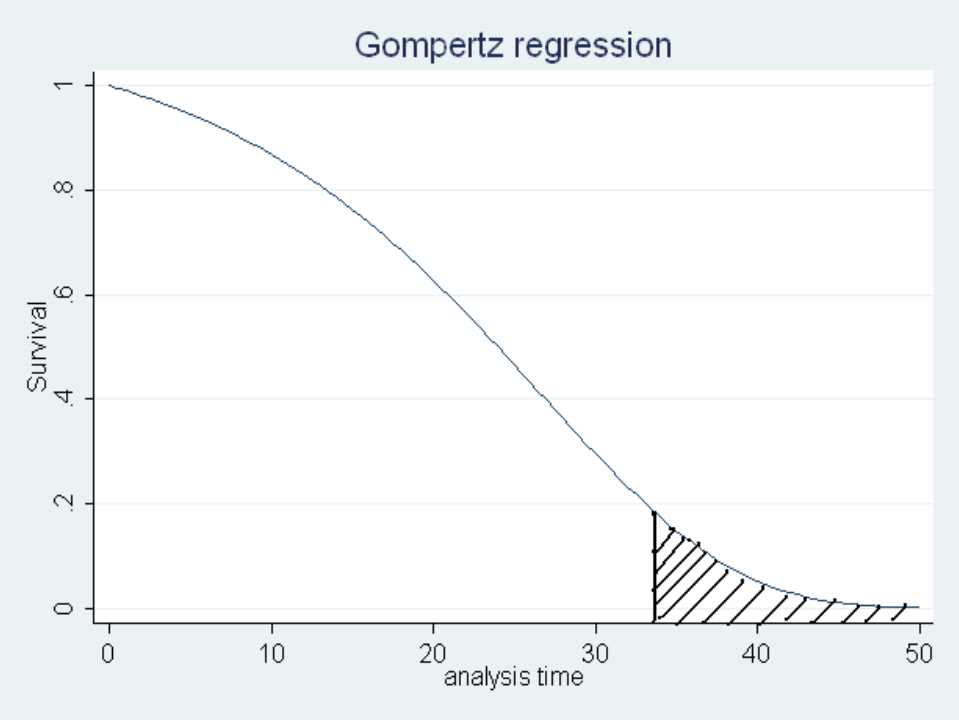

Figure 5-4 Survival curve

5.6 Methods- cost estimation

5.6.1 Descriptive analysis of costs

Costs are observed on a quarterly level and as a result the distribution of these costs is heavily skewed to the right, as can be seen from the histogram of quarterly costs in Figure 5.5 below. Survivors are included here and overall it can be observed that most quarters do not have a cost observation, i.e. hospitalisation. The histogram is truncated at £10,000 in order to facilitate plotting and visualisation of quarterly costs.

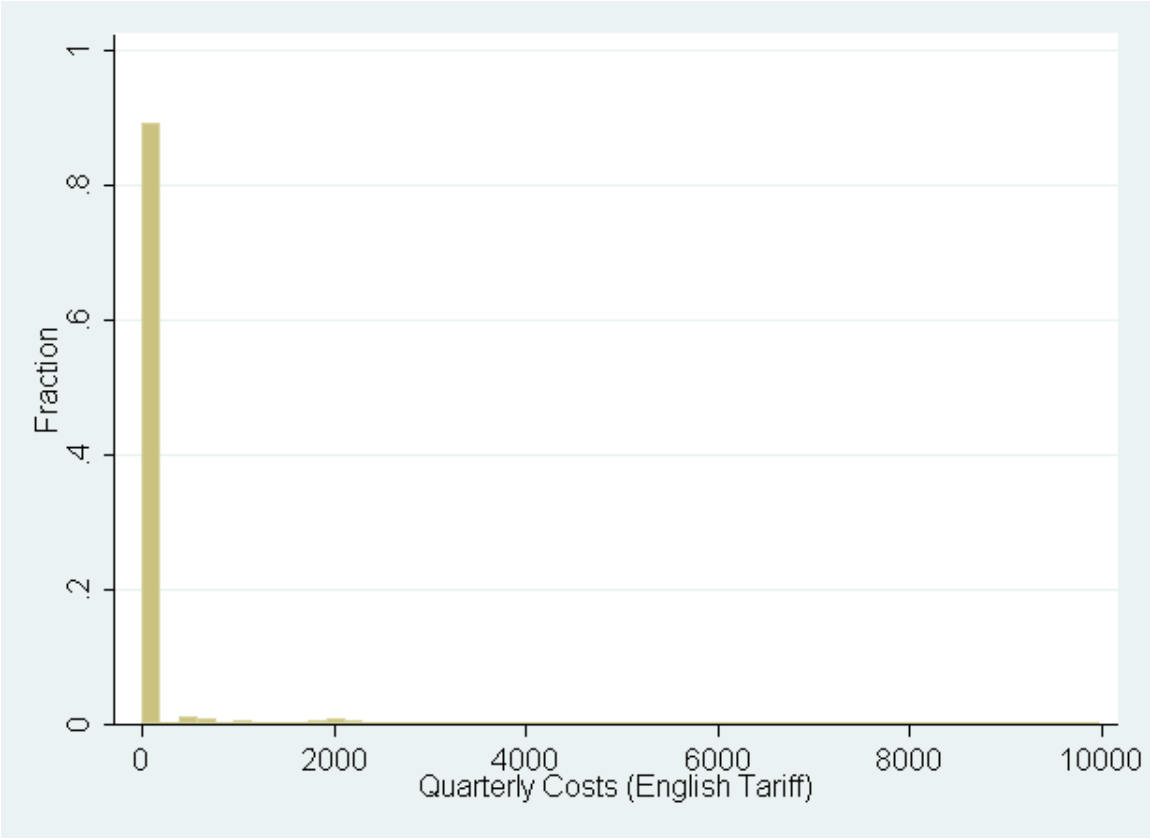

Figure 5-5 Histogram of quarterly costs

Initial descriptive exploration of mean costs incurred in each of the 12 quarters before death is undertaken for decedents and survivors. Figure 5.6 shows observed quarterly costs for the entire sample. Overall, a substantial increase in costs can be observed

from about the third quarter before death. This increase becomes most noticeable when moving from the penultimate quarter of life to the last quarter of life. Further investigation of observed costs towards the end of life is undertaken below using different sample scenarios in order to highlight differences in costs. These are shown in Figures 5.7a, 5.7b, 5.7c and 5.7d, where observed costs for the sample including decedents only (scenario A) seem to be higher in the last quarter of life, compared to scenarios C and D, which also include survivors. Mean observed quarterly costs for scenario D seem to be slightly higher compared to scenario C. Looking at scenario B (Figure 5.7b) it is evident that the distribution of costs follows a different pattern when only survivors are considered and included with the censoring date as their date of death.

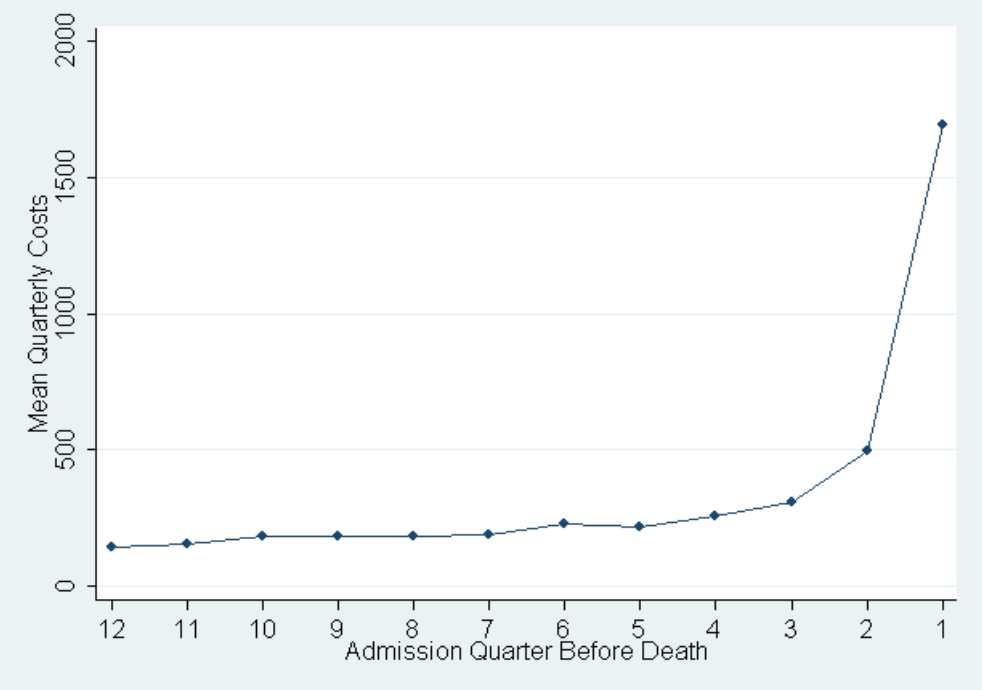

Figure 5-6 Distribution of observed hospital costs (£ sterling, 2006/07 prices) for the entire sample

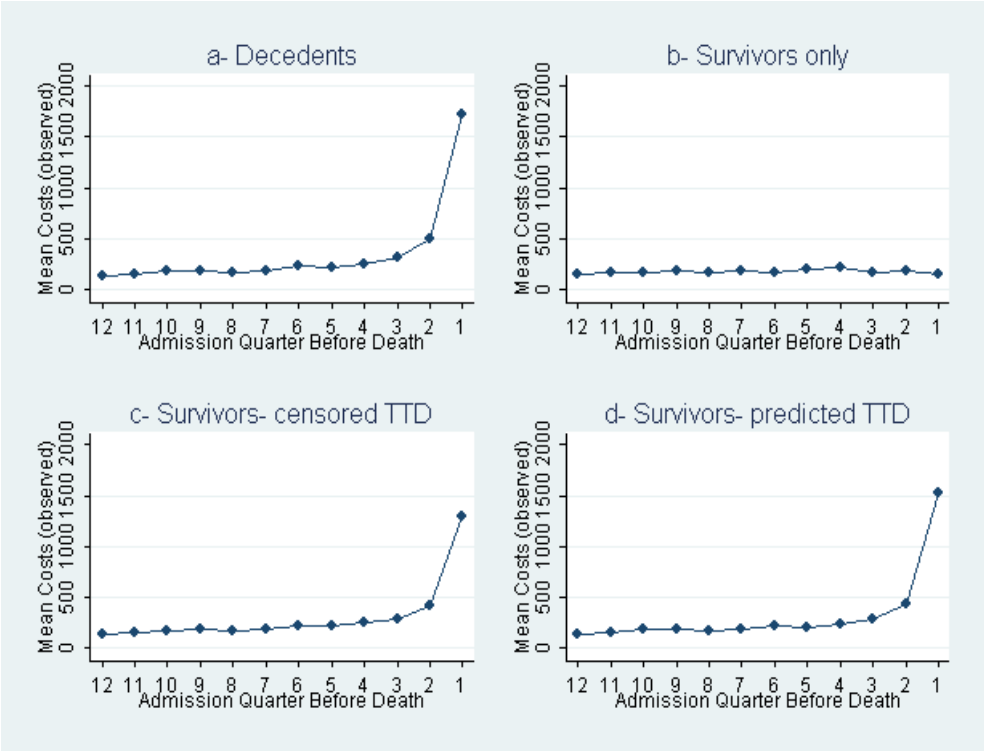

Figure 5-7a, b, c, d Observed hospital costs (£ sterling, 2006/2007 prices) for different sample scenarios

Descriptive analysis of costs by age groups

Figures 5.8a, 5.8b, 5.8c, 5.8d to 5.10a, 5.10b, 5.10c, 5.10d show how observed mean quarterly hospital costs are distributed over different age groups. Figures 5.8a, 5.8b, 5.8c and 5.8d show the distribution of costs as an average over all observed quarters for the three sample scenarios and also separately for sample members that were observed to be alive at the end of the study period. Participants' age was categorised into seven age groups. For sample scenario B (Figure 5.8b) only the four oldest age groups could be observed, as by the time the last 12 quarters before censoring are reached, the surviving part of the cohort is aged at least 75 years, since the minimum age at study entry over 30 years ago was 45 years (see also Table 5.1).

Overall, the distribution of mean quarterly costs shows costs to be higher for the older age groups. This is most pronounced for the sample including decedents only (scenario

A) and less pronounced for the two scenarios including survivors as well (scenarios C and D). Costs for the eldest group (>=90 years) tend to be lower on average than costs for participants aged 85-89 years. When looking at the surviving sample members only (Figure 5.8b), however, an increase in costs for individuals aged 90 and older can be observed, compared to younger age groups. Costs are on average considerably lower for survivors than they are for decedents. When using a sample that includes both survivors and decedents (Figures 5.8c and 5.8d) no marked difference in average costs can be observed between the two methods of accounting for survivors' unknown TTD. Subsequent figures therefore look at certain quarters before death or censoring to investigate differences in more detail.

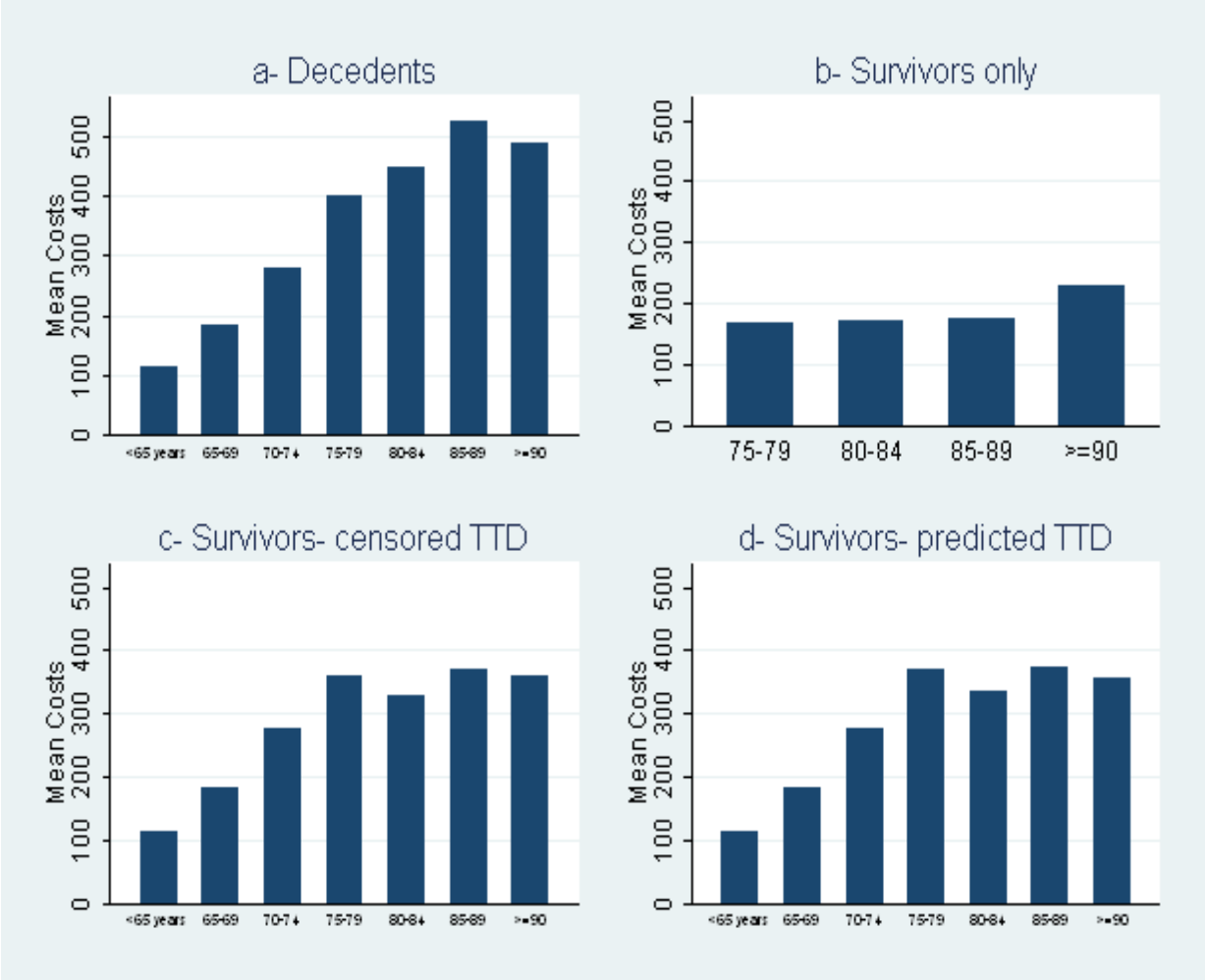

Figure 5-8a, b, c, d Mean observed hospital costs (£ sterling, 2006/07 prices) by age group for different sample scenarios

Figures 5.9a, 5.9b, 5.9c and 5.9d show mean quarterly observed costs for the quarter furthest away from death or censoring (12th quarter). Again, observed costs increase with increasing age and are found to be highest for the oldest age group. The same distribution of costs can be observed for all sampling scenarios with the sample including decedents only showing higher average costs in the 12th quarter before death than the samples including survivors as well as decedents. This could be explained by lower observed costs in the sample that includes survivors only (Figure 5.9b).

Figure 5-9a, b, c, d Mean observed hospital costs (£ sterling, 2006/07 prices) by age group for different sample scenarios in the 12th quarter before death

Finally, Figures 5.10a, 5.10b, 5.10c and 5.10d show the distribution of mean quarterly hospital costs by age group for the last quarter before death/censoring. Costs are

substantially higher on average than those 12 quarters away from death/censoring. Unlike the distribution of costs that could be observed in the 12th quarter before death or the average distribution over all quarters, costs for older individuals tend to be lower in the last quarter before death/censoring. This pattern can be observed for all sampling scenarios and is more pronounced for sample scenarios C and D (Figures 5.10c and 5.10d) and less pronounced for the sample that does not include survivors (Figure 5.10a).

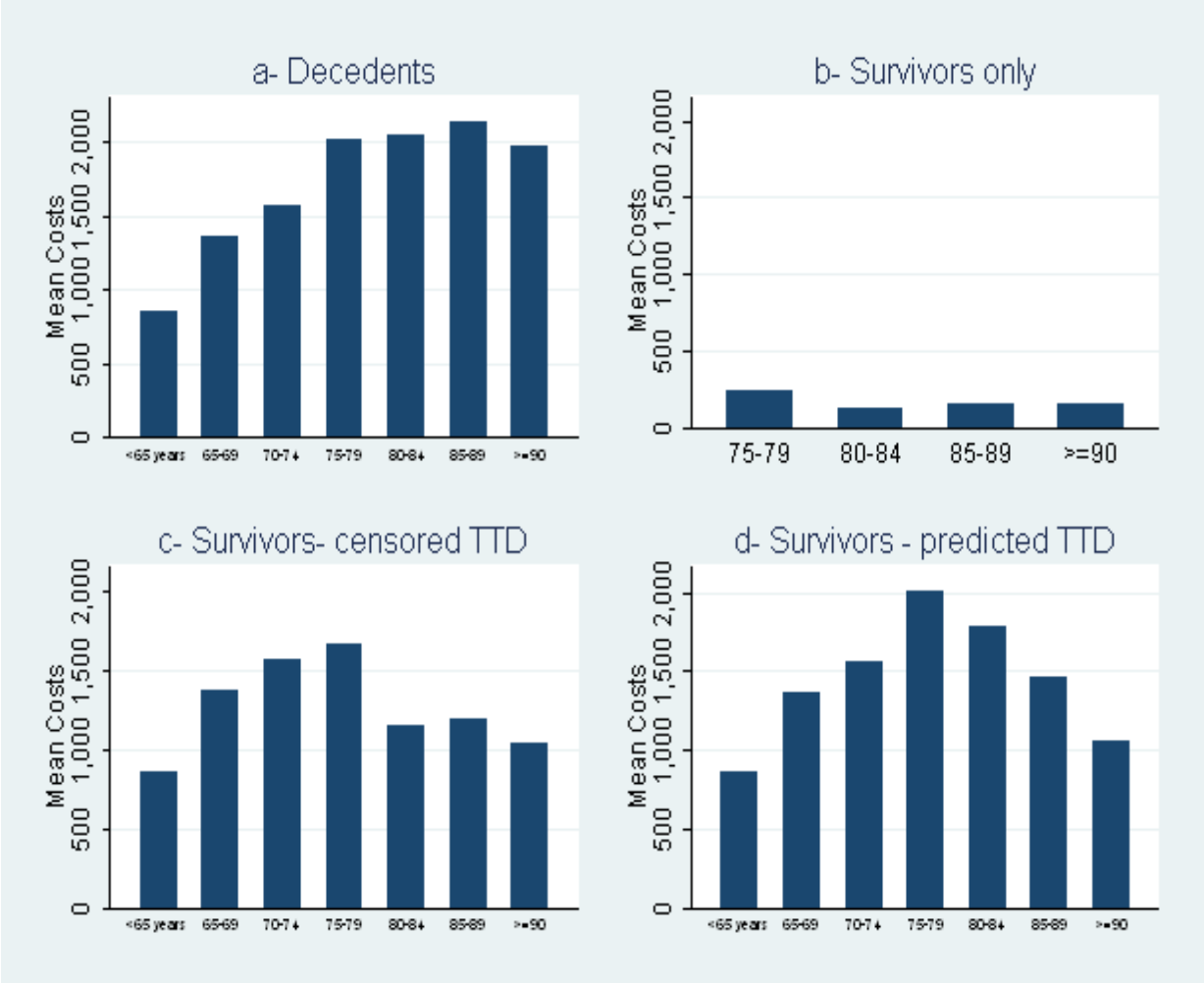

Figure 5-10a, b, c, d Mean observed hospital costs (£ sterling, 2006/07 prices) by age group for different sample scenarios in the last quarter before death

Overall, differences in the distribution over age groups between sample scenarios are more marked in the last quarter before death/censoring than in the 12th quarter. For the

sample containing only decedents (scenario A), costs for participants aged 90 years and older are lower than costs for individuals that are aged between 75-89 years (Figure 5.10a). Costs that are observed for the sample containing only survivors (scenario B) are also lower for the three oldest age groups compared to individuals aged 75-79 years (Figure 5.10b). Costs for survivors are substantially lower on average than they are for the other three samples that include decedents as well as survivors.

Interestingly, costs for the two samples including survivors and decedents using different methods to account for unknown TTD show a different distribution over age groups. Costs for the sample including survivors using the censoring date as their date of death (Figure 5.10c) are substantially lower for participants aged over 80 years and no marked difference can be found between age groups beyond the age of 80. Costs are highest for individuals aged between 65 and 79 and lowest for the youngest age group (<65 years). For the sample including survivors, using a predicted TTD (Figure 5.10d) it can be seen that costs also tend to increase up to the age of 75-79 years, however compared to the sample in Figure 5.10c, costs then steadily decline beyond the age of 80 instead of showing no marked difference as seen in Figure 5.10c.

To summarise these findings, there does not seem to be a marked difference in costs by age group that is incurred through the application of different methods to account for survivors' unknown TTD when looking at the quarter furthest away from death/censoring. However, there is a substantial difference in the quarter closest to death. This is an important finding of how age is associated with costs at the end of life from descriptive analysis. The inclusion of survivors seems to alter observed costs for the eldest age groups considerably, which might be caused, either by the fact that survivors are healthier on average or that these are cared for in different settings, such as nursing homes and therefore do not appear in the acute inpatient dataset (SMR01).

5.6.2 Econometric modelling- explanatory variables

Regression models are employed to estimate the probability of utilising acute inpatient HC services and related costs conditional on positive utilisation, for the three scenarios of accounting for survivors' unknown TTD outlined earlier in this chapter and the comparative scenario where only survivors are included. The following explanatory variables have been identified for inclusion to estimate the model in order to assess the independent effect that population ageing and TTD have on hospital costs.

TTD itself was included as a categorical variable, representing each quarter before death. A series of 12 quarter dummy variables represent the quarter in which an individual's incurred costs were observed with the quarter furthest away from death (12^{th} quarter) serving as the reference category.

Age at death was measured in seven categories (<65 years, 65-69, 70-74, 75-79, 80-84, 85-89, 90 years and over) with the youngest age group serving as the reference category. Interactions between TTD in quarters and age at death categories were included to capture any combined effect of ageing and TTD on HC costs. This has been well documented in the literature (Stearns and Norton, 2004, Moorin and Holman, 2008).

Gender was included to account for any differences in costs incurred by male and female participants. Such differences may be due to gender specific differences in morbidities and/or necessary treatment.[14]

A series of health status and health risk indicators were included. These were % predicted FEV1 (<70%); SBP (>140 mmHg); the cholesterol level (>= 6.2mmol/L); the BMI (>25); a measure of the time individuals spend each day walking to and from work as a proxy for physical activity (<10 minutes); and the smoking status (smoker, i.e. 1 or more cigarettes or pipe/cigars per day).

14 Please note that maternity hospitals and the specialty of obstetrics are not part of SMR01

The Carstairs deprivation score, with category 1 representing the most affluent postcode sectors (reference category) and category 7 the most deprived, was included to account for differences in costs incurred by socio-economic status.[15] The period of admission in which each quarter before death lies, accounts for advances in medical technology over time. This variable is represented in four categories (time1: 1980-1986, time2: 1987-1993, time3: 1994-2000, time4: 2001-2007), with the most historic period serving as the reference category. Finally, for the model including survivors with the censoring date as their date of death, an additional variable is added, which indicates whether sample members were alive at the end of the study period (Dead=0) or whether death could be observed before the 31st December 2007 (Dead=1). This is to control for survivor status and has been conventionally applied in the literature that has used this censoring method to include survivors.

5.6.3 Model structure

The underlying assumption for the model is that the expected value of HC expenditure is a function of these explanatory variables detailed above. A two-part model is employed rather than a Heckman sample selection model. This was discussed in Chapter 3, a two-part model is more appropriate when zero costs (quarters without hospitalisations) are observed rather than unobserved.

The first modelling part employs a probit link and a binomial distribution to estimate the probability of utilising hospital care in any given quarter before death conditional on a set of regressors X (Equation 5.5).

$$\Pr(HCE>0)=\phi(\alpha+\sum_{a=2}^{7}\eta_a A_a+\beta_s S_s+\sum_{h=1}^{6}\omega_h H_h+\sum_{q=1}^{11}\gamma_q Q_q+(\sum_{q=1}^{11}\gamma_q Q_q * \sum_{a=2}^{7}\eta_a A_a)+\sum_{t=2}^{4}\delta_y Y_y+\sum_{d=3}^{7}\mu_d D_d+u_i)$$

Equation (5.5)

[15] Note that the data set included no postcode areas classified as being in deprivation category 2.

Where: A is age at death categories; S represents gender; H is a vector of health status and health risk indicators; Q is the remaining quarters of life (such that Q*A is the interaction of TTD and age); Y a time period dummy indicating the quarter before death into which the admission to hospital falls; and D a dummy for deprivation category[16], u_i represents robust standard errors.

From the second part of the model estimates of HC expenditure are obtained, conditional on HCE being greater than zero and conditional on the same set of regressors X (Equation 5.6).

$$E[HCE] = g(x\beta) \qquad \text{Equation (5.6)}$$

with xβ representing the linear predictor for HC expenditure (HCE).

Quarterly HC expenditure is estimated fitting a GLM clustered on patient identifier. GLM as an extension of OLS has the advantage of being able to specify a link function, which allows transformation of the mean of regressors rather than the mean of the cost variable and therefore mitigates cumbersome re-transformation of cost estimates.

Following conventions for determining the appropriate distribution and link function, diagnostic tests were performed using a user written programme (Glick, 2008), which conducts the modified Park test, the Pearson correlation test, the Pregibon link test and the modified Hosmer and Lemeshow test simultaneously. Details of these goodness of fit tests were described in Section 4.3.3.

Predicted probabilities of positive HC utilisation, obtained from the first part of the model are multiplied with cost estimates from the second part of the model in order to derive average cost estimates conditional on having incurred positive HC expenditure (Equation 5.7).

[16] For sample scenario b), using survivors' censoring date as their date of death an additional variable 'L' was included, indicating whether an individual is dead or alive at the end of study.

$$E(HCE \mid X) = Pr(HCE>0 \mid X) * E(HCE \mid HCE>0, X) \qquad \text{Equation (5.7)}$$

Coefficients obtained from the GLM modelling part are on a log scale and are presented as cost ratios in order to facilitate interpretation of results relating to the original monetary scale.

These estimates are used to compare differences in mean costs by admission quarter before death when estimating the three different modelling scenarios. Scenarios use the same regressors but differ in sample size due to the exclusion of survivors and the unbalanced nature of the panel when predicting survivors' TTD and adjusting observed quarters before death. Four two-part models are estimated in order to facilitate comparison of differences in mean cost estimates that result from the inclusion/exclusion of survivors.

5.7 Results- econometric modelling

5.7.1 Probability of hospital utilisation

The first part of the model estimated the probability of accessing hospital care in any given quarter before death as outlined in Equation 5.5. Table 5.3 presents results for the probit model. Columns (1) and (2) in Table 5.3 show results for the sample based on decedents (scenario A), columns (3) and (4) show results for survivors only (scenario B), columns (5) and (6) show results for decedents and survivors, using the censoring date as the date of death (scenario C), and columns (7) and (8) show results for decedents and survivors, using the predicted date of death for survivors – obtained through survival analysis and extrapolation (scenario D).

Table 5-3 Regression Results: Probability of Hospital Utilisation

	DECEDENTS N=127,982 (11,579)		**SURVIVORS N=38,910 (3,281)**		**SURVIVORS-CENSORED N= 166,892 (14,860)**		**SURVIVORS-PREDICTED N=141,420 (13,686)**	
Scenario	**A**		**B**		**C**		**D**	
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	β	SE	β	SE	β	SE	β	SE
TTD=1	1.821***	(0.114)	0.140	(0.114)	1.819***	(0.114)	1.820***	(0.114)
TTD=2	0.802***	(0.120)	0.064	(0.112)	0.802***	(0.120)	0.802***	(0.119)
TTD=3	0.631***	(0.123)	0.126	(0.108)	0.629***	(0.123)	0.631***	(0.123)
TTD=4	0.512***	(0.123)	0.108	(0.113)	0.511***	(0.123)	0.511***	(0.122)
TTD=5	0.277*	(0.122)	0.222*	(0.110)	0.276*	(0.122)	0.276**	(0.122)
TTD=6	0.417***	(0.132)	0.162	(0.111)	0.415***	(0.128)	0.416***	(0.128)
TTD=7	0.271*	(0.126)	0.023	(0.112)	0.269*	(0.125)	0.270*	(0.126)
TTD=8	0.016	(0.134)	0.113	(0.115)	0.014	(0.145)	0.015	(0.145)
TTD=9	0.211	(0.140)	0.163	(0.114)	0.210	(0.140)	0.210	(0.139)
TTD=10	0.127	(0.134)	0.047	(0.112)	0.127	(0.134)	0.127	(0.134)
TTD=11	0.137	(0.122)	-0.028	(0.115)	0.137	(0.122)	0.137	(0.122)
Age at death 65-69= (2)	0.197	(0.133)	~		0.196	(0.133)	0.195	(0.133)
Age 70-74= (3)	0.247**	(0.123)	~		0.245**	(0.123)	0.243*	(0.123)
Age 75-79=(4)	0.313***	(0.120)	~		0.349***	(0.119)	0.313**	(0.119)
Age 80-84=(5)	0.348***	(0.121)	0.049	(0.097)	0.440***	(0.118)	0.355***	(0.118)
Age 85-89=(6)	0.381***	(0.125)	0.145	(0.103)	0.502***	(0.120)	0.286***	(0.119)
Age > 90= (7)	0.318**	(0.140)	0.133	(0.120)	0.467***	(0.129)	0.419***	(0.128)
TTD x Age[1]	Figure	5.12a	Figure	5.12b	Figure	5.12c	Figure	5.12d
Male	0.018	(0.016)	0.035	(0.029)	0.024*	(0.014)	0.003	(0.015)
Deprivation Category=3	0.102***	(0.036)	-0.080	(0.052)	0.045	(0.029)	0.082**	(0.015)
Deprivation Category=4	0.100***	(0.033)	-0.047	(0.047)	0.052*	(0.027)	0.078**	(0.031)
Deprivation Category=5	0.113***	(0.032)	-0.002	(0.045)	0.073***	(0.026)	0.088***	(0.030)
Deprivation Category=6	0.079**	(0.034)	-0.100*	(0.053)	0.027	(0.028)	0.054*	(0.032)
Deprivation Category=7	0.099**	(0.044)	-0.172**	(0.082)	0.028	(0.038)	0.064	(0.041)
Smoker	0.066***	(0.017)	0.058**	(0.026)	0.0610***	(0.014)	0.069***	(0.016)
BMI <=25	-0.059***	(0.015)	-0.081***	(0.025)	-0.064***	(0.013)	-0.064***	(0.014)
SBP <=140mmHg	0.065***	(0.015)	0.051**	(0.026)	0.058***	(0.013)	0.058***	(0.014)
FEV1 <70%	-0.021	(0.019)	-0.014	(0.046)	-0.017	(0.017)	-0.014	(0.018)
Walking >=10 min	0.003	(0.017)	-0.053*	(0.031)	-0.011	(0.015)	0.003	(0.016)
Cholesterol <6.2mmol/L	0.039***	(0.015)	0.020	(0.026)	0.034***	(0.013)	0.037**	(0.015)
Time period= 1985-1992	0.561***	(0.027)	~		0.562***	(0.027)	0.561***	(0.027)
Time period=1993-2000	0.866***	(0.031)	~		0.868***	(0.030)	0.875***	(0.031)
Time period=2001-2007	0.988***	(0.034)	~		0.998***	(0.033)	0.854***	(0.034)
Dead=1	n/a	n/a	n/a		0.413***	(0.018)	n/a	n/a
Constant	-2.724***	(0.115)	-1.404***	(0.099)	-3.073***	(0.114)	-2.690**	(0.113)
LR Test (TTD*Age)	p<0.001		p<0.001		p<0.001		p<0.001	

*** p<0.01; **p<0.05, *p<0.1; Robust standard errors in parentheses; Deprivation category 1 (most affluent) serves as the reference category; Age category 1 (<65) serves as the reference category; TTD=12 serves as the reference category; ~ age categories 1 to 3: no observations, age category 4 (75-79) serves as the reference category and all admissions fall into the period 2001-2007; [1] Estimates for TTD and Age interactions can be found Appendix IV.

Generally, the TTD results are not substantially different in terms of the size of the effect and statistical significance between scenarios A, C and D. Overall, the probability of being admitted to hospital increases significantly as people approach death. Results for scenario B however are very different compared with the remaining scenarios. No significant effect of TTD (time to censoring) on the probability of accessing hospital services can be observed for this sample. Figures 5.11a, 5.11b, 5.11c and 5.11d show the estimated probability of being hospitalised for all four sample scenarios in their last 12 quarters before death or censoring. For scenarios A, C and D an exponential increase of the probability of accessing hospital care can be observed from the penultimate to the last quarter of life. The sample including decedents only (Figure 5.11a) has a higher probability of accessing HC in their last two quarters of life than the samples including survivors as well as decedents (Figures 5.11c and 5.11d). For scenario B (Figure 5.11b) no increase in the probability of being admitted to hospital as the censoring date approaches can be observed.

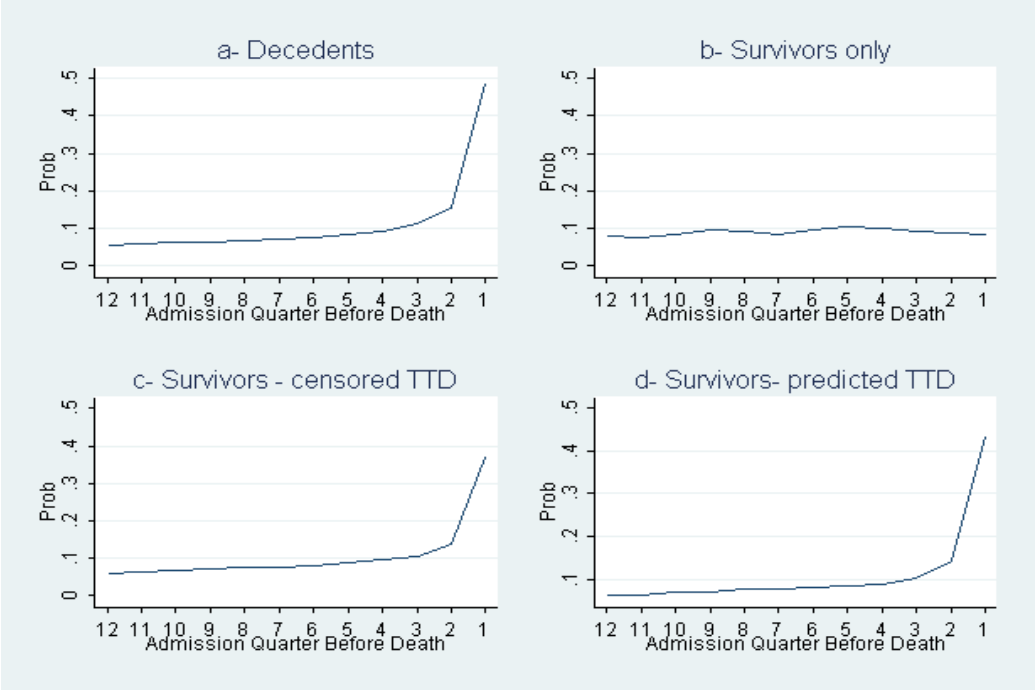

Figure 5-11a, b, c, d Estimated probability of utilising hospital care

The age effects presented in Table 5.3 relate to the 12th quarter before death. Because of the included interaction terms, age is allowed to have a different effect on costs in each quarter before death (Figures 5.12a, 5.12b, 5.12c and 5.12d). An increased probability of accessing hospital care can be observed for individuals aged 70 and older compared to the youngest age group (<65 years) in the sample that includes decedents only (columns (1) and (2)). A similar effect can be found for the samples that include both, decedents and survivors but with a generally increased size of the effect, which is even more pronounced for the sample that uses the censoring date as the date of death for survivors (columns (5) and (6)). No significant effect of age on the probability of being admitted to hospital is found for sample scenario B (columns (3) and (4)).

The model that excludes survivors (columns (1) and (2)) shows that individuals from deprivation categories 3, 4, 5, 6, and 7 are significantly more likely to be admitted to hospital compared to individuals from the most affluent category 1. This significant effect disappears for the two most deprived categories (6 and 7) in the models that include survivors, while for the remaining deprivation categories the size of the effect decreases. For modelling scenario B (survivors only) a significant, but negative association is found between deprivation categories 6 and 7 and the probability of accessing hospital services. Individuals from more deprived areas seem to be less likely to be admitted to hospital than individuals from the most affluent postcode areas.

The coefficient estimates for health status baseline measures reveal that: smokers have a significantly higher probability of being admitted to hospital compared with non-smokers. This effect can be observed across all sample scenarios. Individuals with a BMI below 25 are less likely to access hospital care than people with a BMI above 25. Again this negative association is observed for all samples, with the sample including survivors only (scenario B) showing the strongest effect.

Individuals with a normal SBP (<=140mmHg) are significantly more likely to access hospital care than people with an SBP of over 140mmHg and individuals with a cholesterol level below 6.2mmol/L are significantly more likely to access hospital services than people with a level over 6.2mmol/L. Although statistically significant, the size of the effect for these two health status measures is found to be very small and it has to be noted that the cut-off chosen for these binary variables could have also impacted on results.

No statistically significant association could be found between the probability of being admitted to hospital and the % predicted FEV1, and walking to and from work for more than ten minutes per day for scenarios A, C and D. 'Walking' is marginally statistically significant for scenario B and shows a negative association with the probability of being admitted to hospital, but the effect is very small. The period of admission shows an increased probability for the more recent periods compared with the most historic period (1980-1986). Overall, the results for baseline health indicators and periods are very similar across all sample scenarios, although there are some differences in the magnitude of the coefficients.

For the sample that includes survivors with the censoring date as their date of death (columns (5) and (6)) an indicator variable was added to account for the fact that people were still alive at the end of the study period (Dead=1). Individuals, whose death was observed, showed a higher probability of accessing hospital services than survivors.

Detailed coefficients from the probit model, showing the interaction terms between age and TTD (relative to the youngest age group and the 12^{th} quarter before death) are presented in Appendix IV. Coefficients for interaction terms between age and TTD, varying the reference category for age, are shown graphically in Figures 5.12a, 5.12b, 5.12c and 5.12d. These are presented relative to the 12^{th} quarter before death. A steeper gradient is observed for the younger age groups, especially in the last quarters

of life. This is especially apparent in the two scenarios that include decedents and survivors (Figures 5.12c and 5.12d). Interactions can particularly be observed in Figure 5.12c using the censoring date as date of death for survivors, for the last two quarters of life and also in Figure 5.12d, where TTD was predicted. Sample scenario B (Figure 5.12b) also shows some interactions between age and TTD, or in this case time to censoring. For the sample including decedents only (Figure 5.12a) almost no interaction effects can be found in the last two quarters of life as shown through the parallel lines. A conclusion that could be drawn from these figures is that decedents represent a very homogenous group and that differences in the effect that TTD has in different age groups on the probability of being admitted to hospital are mainly driven by the surviving part of the sample.

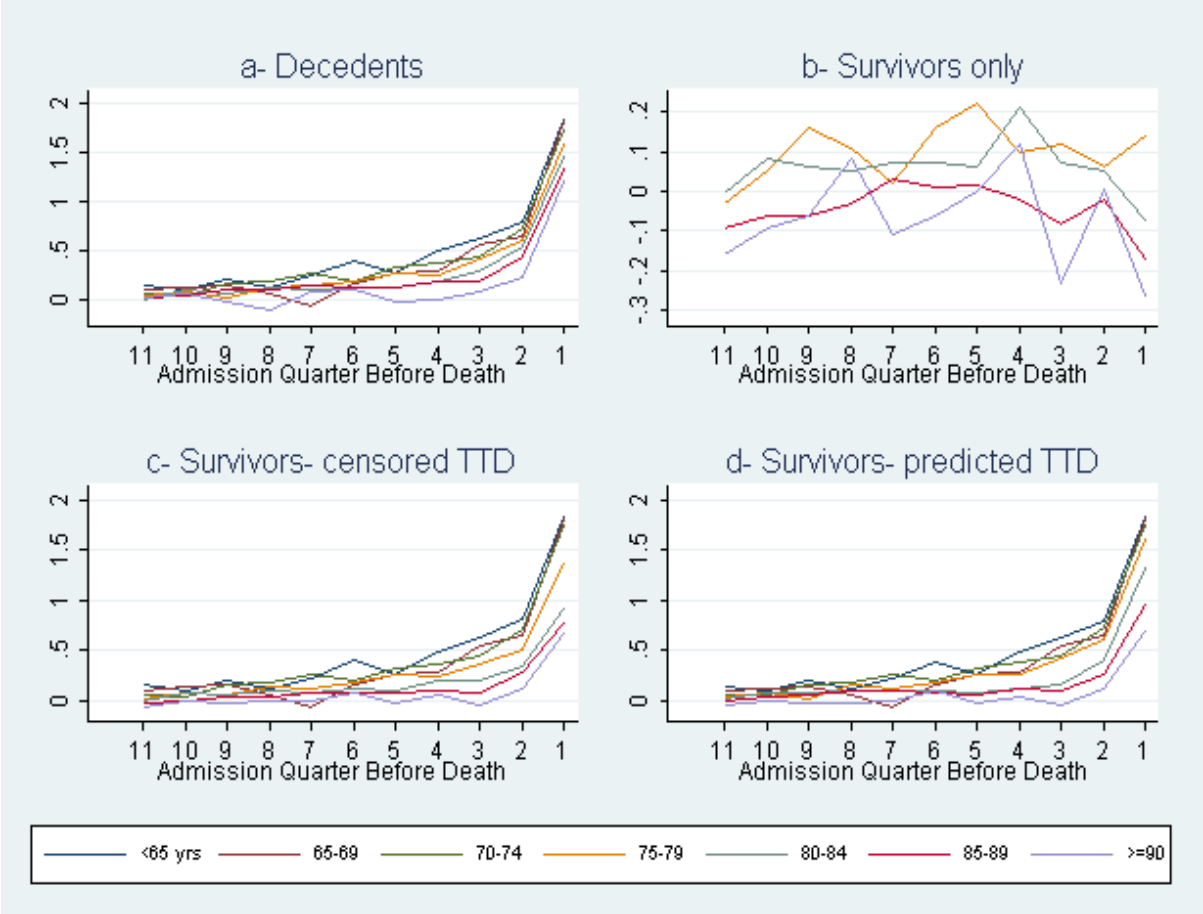

Figure 5-12a, b, c, d Coefficients for probability of hospitalisation by admission quarter: TTD and age interaction terms

5.7.2 Cost estimates

Regression results for the second part of the model, estimating costs given positive HC utilisation, are presented in Table 5.4, columns (1) to (8), again for all sample scenarios. These results are estimates obtained from Equation 5.6 above, so they are conditional on having incurred positive costs. Inverse Gaussian is the recommended distributional family and log has been recommended as the appropriate link function (results for goodness of fit tests are shown in Appendix VI).

Costs are significantly higher in the last eight quarters of life compared with the 12th quarter before death (serving as the reference category), as shown by the indicator variables, representing the quarter before death. This association is found for sample scenarios A (columns (1) and (2)), C (columns (5) and (6)) and D (columns (7) and (8)). The size of the effect decreases the further away from death individuals are, up until the fifth quarter before death, after which an increase is observed up until the eighth quarter before death. From the ninth quarter before death a decrease in costs is found, but this association is not statistically significant. For sample scenario B (columns (3) and (4)) a significant association between costs and the quarter before censoring is only found for TTD=1 and TTD=10, where estimated costs are significantly higher than in the 12th quarter before censoring.

Age at death is a significant predictor of mean quarterly costs for sample scenarios A, C and D, apart from the second youngest age group (65-69). The age effects relate to the 12th quarter before death or censoring. Some of the interaction terms between TTD and age show a statistically significant association with costs (regression results are presented in Appendix V), i.e. the effect on costs of being in a particular quarter before death compared to the 12th quarter also depends on age. Interaction terms show a statistically significant association with costs especially for the older age groups and up until the eighth quarter before death.

Table 5-4 Regression Results 2nd part – Cost Estimates

	DECEDENTS N=13,855 (6,762)		**SURVIVORS N=3,496 (1,798)**		**SURVIVORS-CENSORED N= 17,351 (8,560)**		**SURVIVORS-PREDICTED N=15,052 (13,686)**	
Scenario	**A**		**B**		**C**		**D**	
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Cost Ratio	SE	Cost Ratio	SE	Cost Ratio	SE	Cost Ratio	SE
TTD=1	2.021***	(0.143)	1.730***	(0.209)	2.031***	(0.143)	2.027***	(0.144)
TTD=2	1.957***	(0.180)	1.090	(0.203)	1.975***	(0.180)	1.973***	(0.180)
TTD=3	1.757***	(0.221)	1.249	(0.191)	1.763***	(0.218)	1.757***	(0.218)
TTD=4	1.792***	(0.182)	1.202	(0.244)	1.815***	(0.183)	1.809***	(0.183)
TTD=5	1.588**	(0.236)	1.119	(0.191)	1.639**	(0.245)	1.604**	(0.239)
TTD=6	2.041***	(0.239)	1.050	(0.209)	2.070***	(0.237)	2.064***	(0.239)
TTD=7	3.189**	(0.567)	1.047	(0.165)	3.228**	(0.570)	3.188**	(0.567)
TTD=8	2.693**	(0.428)	1.175	(0.200)	2.671**	(0.419)	2.684**	(0.425)
TTD=9	1.367	(0.224)	1.213	(0.190)	1.374	(0.223)	1.376	(0.225)
TTD=10	0.940	(0.189)	1.746***	(0.200)	0.944	(0.186)	0.942	(0.187)
TTD=11	1.136	(0.222)	1.168	(0.184)	1.116	(0.212)	1.124	(0.218)
Age at death 65-69= (2)	0.890	(0.174)	~		0.887	(0.172)	0.889	(0.174)
Age 70-74= (3)	1.578**	(0.196)	~		1.577**	(0.193)	1.571**	(0.196)
Age 75-79=(4)	1.912***	(0.176)	~		1.893***	(0.167)	1.955***	(0.179)
Age 80-84=(5)	1.989***	(0.165)	1.031	(0.162)	1.921***	(0.153)	1.963***	(0.158)
Age 85-89=(6)	2.134***	(0.167)	1.200	(0.168)	2.147***	(0.156)	1.836***	(0.160)
Age > 90= (7)	2.231***	(0.215)	1.698*	(0.300)	2.601***	(0.212)	2.487***	(0.242)
TTD x Age[1]	Figure	5.13a	Figure	5.13b	Figure	5.13c	Figure	5.13d
Male	0.858***	(0.024)	0.882***	(0.041)	0.868***	(0.021)	0.849***	(0.023)
Deprivation Category=3	0.894*	(0.066)	0.975	(0.092)	0.914	(0.057)	0.913	(0.062)
Deprivation Category=4	0.912	(0.064)	0.974	(0.082)	0.923	(0.054)	0.915	(0.059)
Deprivation Category=5	0.942	(0.063)	0.960	(0.079)	0.937	(0.053)	0.944	(0.058)
Deprivation Category=6	1.028	(0.067)	0.941	(0.094)	1.009	(0.056)	1.009	(0.062)
Deprivation Category=7	0.937	(0.078)	1.178	(0.132)	0.978	(0.069)	0.940	(0.073)
Smoker	0.923***	(0.027)	0.944	(0.041)	0.928***	(0.023)	0.935***	(0.025)
BMI <=25	0.997	(0.023)	0.961	(0.038)	0.987	(0.020)	0.986	(0.022)
SBP <=140mmHg	0.946**	(0.022)	1.003	(0.039)	0.969	(0.020)	0.953**	(0.021)
FEV1 <70%	1.084**	(0.034)	0.909	(0.063)	1.051	(0.031)	1.084**	(0.033)
Walking >=10 min	0.985	(0.026)	0.996	(0.044)	0.991	(0.023)	0.998	(0.024)
Cholesterol <6.2mmol/L	1.025	(0.022)	1.002	(0.038)	1.013	(0.020)	1.014	(0.021)
Time period= 1985-1992	0.880**	(0.051)	~		0.877*	(0.052)	0.880**	(0.052)
Time Period=1993-2000	0.724***	(0.054)	~		0.721***	(0.055)	0.724***	(0.055)
Time Period=2001-2007	0.710***	(0.057)	~		0.706***	(0.058)	0.685***	(0.057)
Dead=1	n/a		n/a		1.348***	(0.028)	n/a	
Constant	1897***	(0.159)	1677	(0.171)	1383***	(0.158)	1877***	(0.158)
LR Test (TTD*Age)	p<0.001		p<0.001		p<0.001		p<0.001	

*** p<0.01; **p<0.05, *p<0.1; Robust standard errors in parentheses; Deprivation category 1 (most affluent) serves as the reference category; Age category 1 (<65) serves as the reference category; TTD=12 serves as the reference category, ~ age categories 1 to 3: no observations, age category 4 (75-79) serves as the reference category and all admissions fall into the period 2001-2007

A marginally statistically significant association of age with costs is found for scenario B, where only the eldest seem to incur higher costs compared to the age group aged 70-74. These results are very different and it has to be noted again, that this sample does not include decedents and the reference group is different from the one used for the other three sample scenarios.

Figures 5.13a, 5.13b, 5.13c and 5.13d show interaction effects for each age group plotted against the admission quarter before death relative to the 12th quarter. On average, the two youngest age groups seem to incur higher costs in their last 11 quarters of life compared with the 12th quarter and also compared with the last 11 quarters of life of all other, older age groups. For sample scenarios A, C and D increasing costs can be observed for the last three quarters of life, compared with the 12th quarter before deaths for all age categories. Costs in the last quarters of life seem to be much more influenced by age if individuals are younger, as can be seen from the blue and red line in the graphs, which show a much more unparallel pattern than the lines representing the interactions between TTD and age for the older ages. Also, costs seem to be higher for the younger age groups. For the four oldest age groups, beyond the age of 75, interaction effects are less pronounced and show a similar pattern across all sample scenarios.

On average, male individuals incur significantly less costs than females (~14%). This effect can be observed in all four modelling scenarios. The effect that the socio-economic status has on costs, given positive utilisation is very small. Interestingly, it also does not seem to have a significant association with costs incurred, which can be observed across all four sample scenarios. The significant effect of deprivation category on the probability of hospitalisation that was observed earlier (Table 5.3) for scenario A (decedents), was found to disappear for the two most deprived post code areas when survivors (scenarios C and D) were included in the regression (while the magnitude of the coefficients on the other deprivation categories was reduced); this may mean that

any effect of socio-economic status might be spurious, which seems to be confirmed by the results obtained from this second part of the regression model, where no effect of deprivation could be observed.

Once hospitalised, the deprivation effect for those in categories 3, 4 and 5 disappears entirely, so while these individuals might be more likely to be admitted to hospital, they do not consequently incur higher costs. The significant association for the two most deprived categories regarding the probability of accessing hospital care for the 'decedent sample', which subsequently disappears when survivors are included may be caused by the higher socio-economic status in the survivor group (see Table 5.1). An alternative explanation may lie in the method of deriving the cost variable. People from more deprived areas are known to have longer stays in hospital, often due to a lack of available care in their own homes. Any deprivation category effect that might be present could have been modified by the fact that LOS plays a role when assigning costs using the HRG-Grouper software. This is an issue that could be explored in future research that could investigate the effect that different costing methods have on costs incurred at the end of life.

Smokers seem to incur less costs on average than non-smokers (~7%), although this association can only be found in sample scenarios A, C and D. The effect of the BMI is found to be very small and not statistically significant across sample scenarios. An SBP of below 140mmHg at baseline leads to a significant reduction in costs by about 5% for scenarios A and D, whereas a % predicted FEV below 70% leads to a significant increase in costs in these two sampling scenarios (~8%). No significant effect can be found for the health status indicator of walking to and from work for more than ten minutes a day.

The period of admission shows a negative association with costs, with costs being on average about 30% percent lower for the two most recent periods compared with

admissions between the years 1980-1986. Again, a similar effect can be observed for sample scenarios A, C and D. Since for sample scenario B all admissions in the last 12 quarters before censoring were observed to be in the most recent period, this variable was omitted from regression analysis. The indicator variable to control for survivor status in columns (5) and (6) reveals that deceased individuals incurred significantly higher costs than surviving sample members in sample scenario C.

Figure 5-13a, b, c, d Cost estimates (ratios) by admission quarter: TTD and age interaction terms

5.7.3 Comparison of quarterly costs

Table 5.5 compares quarterly costs estimates for all modelling scenarios. These are predicted costs that were calculated from Equation 5.7, which multiplied the first modelling part (probability of accessing hospital services) with the second modelling part (cost estimates, given positive utilisation). Differences in costs can especially be observed in the last quarter before death, where estimates range from £1,179 (SD=429) for the sample including decedents and survivors (using the censoring date as their date of death; scenario C) to £1,670 (SD=469) for a sample which excludes survivors (scenario A). It has to be noted though that there might be some bias in results, since the samples are not independent from each other. For sample scenario B (survivors only) very low costs are observed in the quarter closest to censoring (£184; SD=62).

Costs show a sharp decrease when moving from the last quarter of life to the penultimate quarter of life for scenarios A, C and D. Overall, differences in costs between groups become less marked the further away from death an individual is. However, given interaction effects between TTD and age, these estimates are also influenced by age. Figure 5.14 shows these effects for all age groups for the last four quarters before death or censoring. Cost predictions can so be compared across sample scenarios and across age groups. In particular for the last quarter of life differences in costs by age group can be observed between sample scenarios. For the sample including decedents only (scenario A) slightly higher costs for the older ages are observed compared to the two scenarios that also include surviving sample members, where costs for the older ages seem to be lower in the last quarter of life compared with the younger sample members. A difference in costs is also found between scenario C and D, with the sample predicting the remaining TTD producing higher cost estimates in the last quarter of life across all ages, but in particular for the three oldest age groups.

Table 5-5 Mean Hospital Costs in GBP (2006/07 prices)

	DECEDENTS		**SURVIVORS**		**SURVIVORS CENSORED**		**SURVIVORS PREDICTED**	
Scenario	**A**		**B**		**C**		**D**	
TTD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	1,670	469	184	62	1,179	429	1,658	462
2	463	223	156	57	386	190	456	212
3	296	163	163	28	261	147	289	154
4	233	137	183	43	233	141	233	126
5	193	111	183	34	200	122	196	107
6	196	111	154	22	192	111	191	95
7	173	122	145	39	179	124	173	105
8	168	108	151	24	168	108	170	97
9	150	90	174	27	166	105	153	81
10	156	118	177	38	161	117	160	105
11	129	99	145	45	148	117	133	87
12	119	92	127	38	130	102	129	87

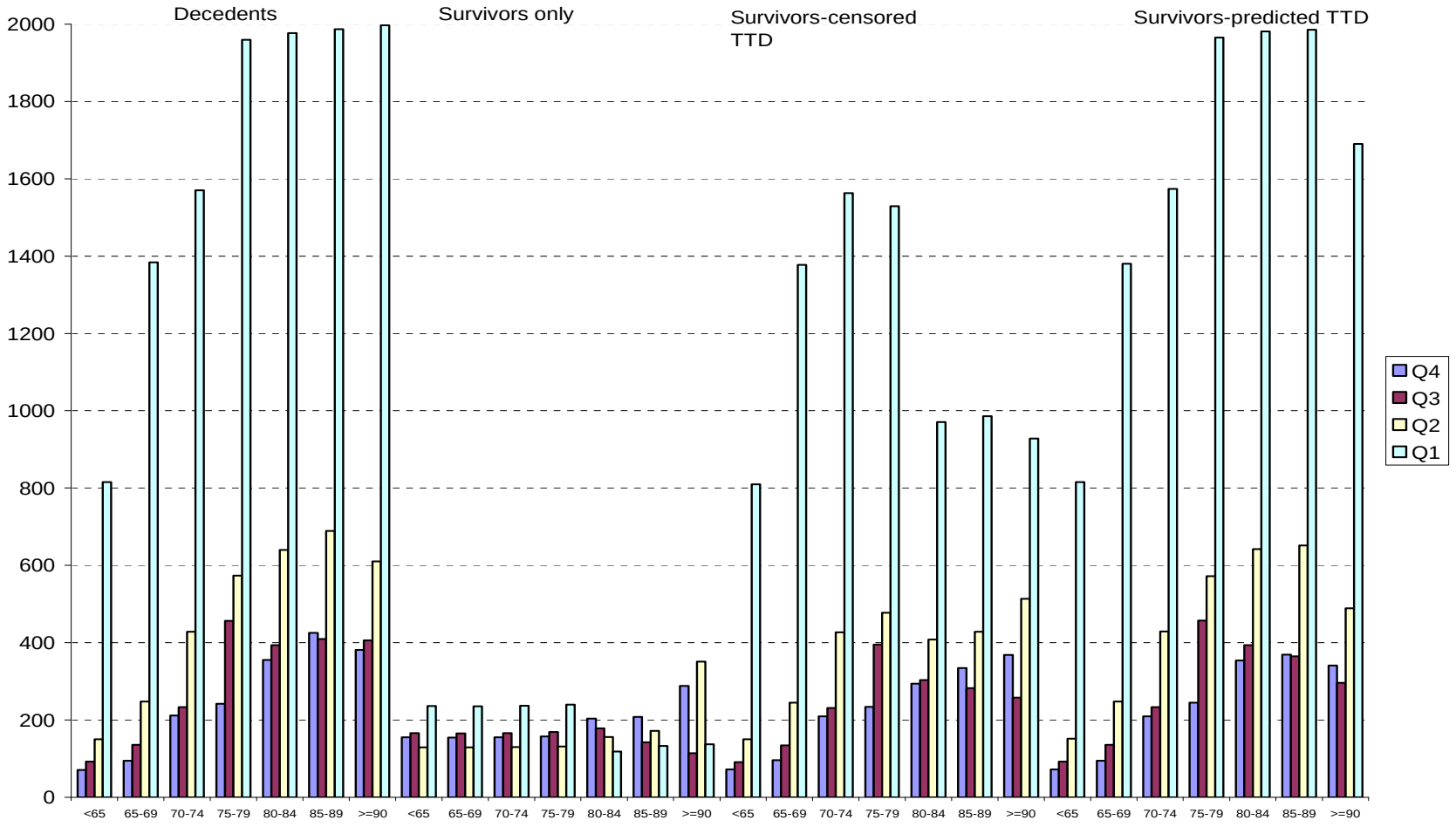

Figure 5-14 Interactions between TTD and age for the last four quarters before death

5.8 Validation of the survival analysis approach

Given the very long period for which sample members of the Renfrew/Paisley study were observed for, it is possible to validate the method of applying survival analysis to predict TTD for survivors and further test how accurately this would predict costs at the end of life. The rationale behind this is to apply an earlier censoring date than the 31st December 2007, thus right censor observations artificially.

5.8.1 Methods - early censoring

The new 'artificial' censoring date chosen for this example is the 31st December 2000. Any 'real' survivors, i.e. individuals, who had not died by the 31st December 2007, were discarded from the analysis of this validation approach. At the end of the year 2000, there were 24% survivors and 76% decedents. For all participants who survived until the end of December 2000, a date of death could subsequently be observed. These were individuals who died between the 1st January 2001 and the 31st December 2007.

This experiment is to show what the estimated costs would be in the last 12 quarters of life if these were predicted from survival analysis for those sample members that were observed to be alive on the 31st December 2000. These cost estimates are then compared with cost estimates obtained using survivors' observed date of death after the 31st December 2000 and before the 31st December 2007 (akin to scenario A). A comparison of cost estimates from both approaches provides an estimate of the magnitude by which costs at the end of life might be over-or under-estimated if survival analysis is used to predict remaining TTD compared to having perfect information of the actual TTD.

Following the methods outlined in Section 5.4.2, a Gompertz regression is employed, using the earlier censoring date and the same set of regressors. The Kaplan-Meier survival estimate for this sub-sample is shown in Figure 5.15.

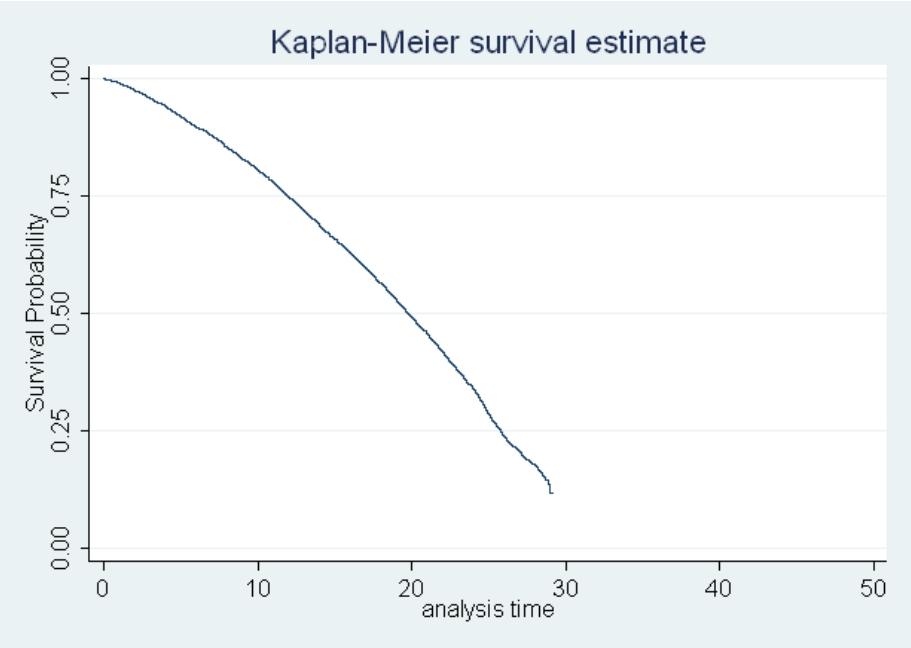

Figure 5-15 Kaplan-Meier SE- early censoring

Coefficients obtained from the Gompertz regression are used to calculate the linear predictor of time until failure for each surviving participant. Again, the interest lies in calculating the area under the survival curve resulting from the Gompertz regression for that part of the curve that is beyond the new censoring date (>29 years in Figure 5.16 below). By applying the trapezoid rule and adding up values for each segment that is beyond the censoring date, additional predicted years of life are calculated for survivors (that is survivors on the 31st December 2000). These are then converted into additional days and added to the censoring date. The resulting date constitutes the predicted date of death and TTD is calculated counting 12 quarters backwards. Cost observations are adjusted accordingly.

Following this procedure, the two-part model which had been described in detail in Section 5.6.3 is run first for the entire sample using the predicted date of death for the surviving part of the sample (that is alive on 31st December 2000) and a second time, for the same sample using the observed date of death for those alive on the 31st December 2000. Estimates from the first (see Equation 5.5) and the second (see Equation 5.6)

modelling part are multiplied and the resultant predicted costs (see Equation 5.7), given positive utilisation are compared for the two different approaches of including survivors' TTD.

5.8.2 Results - early censoring

This analysis was undertaken as a sensitivity test for the method using survival analysis to account for survivors' unknown TTD. Results for the survival analysis using an earlier censoring date, as outlined above, are presented in Table 5.6.

Table 5-6 Results- Gompertz Regression- early censoring

Variable	Hazard Ratio	Standard Error
Gender	1.491***	(0.032)
Age at Study Entry	1.054***	(0.002)
Deprivation Category=3	1.111**	(0.060)
Deprivation Category=4	1.133***	(0.058)
Deprivation Category=5	1.214***	(0.059)
Deprivation Category=6	1.339***	(0.068)
Deprivation Category=7	1.494***	(0.100)
Gamma	0.100***	
No. of subjects	11,587	
No. of failures	8,802	

*** p<0.01; Deprivation Category 1 serves as the reference category, no observations for deprivation category 2

Regression results are presented as hazard ratios. Male individuals show a higher risk of dying. Each additional year of age at study entry increases the risk of dying by about 5%. Individuals' socio-economic status also has a significant impact on the risk of dying. Study participants from more deprived areas show an increased risk compared to those living in the most affluent areas. The size of the effect increases as deprivation increases. The positive shape parameter gamma determines an exponentially increasing hazard of dying as time progresses. The resulting survival function following the Gompertz regression is presented in Figure 5.16.

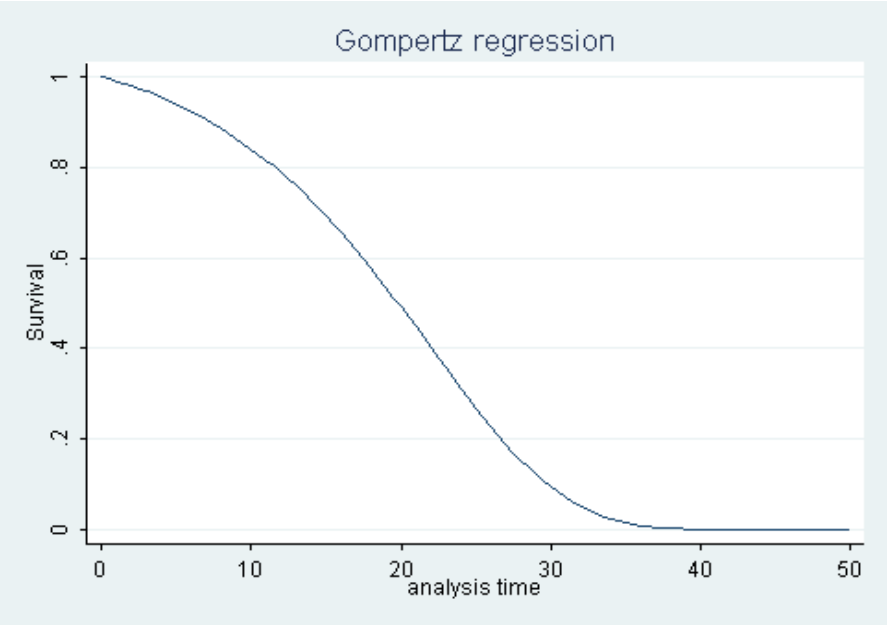

Figure 5-16 Survival curve- early censoring

Regression results for both approaches and for both modelling parts are presented in Table 5.7. Columns (1) and (2) show results for the probability of being admitted to hospital when using survival analysis to predict TTD and columns (3) and (4) present probabilities for the same sample, but using observed rather than predicted TTD. Columns (5) and (6) show cost ratios for the second part of the model using predicted TTD and in columns (7) and (8) these cost ratios are presented using the observed TTD.

Probability estimates obtained from the two approaches are very similar for almost all explanatory variables and show the same statistical significance. One exception is gender which is positive for males and significant at a 5% level in the model that uses the predicted TTD (columns (1) and (2)), but seems to lose its significance when the observed TTD is used (columns (3) and (4)). Other differences can be found for the second oldest age group, where the size and statistical significance of the effect on costs seems to depend on the approach that is being employed to measure TTD.

Table 5-7 Regression results- early censoring

	PREDICTED TTD Probability Estimates N= 129,149 (11,551)		**OBSERVED TTD Probability Estimates N= 129,149 (11,551)**		**PREDICTED TTD Cost Ratios N= 13,588 (6,780)**		**OBSERVED TTD Cost Ratios N= 13,588 (6,780)**	
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	β	SE	β	SE	Cost Ratio	SE	Cost Ratio	SE
TTD=1	1.946***	(0.066)	1.947***	(0.066)	2.074***	(0.142)	2.038***	(0.136)
TTD=2	0.963***	(0.068)	0.963***	(0.068)	2.071***	(0.183)	2.041***	(0.176)
TTD=3	0.724***	(0.066)	0.724***	(0.066)	1.921***	(0.228)	1.925***	(0.222)
TTD=4	0.578***	(0.069)	0.578***	(0.069)	1.874***	(0.193)	1.890***	(0.190)
TTD=5	0.369***	(0.071)	0.369***	(0.071)	1.776**	(0.260)	1.791**	(0.269)
TTD=6	0.407***	(0.071)	0.407***	(0.071)	1.511**	(0.183)	1.495**	(0.172)
TTD=7	0.305***	(0.075)	0.305***	(0.075)	2.974**	(0.556)	2.841*	(0.561)
TTD=8	0.246***	(0.075)	0.246***	(0.075)	2.303**	(0.355)	2.245**	(0.345)
TTD=9	0.202***	(0.075)	0.202***	(0.075)	1.156	(0.211)	1.142	(0.204)
TTD=10	0.128*	(0.075)	0.128*	(0.075)	0.908	(0.180)	0.879	(0.175)
TTD=11	0.140*	(0.073)	0.139*	(0.073)	1.044	(0.184)	0.990	(0.171)
Age at death 65-69=(2)	0.128	(0.080)	0.129	(0.080)	0.911	(0.183)	0.898	(0.174)
Age 70-74=(3)	0.169**	(0.075)	0.169**	(0.075)	1.427*	(0.210)	1.519**	(0.211)
Age 75-79=(4)	0.176**	(0.074)	0.186**	(0.077)	1.740**	(0.241)	1.631***	(0.163)
Age 80-84=(5)	0.211***	(0.074)	0.251***	(0.081)	1.413*	(0.200)	2.089***	(0.181)
Age 85-89=(6)	0.135*	(0.080)	0.259***	(0.094)	1.636**	(0.218)	2.555***	(0.223)
Age > 90= (7)	-0.019	(0.101)	0.175	(0.123)	3.986***	(0.301)	2.874***	(0.354)
Male	0.026**	(0.014)	-0.007	(0.015)	0.752***	(0.039)	0.854***	(0.025)
Deprivation Category=3	0.080**	(0.032)	0.090***	(0.033)	1.115	(0.080)	0.972	(0.053)
Deprivation Category=4	0.056*	(0.030)	0.073**	(0.031)	1.250***	(0.076)	1.010	(0.051)
Deprivation Category=5	0.067**	(0.029)	0.081***	(0.030)	1.232***	(0.075)	1.023	(0.051)
Deprivation Category=6	0.035	(0.031)	0.058*	(0.031)	1.442***	(0.078)	1.128**	(0.054)
Deprivation Category=7	0.011	(0.040)	0.041	(0.040)	1.370***	(0.102)	1.036	(0.070)
Smoker	0.047***	(0.015)	0.047***	(0.015)	0.972	(0.040)	0.948**	(0.026)
BMI <=25	-0.043***	(0.013)	-0.042***	(0.013)	0.962	(0.033)	0.998	(0.023)
SBP <=140mmHg	0.068***	(0.014)	0.066***	(0.014)	0.946	(0.034)	0.961*	(0.022)
FEV1 <70%	-0.015	(0.016)	-0.013	(0.016)	1.060	(0.047)	1.076**	(0.036)
Walking >=10 min	-0.008	(0.015)	-0.006	(0.016)	0.994	(0.040)	0.968	(0.026)
Cholesterol <6.2mmol/L	0.053***	(0.013)	0.052***	(0.013)	0.983	(0.034)	1.020	(0.023)
Time period= 1985-1992	0.232***	(0.021)	0.234***	(0.021)	0.989***	(0.063)	0.967	(0.056)
Time Period=1993-2000	0.437***	(0.025)	0.418***	(0.025)	0.681***	(0.061)	0.745***	(0.053)
Time Period=2001-2007	0.816***	(0.030)	0.505***	(0.030)	0.179***	(0.079)	0.728***	(0.058)
Constant	-1.976***	(0.069)	-1.974***	(0.069)	1436***	(0.168)	1637***	(0.146)

*** p<0.01; **p<0.05, *p<0.1; Robust standard errors in parentheses; Deprivation category 1 (most affluent) serves as the reference category; Age category 1 (<65) serves as the reference category; TTD=12 serves as the reference category
Interaction terms for TTD*Age have been included in the estimation, but a presentation is not shown here

Estimated cost ratios for both approaches (columns (5) to (8)) also show very similar results in terms of the size and statistical significance of the effect. Differences can be observed for the association of socio-economic status with estimated costs, where the approach that uses the predicted TTD for survivors seems to produce estimates that are statistically significant and larger compared with the approach of using observed TTD. This could potentially be caused through the inclusion of the socio-economic status in survival analysis regression in order to predict remaining TTD.

It is very difficult to draw any conclusions from the comparison of coefficients or cost ratios regarding the effect on predicted costs. Table 5.8 below therefore provides cost estimates obtained from multiplying the two modelling parts as specified in Equation 5.7.

Table 5-8 Predicted costs in £- early censoring

	PREDICTED TTD		**OBSERVED TTD**	
Admission Quarter before Death	Mean Costs	SD	Mean Costs	SD
TTD=1	2,163	661	2,087	328
TTD=2	745	246	730	152
TTD=3	433	149	455	114
TTD=4	339	128	373	103
TTD=5	289	104	297	71
TTD=6	247	90	297	85
TTD=7	221	94	266	98
TTD=8	209	68	269	86
TTD=9	179	87	242	95
TTD=10	169	90	236	153
TTD=11	132	54	183	105
TTD=12	123	59	157	99

Using survivors' predicted TTD through survival analysis seems to produce predicted costs that are slightly higher than those obtained from using their actual, observed TTD in quarters one and two before death. In the last quarter of life costs are on average £76 higher. From quarter three before death cost predictions are found to be lower for the

method of predicting TTD. However differences are found to be small and decrease the further away from death people are.

5.9 Discussion

The main focus of this chapter was to estimate the independent effect that TTD and age have on HC expenditure for acute inpatient care. For the first time in Scotland this could be done using a longitudinal survey based dataset (Renfrew/Paisley study) linked to acute inpatient records (SMR01).

5.9.1 Effect of TTD and age on HC expenditure

Results from the analyses undertaken in this chapter show that TTD, age at death and the interaction between these two have a significant effect on HC costs. This confirms previous results obtained by other researchers (Zweifel et al., 1999, Stearns and Norton, 2004, Seshamani and Gray, 2004b) for a sample of the Scottish population. TTD is found to influence HC expenditure differently for different age groups. Special attention was paid to the interactions between TTD and age and it was shown that estimated costs at the end of life were higher for the younger age groups in the sample compared with the older ages. This highlights the importance of the inclusion of both TTD and age when endeavouring to explain the impact that an ageing population might have on HC expenditure.

5.9.2 Impact of health measures

This chapter also sought to investigate how health status and health risk measures that were obtained at baseline influenced future costs. In total, six of these indicators were included. Although the size of the effect that these variables had on the probability of being admitted to hospital was small, statistical significance could be observed for four

of these measures. Interesting results were found for two measures, SBP and the cholesterol level, where individuals with healthy readings were observed to have a higher probability of accessing hospital care. This might be explained with the 'worried well' seeking medical attention earlier and perhaps more frequently. This seems to be confirmed when looking at estimated costs (the second modelling part), given positive utilisation, where the significant effect on the probability of accessing hospital care does not translate into significantly higher costs being incurred, i.e. medical interventions may not need to be performed on these individuals. However, if this was the case much lower costs would be expected. Another possible explanation could be provided through the cut-offs that was chosen for these measures, i.e. different thresholds might reveal different results. Significant effects on costs could be found for the following health indicators: smoking status, SBP, % predicted FEV1. Of interest is the effect that smoking has on costs. On average, smokers seem to incur lower quarterly costs in their last 12 quarters of life (£283) than non-smokers (£318).

Findings for the impact that health status and health risk indicators have on costs are very informative, given the time span over which individuals were followed up in terms of their HC utilisation. Health status and health risk measures seem to be able to provide a good indication of individuals probability of needing medical attention later in life (as far as 30 years away) and also of associated costs. This shows that utilising a linked dataset, where such measures can be used in regression modelling can add substantially to our ability of being able to explain the relationship between TTD and costs.

5.9.3 Right censoring of survivors

As outlined in Section 5.1.1, this chapter presented different methods of accounting for survivors' unknown TTD due to right censoring. It was shown how various sample scenarios impact on results obtained for the probability of being admitted to hospital and any subsequently incurred costs. Survival regression analysis was presented as a novel

method to predict remaining TTD for surviving sample members and to adjust their cost observations accordingly (scenario D). This was compared with alternative methods of using the censoring date as date of death (scenario C) and also excluding survivors from the regression analysis (scenario A). Observed differences in age between model scenarios are most likely caused by the fact that survivors are older on average, as seen in the analysis of scenario B. The validation experiment presented in Section 5.8 compared predicted costs using survival analysis to estimate remaining TTD for a sample that was censored artificially and for which a 'real' date of death could subsequently be observed. Cost predictions were also obtained using the observed date of death and costs were compared. Small differences were found when analysing quarterly costs, providing evidence that the method of using survival analysis in order to predict TTD produces estimates that are very close to the 'true' estimates. This validation means that a similar approach is implemented in Chapter 6 which uses a representative sample of the Scottish population to investigate further research questions, i.e. how are HC expenditure projections influenced through the application of two different approaches, a demographic approach and an approach that also accounts for the TTD component.

Another question that is investigated in more detail in Chapter 6 is that of the association between socio-economic status and costs at the end of life. An initial investigation of this association was included in the analysis undertaken in this present chapter, however, some interesting results, such as the finding that costs, given positive utilisation, are not affected by socio-economic status to the extent that would be anticipated, deserve further attention.

5.9.4 Limitations

One limitation of the data arises as study participants may have had hospital admissions outside Scotland, i.e. the rest of the UK, which are not recorded in the linked Renfrew/Paisley -SMR01 data. One further issue stems from using survival analysis to

predict survivors' additional TTD. Any hospital episodes that might have occurred after the official study end are unobserved, however, hospital episodes are also unobserved before 1980.

Age, gender and socio-economic status were utilised to predict remaining TTD. Future analysis could also include a measure of seasonality, which would very likely influence mortality.

The admission quarter has been used to assign costs to a specific quarter before death. This has been done, since this marks the time when costs are incurred. However, using the admission quarter as an indicator of when costs are incurred will have the effect of pushing costs away from death which could lead to an underestimation of costs in the quarters closest to death. As older people tend to be closer to death on average, this may also affect the distribution of costs in the last quarters of life by age category.

The approach of utilising different samples for the four scenarios presented could also have lead to biased results. Also, the health risk and health status measures were only obtained once, when sample members entered the study and no repeated measures were taken after the 1970s. Hence, careful interpretation of these results is required. One final limitation is that the Renfrew/Paisley sample might not be representative of the whole of Scotland in terms of its geographic measures of deprivation, something that could be rectified in the following chapter.

6 POPULATION AGEING IN SCOTLAND: IMPLICATIONS FOR HC EXPENDITURE USING LINKED SLS – SMR01 DATA

6.1 Introduction

6.1.1 Socio-economic status and costs at the end of life

The previous empirical chapter analysed the association between TTD, population ageing and HC expenditure using baseline survey data from the West of Scotland linked to hospital admission records and death records. The analysis focused on the implications of excluding survivors from the analysis and estimated the effect that TTD and age had on costs for acute inpatient care. In addition to health risk and health status measures, the association between the socio-economic status and costs at the end of life was analysed. This association was not found to be as strong as expected.

In order to further investigate and validate these results and to fully explain the driving factors behind HC expenditure at the end of life in Scotland it is vital to expand the analysis using a sample that is representative of the Scottish population. This is especially important for any inferences that can be made for the association between socio-economic status and HC expenditure, as previous research suggested that 'the poor cost more' (Cookson and Laudicella, 2011). Although, potentially confounding this is that those with lower socio-economic status are closer to death due to their shorter than average life expectancy. This is highly relevant particularly in Scotland, where life expectancy for males is as low as 54 years in one area of Glasgow (WHO, 2007) and where there is a generally poor record of premature deaths in areas with very high levels of deprivation. Previous studies analysing Scottish data have shown a clear association between socio-economic status and premature death (Chalmers and Capewell, 2001)

A review of the wider international literature also suggested differences in HC costs incurred by socio-economic status, which is mostly measured using individuals income as a proxy for socio-economic status. Research from Sweden showed that people with a lower income incurred higher HC costs (Beckman et al., 2004). A study carried out in Canada looked at differences in HC utilisation between income groups and found that individuals with a lower income were responsible for a disproportionate utilisation of hospital services. The authors argued that this was mainly due to a higher prevalence of diseases (Lemstra et al., 2009). A comparative study of U.S. and Canadian individuals however found a similar pattern of hospital utilisation across socio-economic status (Blackwell et al., 2009).

As pointed out in the previous chapter, in this thesis, the association between HC costs and socio-economic status is determined by two processes. The first one being access to HC services, i.e. utilisation and the second is the costs incurred given positive utilisation. The question remains: do individuals from more deprived areas cost more, and to what extent are costs influenced by utilisation?

Preliminary, descriptive analysis undertaken in Scotland suggested a socio-economic gradient in terms of costs incurred towards the end of life, with decedents from more deprived areas incurring lower costs in younger age groups with the effect reversing in the very old age groups (over 75), where significantly higher costs were observed for people living in more deprived areas (Graham and Normand, 2001). Limitations occurring from this study were described in detail in Section 3.9, which reviewed the existing TTD literature in Scotland. Other research undertaken for the Health Board ‘Ayrshire and Arran’ has shown that the association between socio-economic status and the probability of accessing hospital services and subsequent costs is not as clear cut as might be expected (Lowe, 2005).

This chapter expands preliminary research that has been undertaken in Scotland to date (Lowe, 2005, Graham and Normand, 2001) by estimating the independent effect that TTD, age and socio-economic status have on HC expenditure while utilising a representative sample of the Scottish population. In addition, two methods of costing hospital episode statistics are compared in order to highlight implications that costing methods have when analysing the association between HC expenditure, population ageing and TTD. This will be based on the analysis of alternative costing methods for hospital episode statistics that was presented in Chapter 4, and will provide a second empirical application.

6.1.2 HC expenditure projections

The main challenge that HC systems and policy makers face in light of an ageing population is the potential, although difficult to quantify, increase in future HC expenditure. The review of the literature in Chapter 3 outlined the main methods that have been employed in order to project future HC expenditure. It has been found that the standard method of assuming a constant age profile for HC expenditure over time, as used in some studies (Dang et al., 2001, Jacobzone, 2000, Serup-Hansen et al., 2002), might lead to an overestimation of the future financial burden an ageing population might be responsible for. Constant age profiles for HC expenditure do not account for changing morbidity scenarios as described in Chapter 3 and ignore that a compression of morbidity might lead to lower HC costs at any given age.

The analysis in this chapter is able to utilise to its advantage a large and representative sample which allows for an estimation of future HC expenditure for Scotland. In order to draw conclusions about any hypothesised overestimation of future HC costs two scenarios will be investigated. The first scenario projects HC costs, purely based on demographic changes and not accounting for remaining TTD, while the second scenario also takes into account remaining TTD. A comparison of projected costs between both scenarios quantifies the extent of a possible overestimation of costs, thus emphasises

the implications of including/excluding TTD on projected HC expenditure and providing valuable information for any budgeting and resource allocation decisions.

6.1.3 Inclusion of survivors

Also in Chapter 5, a method to account for survivors' unknown TTD with censoring was presented and the subsequent analysis concluded that a modelling approach that is based on the exclusion of survivors is at risk of overestimating costs. It was also shown that methods employed in previous research might not be appropriate in order to account for survivors' unknown TTD. Two methods of accounting for survivors' unknown TTD were presented: using the censoring date as their date of death and employing survival analysis to predict remaining TTD and adjustment of cost observations. Both methods produced lower cost estimates than the approach of excluding survivors. Section 5.8 presented an experiment to validate the method of utilising survival analysis in order to account for right censoring of survivors and concluded that differences in costs obtained through regression analysis were small and that survival analysis performed well in terms of predicting TTD and associated costs. It seems therefore valid to apply survival analysis in the context of analysing the SLS in this chapter.

One difference of the SLS sample compared with the Renfrew/Paisley sample is the fact that the Renfrew/Paisley sample is characterised by a very high proportion of observed deaths at the end of the study period and a reasonably high average age for survivors, which meant their date of death was predicted as being not too far away in the future. The sample utilised in this chapter, however is characterised by a younger population on average and a higher proportion of surviving sample members at censoring. The analysis period is therefore extended to five years before death instead of three years.

The remainder of this chapter is structured as follows. Section 6.2 describes in detail the linked dataset. This section also summarises the data manipulation procedure and the resulting number of available observations for the analysis. The two costing methods

employed are also briefly summarised in Section 6.2, followed by a presentation of descriptive results. Section 6.3 outlines methods and results for the survival analysis. The econometric modelling framework and regression results are presented in Section 6.4 and Section 6.5 describes the methods for projecting future HC expenditure as well as presenting their results. The final Section 6.6 discusses the main findings and concludes.

6.2 Methods - Data and descriptive analysis

6.2.1 Scottish Longitudinal Study

The Scottish Longitudinal Study (SLS) is an anonymised dataset of a representative sample of the Scottish population (5.3%), which draws on data from a series of statistical and administrative sources, such as the Scottish Census, Vital Events (births, marriages and deaths), data from the National Health Service Central Register (NHSCR), which collects data on migration in and out of Scotland and NHS data on health events of sample members (maternity data, cancer registrations and hospital admissions). Through its longitudinal nature, the SLS provides a means to draw conclusions about the health status and socio-economic indicators of the Scottish population and how these have changed over time.

The SLS started with data from the 1991 census from which about 270,000 SLS members were identified based on 20 semi-random dates of birth in any year. It has a very large sample size, very low attrition rates and very high rates for successful linkage of events as it collects data that is either required by law (Census, birth registration, death registration, marriage registration) or is a standard administrative function within Scotland. The linkage mechanism is provided by the National Health Service Central

Register (NHSCR), which holds a database of people who have at any point been registered with a General Practitioner in Scotland.

The SLS contains some sensitive and personal information about sample members. Due to its confidential nature, only a small group of researchers who are responsible for maintaining the dataset are aware of the 20 birthdates based on which sample members are selected. After linkage across datasets, the final dataset is de-identified and neither names nor addresses are included. Furthermore no raw micro-data is provided to users. Instead, access to the data is via a strict application/access process, including an application to the Privacy Advisory Committee (PAC) if the SLS is to be linked to hospital admission records. The application is further reviewed by the SLS Research Board and a final decision is made- on access- based on the quality of the proposed project (the ethics approval form and the project clearance form can be found in Appendices VII and VIII). Data analysis can be undertaken in a 'Safe Setting' at the National Records of Scotland in Edinburgh alongside an assigned support officer. Datasets can also be accessed remotely by sending syntax to the support officer, who will then run it on the respective dataset. All results from the analyses are checked for possibly disclosive contents and need to be cleared by the SLS support officer. All output files are emailed in encrypted form to the SLS user (Hattersley and Boyle, 2007).

One main advantage of the SLS over its English equivalent, the Longitudinal Study, is the ability to link with data on hospital admissions. Information on hospitalisations (and its associated costs) together with SLS data on economic activity, socio-economic status, health and demographic provides a novel platform from which to analyse the cost of ageing and the cost of dying. One additional advantage of using linked data is the possibility of including individuals without HC utilisation towards the end of life. This is something not all previous studies were able to do, especially when relying on expenditure claims data, which would only cover HC users in any period.

Further information on selection, tracing and linkage of SLS sample members as well as on the quality of sampling and linkage methods can be found in a series of SLS working papers by Hattersley and Boyle (2007, 2009a, 2009b) and Hattersley et al. (2007).

Data Preparation and Manipulation

A subset of the SLS dataset is used for this study, which is initially based on all traced SLS members enumerated at either the 1991 census or the 2001 census and aged 45 or older at the 2001 census. This age group was chosen, as it was required that a sufficient number of deaths could be observed before censoring. This subset was then linked with SMR01 resulting in an initial number of 1,110,169 hospital records. These records relate to 141,964 sample members whose hospital use was observed between 1986 and the 29th April 2010, which was the censoring date for the linked dataset. SMR01 has been described in detail in Sections 4.3.1 and 5.2.2 and a repeated explanation is dispensed with.

Due to the fact that there can be multiple observations (that is hospital episodes) for individuals there are also different observation levels. The following paragraph describes the manipulation of the dataset on an individual's level. STATA 11/MP was used throughout the analysis for this present chapter.

SLS sample members, which could not be successfully flagged through the NHSCR (N=803) were deleted and not used for the analysis. Further, those SLS sample members that were present at the 1991 census, but not traceable afterwards were also discarded from the analysis (N=28). Additional checks for inconsistencies in the data revealed individuals that were aged less than 35 years in 1991 (N=1,198) and those that were aged less than 45 years in 2001 (N=561). These were also discarded from the analysis.

Subsequent data manipulation that was undertaken on an episode level includes the following. 3,863 episodes were deleted as these were admissions to ‘Geriatric Long Stay’ wards. These episodes were only part of SMR01 until 1997 and, due to this inconsistency could not be used for the analysis. 139 observations (episodes) were identified where the admission date was observed to be after the discharge date; these observations were discarded from any further analyses.

The analysis in this chapter examines HC expenditure in the last five years (20 quarters, the justification for using quarters is explained below) of life. Any hospital episodes that occurred out with these five years before death (N= 519,792) were deleted. 17,382 sample members never had any recorded acute inpatient hospital episodes during the observational period. These sample members only provide information from the SLS part of the linked dataset. These observations are important and have been neglected in previous research in Scotland (Graham and Normand, 2001, Lowe, 2005) that only analysed hospital admission records without establishing a link to a survey based dataset that contributes information on important baseline characteristics of those individuals, who subsequently do not access hospital services.

The set up of the data is in long format with each row representing one episode of care. There is no information for periods in which no hospital costs were incurred, i.e. periods without a SMR01 record. The data are manipulated such that each row now represents one quarter (90 days) before death. Quarters in which no hospitalisation was observed, as recorded by a row of zeros, enter the model as zero cost observations. This provides an initial sample size of 2,095,060 observations (quarters), relating to 104,753 sample members (e.g. 20 quarters, four each year for five years).

The remaining TTD in quarters for surviving sample members is predicted using the method of survival analysis as presented in the previous chapter. For instance, if an individual’s death is predicted to occur in April 2011, the last 20 quarters of life for that

individual start in April 2006. This is extended to April 2015, which results in the censoring date (April 2010) being the latest start date for the last 20 quarters of life which will be included in subsequent analyses. Observations for sample members who were predicted to live beyond 2015 were deleted and the final number of observations that is used in subsequent analyses is 1,131,361, relating to 60,808 SLS sample members, 42,668 of which had a death record at the time of censoring on 29th April 2010 and 18,140 were alive and projected to die within the following five years. Five years (20 quarters) were chosen as compared to three years in Chapter 5, since the SLS sample was younger on average with deaths to be observed further away in the future. Figure 6.1 below illustrates how the data were set up and manipulated.

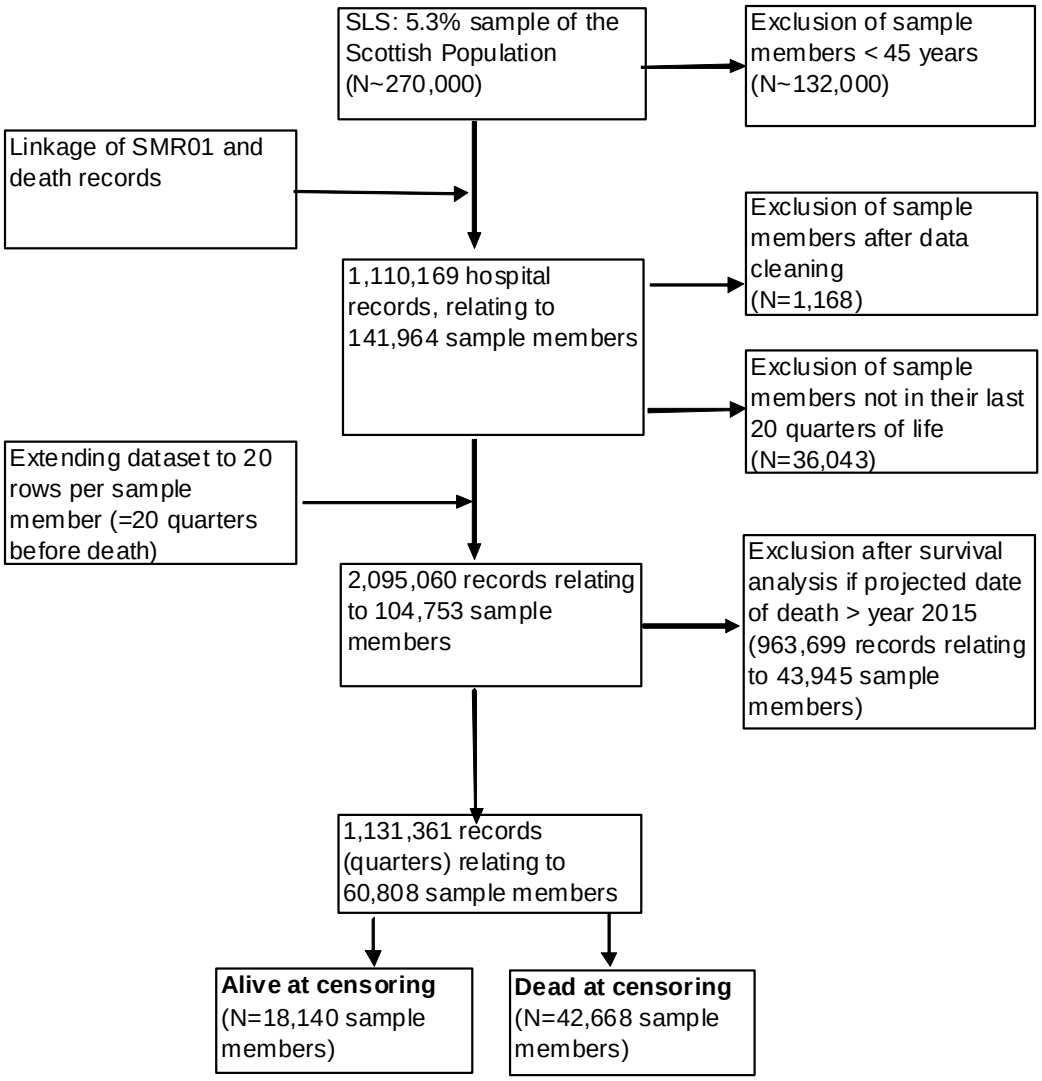

Figure 6-1 Flowchart of dataset manipulation

6.2.2 Costs for hospital episode statistics

The costing methods that are applied in this analysis utilise HRGs as the basis on which unit costs are assigned to episodes of care. The same reference year for costs was chosen (2006/07) to ensure consistency within this thesis. Following the methods outlined in Section 4.3.2, admissions (as detailed in the SMR01 data) with ICD9 codes (pre 1992) were converted into ICD10 codes using a look-up file (New Zealand Health Information Service, 2010).

The procedure of assigning HRGs and costs to hospital episodes has been described in detail in Section 4.3.2 and is only briefly summarised here: The HRGv3.5 Grouper software is used to assign an HRG to every patient record (The Health and Social Care Information Centre, 2010a). After that episodes that form a CIS are taken account of by selecting the dominant HRG within each CIS. This is achieved by using the 'Spell Converter' software (The Health and Social Care Information Centre, 2010b). Both, the English Tariff and the SNT are assigned to the chosen dominant HRG and summarised into quarterly costs. Information on the type of admission was used to distinguish between tariffs for elective and non-elective admissions and LOS information has provided the basis for the decision whether to assign extra per diem costs. As outlined previously, the SNT does not provide information on extra daily costs for hospital stays that exceed a trim point. It will consequently give less weight to individual LOS.

The application of two different costing methods facilitates a further empirical analysis of how alternative methods impact on regression results obtained- not only on an absolute level, but also in terms of the marginal effects that explanatory variables have on costs.

6.2.3 Results - descriptive analysis

Characteristics for the sample utilised in the regression analyses (N=60,808) are presented in Table 6.1, for the entire sample and by survivor status at the end of the observational period. 18,140 individuals (29.8%) did not have a death record at the end of the study period on the 30th April, 2010. Survivors are those individuals who are predicted to die within the following five years (until 2015) given how the data have been set up for the analysis. A significantly higher proportion (62.98%) of decedents is found to have been enumerated at the 1991 census only, compared to 10.89% of survivors. A higher proportion of survivors than decedents is observed to have been enumerated at the 2001 census and a similar observation can be made for survivors and decedents that were part of both, the 1991 and the 2001 census. This reflects mainly the younger age groups present at the later census. A similar distribution of males and females can

be found in both, the survivor group and in the decedent group, proportions that nevertheless are significantly different from each other ($p<0.01$). The distribution of females and males in the decedent and survivor subgroup is very similar to their overall distribution in the entire sample.

7.3% of the entire sample population had never accessed hospital care, a proportion that also differs significantly ($p<0.01$) by survival status. A higher proportion of individuals that had never accessed hospital care while observed can be found in the survivor group (13.3%). A slightly higher proportion of survivors live in postcode areas that belong to the most affluent deprivation quintile compared to the decedent group, while a slightly lower proportion of survivors can be found living in areas that belong to the most deprived quintile, compared to the decedent group. The difference between survivors and decedents in terms of their socio-economic status was found to be highly significant ($p<0.01$). Socio-economic status is measured using the Carstairs deprivation score quintiles. These are based on postcode sectors and the lowest quintile (1) represents the most affluent areas, while the highest quintile (5) represents the most deprived areas (Carstairs and Morris, 1991)[17]. Area based variables such as the deprivation quintiles were available at different geographical levels. Since information from both the 1991 and the 2001 census is used in this analysis it was decided that a spatial level should be chosen that would facilitate comparability of variables in 1991 and 2001. The so called ‘Consistent Areas Through Time’ (CATT) possesses these characteristics and are still meaningful as areas are relatively small (10,058 CATTs in Scotland[18]).

[17] Please note that this measure of deprivation, although using the same definitions, is different from the one used in Chapter 5, where the seven categories were used instead of quintiles.

[18] To put CATTs into perspective; there are 32 council areas in Scotland that are split into 1,222 electoral wards

Overall, 53.2% of all sample members reported to have a limiting long-term illness (LTI) in either census. A significantly higher proportion of decedents reported having a limiting long-term illness (56.3%), while 45.8% of survivors stated that they suffered from an LTI. This proportion differs significantly between both groups ($p<0.01$).

On average deceased SLS sample members spent 20.6 days in hospital (SD=59.7), whereas individuals who had survived until the censoring date had spent an average of 12.5 days in hospital (SD=31.0). LOS differs significantly between survivors and decedents ($p<0.01$). Overall mean age at study entry was 67.9 years (SD=10.9). Decedents were significantly older at study entry than survivors (68.8 years vs. 65.8 years).

Age at death was measured in seven categories. Sample characteristics for age at death are presented for observed deaths for decedents and for predicted deaths for the surviving part of the sample. For decedents, most deaths were observed to occur between 80-84 years and most survivors are predicted to die between the age of 85 and 89.

Table 6-1 Sample characteristics

VARIABLE	FREQUENCY (%) Sample N=60,808 (100%)	FREQUENCY (%) Decedents N=42,668 (70.2%)	FREQUENCY (%) Survivors N=18,140 (29.8%)	Differences between survivors and decedents p-value*
Enumerated at 1991 Census	28,848 (47.44%)	26,873 (62.98%)	1,975 (10.89%)	
Enumerated at 2001 Census	3,631 (5.97%)	1,401 (3.28%)	2,230 (12.29%)	
Enumerated at both Censuses	28,329 (46.59%)	14,394 (33.73%)	13,935 (76.82%)	Overall: p<0.01
Male	28,481 (46.8%)	19,978 (46.8%)	8,503 (46.9%)	
Female	32,314 (53.1%)	22,686 (53.2%)	9,628 (53.1%)	p<0.01
Missing Gender	13 (0.02%)	4 (0.01%)	9 (0.05%)	
Number of HC users	56,362 (92.7%)	40,633 (95.2%)	15,729 (86.7%)	
Number of non-users	4,446 (7.3%)	2,035 (4.8%)	2,411 (13.3%)	p<0.01
Deprivation Score Quintile 1	8,445 (13.9%)	5,855 (13.7%)	2,590 (14.3%)	
Deprivation Score Quintile 2	14,150 (23.3%)	9,822 (23.0%)	4,328 (23.9%)	
Deprivation Score Quintile 3	14,056 (23.1%)	9,886 (23.2%)	4,170 (23.0%)	
Deprivation Score Quintile 4	12,603 (20.7%)	8,826 (20.7%)	3,777 (20.8%)	
Deprivation Score Quintile 5	11,495 (18.9%)	8,221 (19.3%)	3,274 (18.0%)	
Deprivation Score Quintile (missing)	59 (0.1%)	58 (0.1%)	Low cell count**	Overall: p<0.01
LTI - Yes	32,318 (53.2%)	24,005 (56.3%)	8,313 (45.8%)	
LTI - No	28,177 (46.3%)	18,535 (43.4%)	9,642 (53.2%)	
LTI (missing)	313 (0.5%)	128 (0.3%)	185 (1.0%)	p<0.01
Age at death <65 years***	n/a	6,078 (14.24%)	22 (0.12%)	
Age at death 65-69 years	n/a	4,489 (10.52%)	4 (0.02%)	
Age at death 70-74 years	n/a	6,127 (14.4%)	Low cell count**	
Age at death 75-79 years	n/a	7,249 (16.99%)	22 (0.12%)	
Age at death 80-84 years	n/a	7,679 (18%)	1,671 (9.21%)	
Age at death 85-89 years	n/a	6,184 (14.49%)	8,410 (46.36%)	
Age at death >= 90 years	n/a	4,862 (11.39%)	8,009 (44.15%)	p<0.01
Mean age at study entry (SD)	67.9 (10.3)	68.8 (11.4)	65.8 (6.7)	p<0.01
Total LOS (SD)	18.3 (53.4)	20.6 (59.7)	12.5 (31.0)	p<0.01

* p-values were obtained through t-tests or chi2-tests; ** low cell count: results with cell counts <3 can not be displayed as these might potentially be disclosive, this is a requirement of accessing the SLS; *** Age at death for survivors is the age that was predicted through survival analysis and extrapolation

6.2.4 Results - descriptive analysis of costs

The initial exploration of observed mean costs in each quarter before death (observed and predicted through survival analysis) shows a substantial increase in costs as people approach death. This increase is most pronounced for the last three quarters of life and shows an almost threefold rise when moving from the penultimate quarter of life to the last quarter of life. A similar distribution of costs towards the end of life can be observed for both costing methods, the English Tariff (blue line) and the SNT (red line) (Figure 6.2), with the SNT producing marginally higher mean costs than the English Tariff.

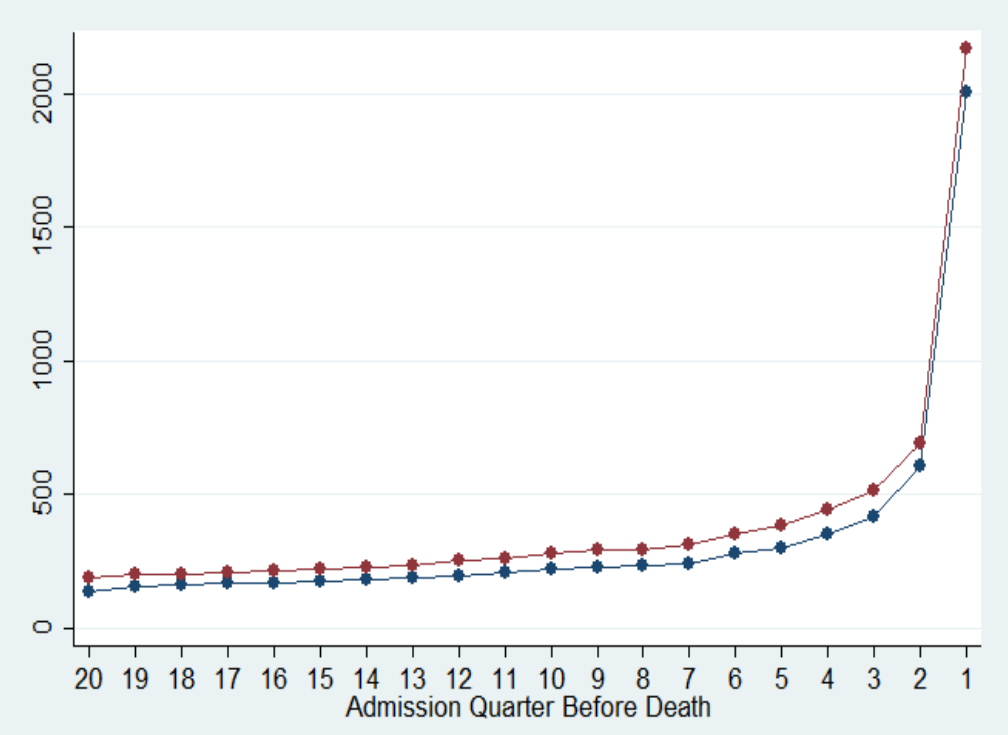

Figure 6-2 Mean quarterly costs in the last 20 quarters of life

Similar to the descriptive analysis of mean costs undertaken in Chapter 5, it can be observed here that quarterly costs are highly skewed to the right. Figure 6.3 (English Tariff) and Figure 6.4 (SNT) show the distribution of quarterly costs. The presentation is restricted to £10,000 to facilitate plotting of the histogram.

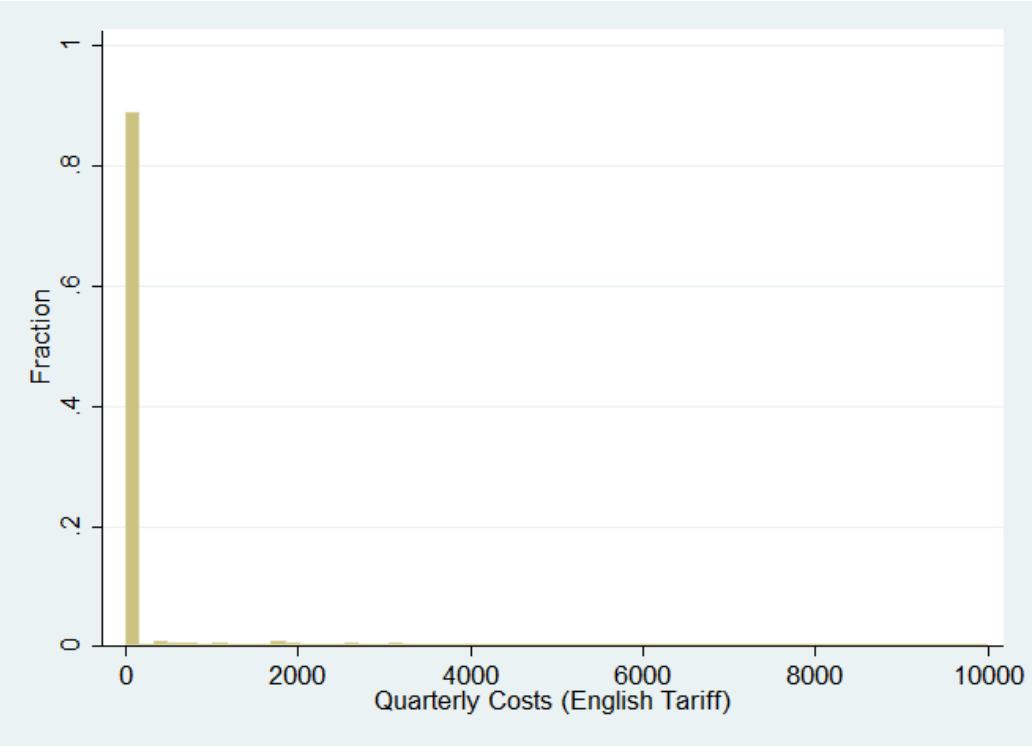

Figure 6-3 Histogram quarterly costs (English Tariff)

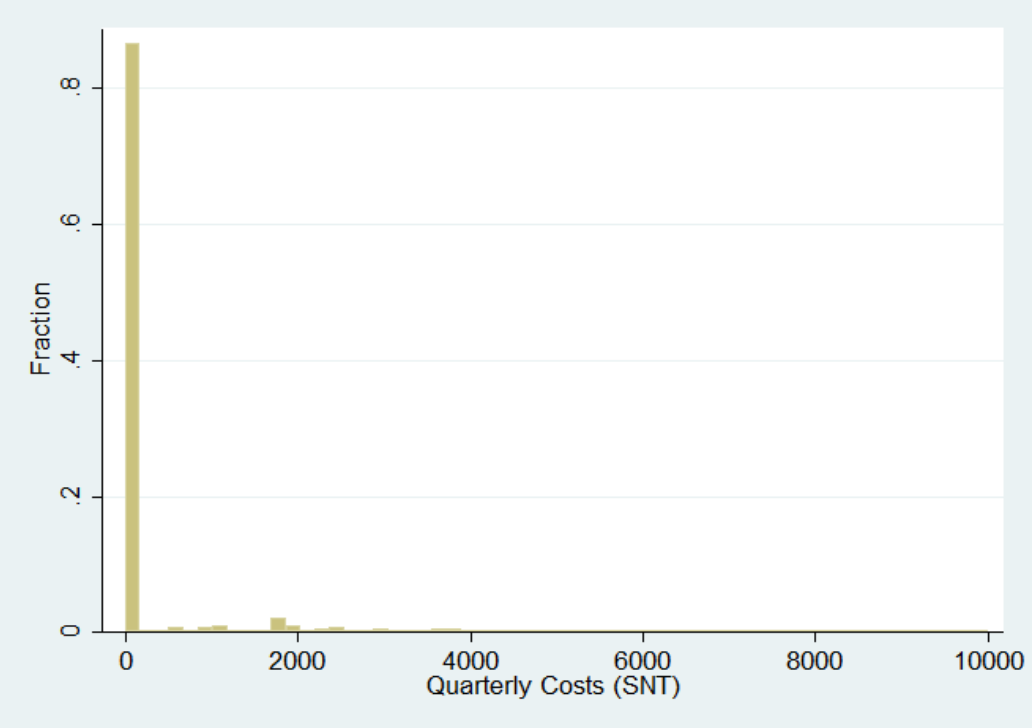

Figure 6-4 Histogram quarterly costs (SNT)

Figure 6.5 (English Tariff) and Figure 6.6 (SNT) illustrate how observed mean quarterly costs are distributed over different age groups. This is done for three periods, with the first graphs showing average costs over 20 quarters, the second graph showing mean costs for the last quarter of life and the third graph showing mean costs for the quarter furthest away from death (20^{th} quarter before death). Average costs over all 20 quarters before death show very little differences in costs by age groups. A very small decrease in costs can be observed for the oldest age groups (>= 90 years) compared to individuals age 85-89 years. Comparing the two costing methods, no difference in mean costs over the entire period of 20 quarters can be found.

Examining how costs are distributed over age groups for the last quarter of life shows a difference that is much more pronounced. Overall a slight increase in costs is found up until the age of 80, after which costs seem to decrease steadily. Costs are observed to be lowest for the oldest age group. A similar pattern is found for both, the English Tariff and the SNT. Similar to the distribution of costs by age group over the entire 20 quarters, little difference in costs is found between age groups for the quarter furthest away from death for both costing methods. To summarise these descriptive findings, there does not seem to be an observed difference in costs that is caused through the application of alternative costing methods. Differences in costs by age groups can mainly be found in the last quarter of life, where older individuals seem to incur lower costs than their younger counterparts.

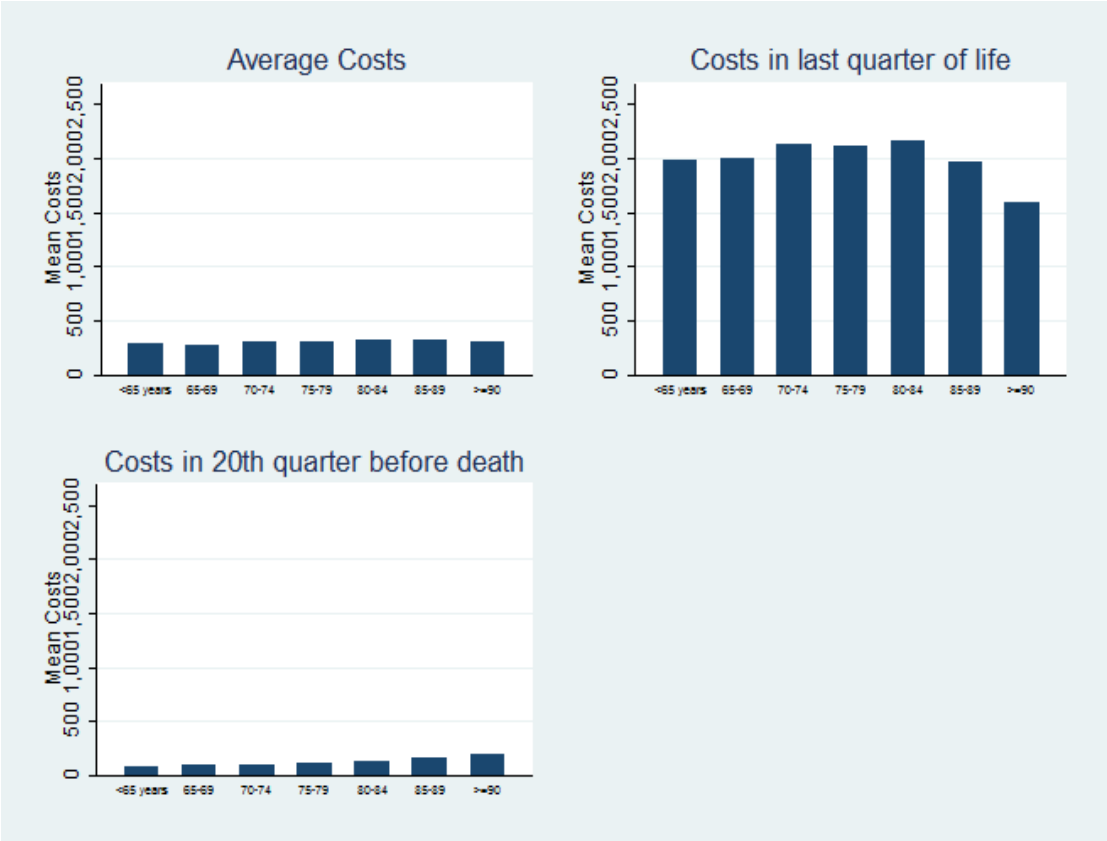

Figure 6-5 Mean quarterly costs by age group- English Tariff

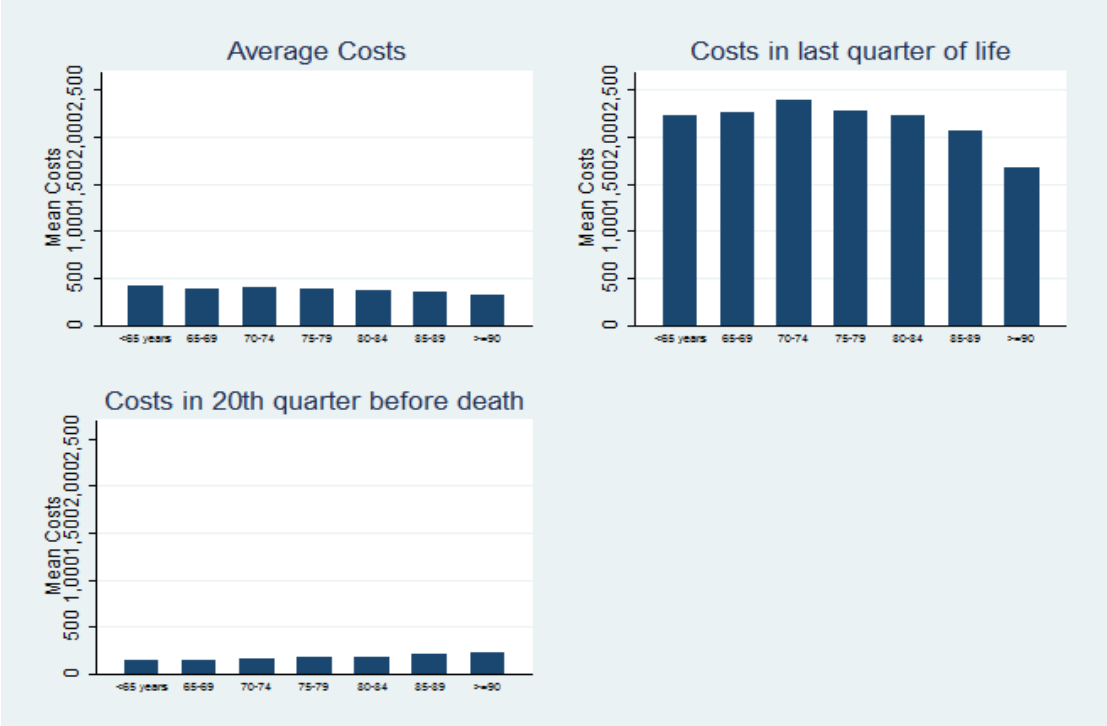

Figure 6-6 Mean quarterly costs by age group- SNT

Further investigation of observed differences in costs is undertaken for individuals' socio-economic status. Figure 6.7 (English Tariff) and Figure 6.8 (SNT) show the distribution of mean quarterly costs over all 20 quarters, over the last quarter of life and over the 20th quarter before death by deprivation score quintiles. No marked differences in costs by socio-economic status can be observed when using average costs over the entire 20 quarters before death. A very small difference in observed costs can be seen when comparing the English Tariff with the SNT, which seems to produce slightly higher costs for all deprivation score quintiles, however this seems to be a very small effect.

The distribution of costs over deprivation score quintiles in the last quarter of life does not show any marked differences, although costs using the SNT are marginally higher over all deprivation score quintile compared to costs produced when using the English Tariff to cost hospital episodes. Costs by socio-economic status in the quarter furthest away from death are, again, very similar for both costing methods and no marked difference is observed between deprivation score quintiles. Therefore, further investigation in regression analyses that is to follow in Section 6.4 is to reveal whether there is a statistically significant effect of the socio-economic status on the probability of hospital utilisation and subsequent costs towards the end of life in a multivariate model and, equally important, what the size of any such effect might be.

Figure 6-7 Mean quarterly costs by deprivation quintile- English Tariff

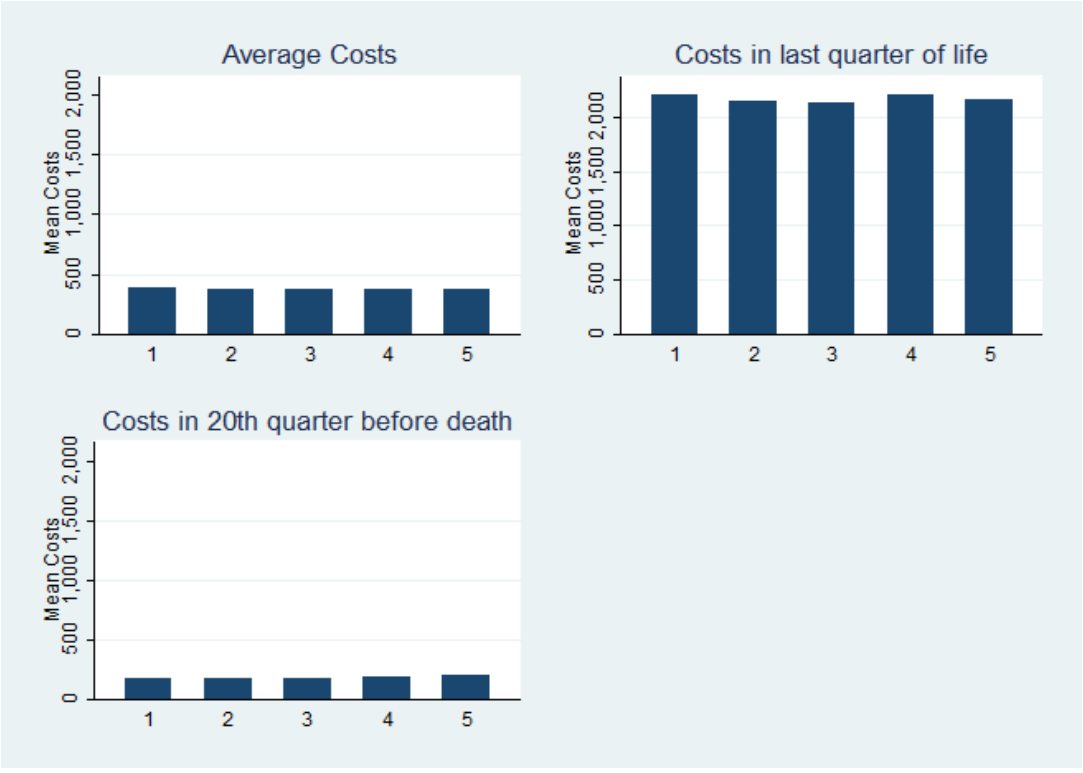

Figure 6-8 Mean quarterly costs by deprivation quintile- SNT

6.3 Survival analysis - SLS sample

6.3.1 Methods - survival analysis

The survival analysis to predict additional quarters of life beyond censoring for SLS sample members in this chapter follows the methods described earlier in Section 5.4.2.

Based on findings in Chapter 5, which outlined the implications of excluding surviving sample members from the analysis, the analysis in this chapter includes individuals that were observed to be alive at censoring (April, 2010) and were projected to die within the next five years. This is especially important as results obtained from regression analysis are to be utilised to project future HC expenditure in Section 6.5. Projections of future HC expenditure should ideally be performed on a population level, which requires the inclusion of survivors as well as individuals, who did not utilise HC services. This second empirical application of using survivors' predicted TTD after survival analysis will also highlight implications of applying this method for a sample that has a higher proportion of surviving participants at the censoring date, which were on average noticeably younger than participants from the Renfrew/Paisley study, analysed in Chapter 5.

In order to obtain a predicted date of death, time until failure (death) is predicted for both survivors and decedents utilising the entire sample (N=140,753). Results then guided the decision to exclude those, whose death was predicted to be beyond April 2015. The resulting sample (N=60,808) had consequently been used in the analysis. The following covariates are included to predict failure (death): age at study entry (in either 1991 or 2001), gender, and the socio-economic status (measured in deprivation score quintiles and with quintile 1 serving as the reference group). These covariates are similar to those utilised in Chapter 5.

Predicted additional years of life are transformed into quarters and the observed quarters before death are adjusted according to the number of additional quarters of life that were predicted. Adjustment of quarters is displayed in Figure 6.9 below. In addition to adjusting observed quarters before death, the age at death is aligned accordingly.

Surviving individuals will not contribute any cost observations for the quarters closest to death, which had been predicted as additional quarters of life. This will result in missing cost observations and right censoring in a similar way as any cost observations are missing and left censored before the observation of SLS sample members started, i.e. 1986.

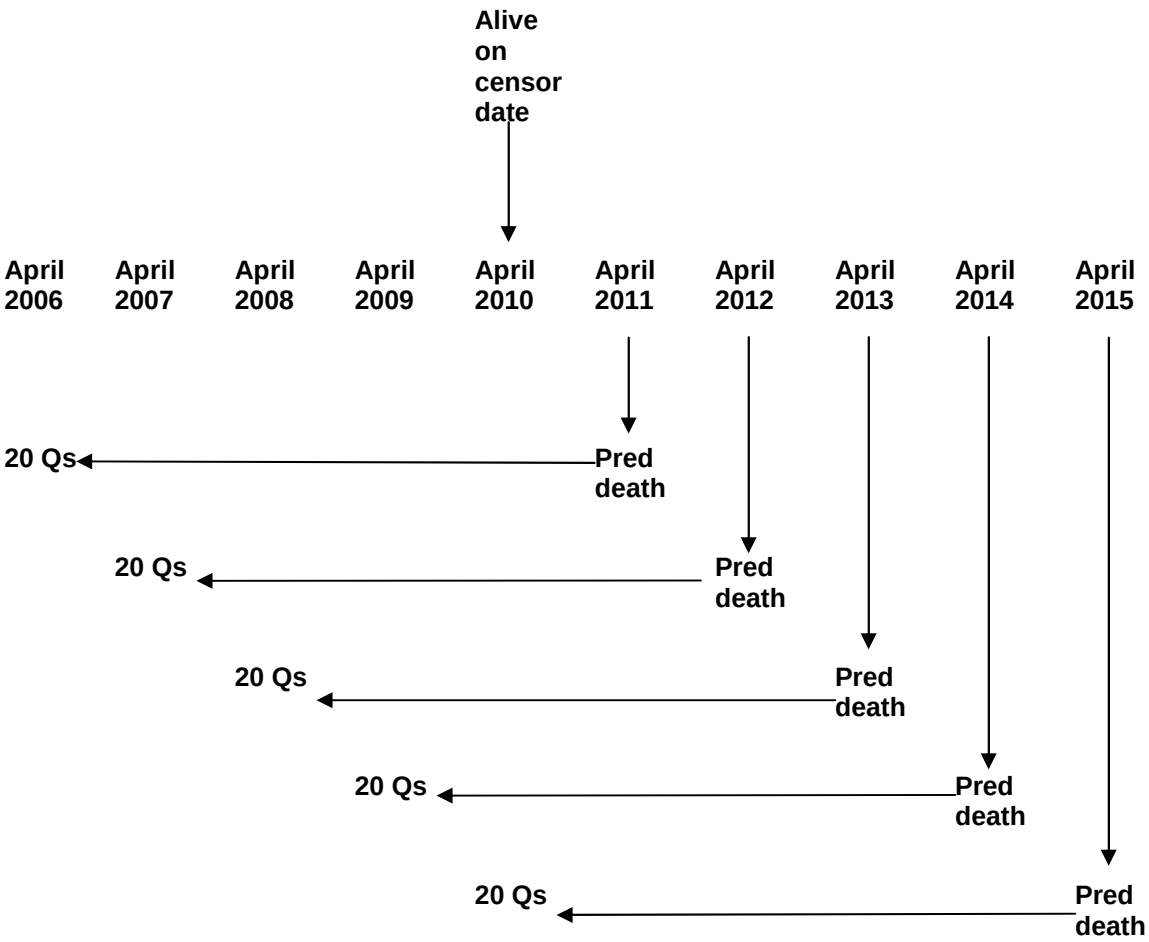

Figure 6-9 Adjusting quarters before death

6.3.2 Regression results - survival analysis

Regression results for the Gompertz survival analysis are presented in Table 6.2. Estimates are presented as hazard ratios and show the expected signs with the risk of failing (dying) increasing as age at study entry increases. Similar to results found in Section 5.5, each additional year at study entry increases the risk of dying by about 10%. Male SLS sample members also show a higher risk (47%) of dying than their female counterparts and an overall significant effect of socio-economic status on the risk of dying is observed. Individuals from the most deprived quintile show a risk of dying that is 65% higher than that of individuals living in the most affluent quintile. The size of the effect increases as deprivation increases. The shape parameter 'gamma' shows a positive value, indicating an exponentially increasing risk of failure.

Table 6-2 Regression results Gompertz regression

Variable	Hazard Ratio	Standard Error
Gender	1.469***	(.009)
Age at Study Entry	1.094**	(.0004)
Deprivation Score Quintile=2	1.169**	(.016)
Deprivation Score Quintile=3	1.284**	(.017)
Deprivation Score Quintile=4	1.429**	(.017)
Deprivation Score Quintile=5	1.650***	(.017)
Gamma	.044***	(.0009)
No. of subjects	104,567	
No. of failures	42,516	

*** p<0.01; **p<0.05, *p<0.1;
Robust standard errors in parentheses;
Deprivation quintile 1 (most affluent) serves as the reference category

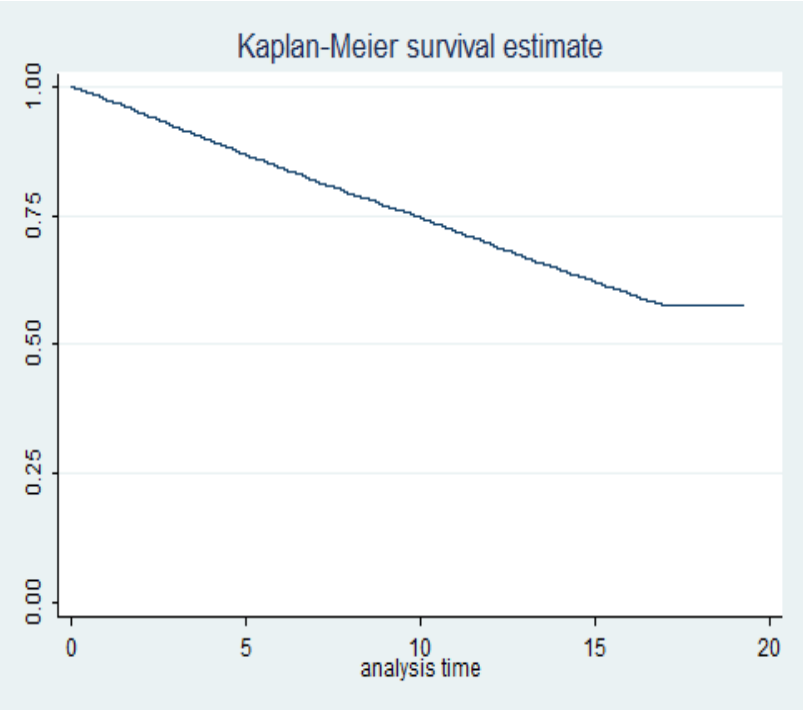

Figure 6-10 Kaplan Meier (average over 1991 and 2001)

Both Figures, 6.10 and 6.11 relate to the survival analysis undertaken for the entire sample (N=104,753) as this guided the subsequent exclusion of survivors whose predicted death was further away than five years. Figure 6.10 shows the Kaplan Meier survival estimates averaged over participants who entered the SLS in 1991 and 2001. A reasonably high proportion of surviving sample members can be observed, which is mainly caused by SLS sample members that entered the study in 2001. However the analysis in this chapter does not utilise the entire proportion of surviving sample members as their last 20 quarters of life were judged to be too far in the future to be of use in the analysis of costs towards the end of life.

In Figure 6.11 Kaplan Meier survival estimates are shown for the entire sample by socio-economic status, confirming the regression results shown in Table 6.2. On average, individuals from less affluent areas show a higher risk of dying at any one point in time. This risk increases with increasing deprivation.

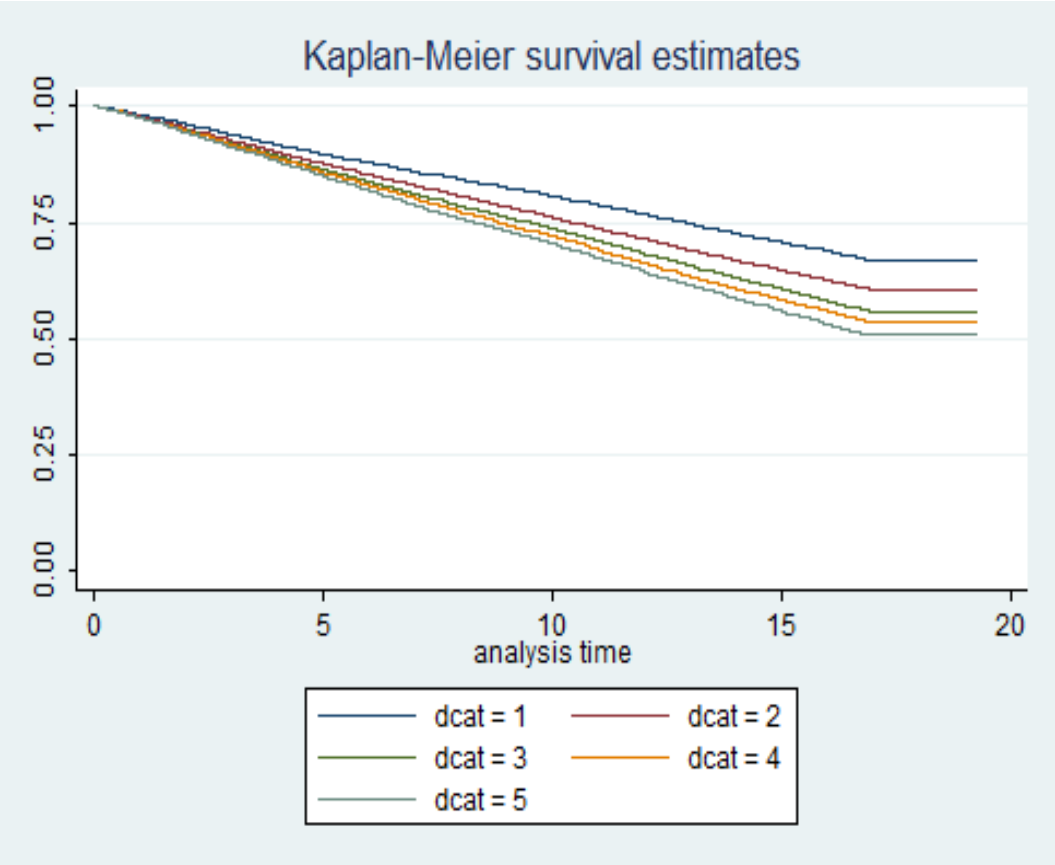

Figure 6-11 Kaplan Meier survival estimates by socio-economic status

6.4 Methods - econometric modelling

Following the methods detailed in Section 5.6.3, costs for acute inpatient care are estimated using a two-part model with the first part estimating the probability of accessing HC and the second part estimating costs conditional on positive HC utilisation.

6.4.1 Explanatory variables

The following explanatory variables have been identified within the SLS dataset in order to assess the independent effect that population ageing and TTD have on hospital costs utilising a representative sample from the SLS.

To represent TTD, a series of 20 quarter dummies are defined, where 1 represents the last quarter of life, 2 the penultimate quarter of life, etc. The quarter furthest away from death (20^{th} quarter) serves as the reference category. 20 quarters (five years) have been chosen based on exploratory analysis of observed hospital costs as people approached death. These were shown to increase substantially during the last year (four quarters) of life. Costs in the last quarter of life were found to be substantially higher than in the preceding three quarters. The same pattern was found for the probability of being admitted to hospital. It was therefore deemed appropriate to use a small observational unit (quarters), which has also been used in previous studies (Zweifel et al., 1999, Seshamani and Gray, 2004b).

Consistent with age categories from the previous empirical example in Chapter 5, age at death is measured in seven categories (<65 years, 65-69, 70-74, 75-79, 80-84, 85-89, 90 years and over) with the youngest age group serving as the reference category which, in both datasets, are ages 45 to 65. Interaction terms between TTD in quarters and age at death are included to capture any combined effect of ageing and TTD on HC costs.

Gender is included to account for differences in costs incurred by males and females. To account for differences in costs incurred by socio-economic status a measure of deprivation is included using the Carstairs deprivation score quintiles, where the lowest quintile (1) serves as the reference category. Interaction terms between TTD and deprivation quintiles are included to control for any combined effects. The assumption is that TTD affects costs differently for different socio-economic groups.

An indicator to capture any time trends, especially to reflect advances of medical technology is included. This variable is measured in 6 categories (1986-1990; 1991-1995; 1996-2000; 2001-2005; 2006-2010 and 2011-2015), with the most historic period serving as the reference group.

A measure of individuals' health status at baseline is included using information on self reported health problems (yes/no). In 1991 participants were asked whether they had a health problem or not. This question was worded slightly different in 2001, asking SLS sample members whether they would perceive themselves as having a limiting long-term illness, a health problem or disability that limits them in carrying out their daily activities and the work they are able to do. Therefore, a composite measure is used whereby an individual was categorised as having a health problem if they had replied 'yes' in either 1991 or 2001 or in both years. Individuals, who had replied 'no' in both years or in one of the two years if they were only present at either the 1991 or the 2001 census were classed as not having a health related problem.

The underlying assumption is that the expected value of HC expenditure is a function of these explanatory variables.

6.4.2 Econometric model

Similar to the model used in Section 5.6.3, the first modelling part employs a probit link and a binomial distribution to estimate the probability of utilising hospital care in any given quarter before death conditional on regressors X (Equation 6.1).

$$\Pr(HCE>0) = \alpha + \sum_{a=2}^{7}\eta_a A_a + \beta_s S_s + \omega_h H_h + \sum_{q=1}^{19}\gamma_q Q_q + (\sum_{q=1}^{19}\gamma_q Q_q * \sum_{a=2}^{7}\eta_a A_a) + (\sum_{q=1}^{19}\gamma_q Q_q * \sum_{d=2}^{5}\mu_d D_d) + \sum_{t=2}^{6}\delta_i Y_i + \sum_{d=2}^{5}\mu_d D_d + u_i$$

Equation (6.1)

Where: A is age at death categories; S represents gender; H is a dummy variable representing self reported health; Q is the remaining quarters of life (such that Q*A is the interaction of TTD and age); Y a time period dummy for hospital admissions; and D a dummy for deprivation score quintiles (such that Q*D is the interaction of TTD and deprivation), u_i represents robust standard errors.

From the second part of the model estimates of HC expenditure are obtained, conditional on HCE being greater than zero and conditional on the same set of regressors X (equation (6.2)).

$$E [HCE] = g(x\beta) \qquad \text{Equation (6.2)}$$

with xβ representing the linear predictor for HC expenditure (HCE).

Quarterly HC expenditure is estimated fitting a Generalised Linear Model (GLM) clustered on patient identifier. Diagnostic tests were run in order to determine the appropriate distributional family and link function that would fit the data best. This follows the procedure described in Section 4.3.3.

Predicted probabilities of positive HC utilisation, obtained from the first part of the model are multiplied by cost estimates from the second part of the model in order to derive average cost estimates conditional on having incurred positive HC expenditure (Equation 6.3).

$$E (HCE \mid X) = Pr (HCE>0 \mid X) * E (HCE \mid HCE>0, X) \qquad \text{Equation (6.3)}$$

In order to mitigate problems arising from serial correlation a CIS was used as the basis for the cost variable, summarising single hospital episodes if more than one episode formed the entire hospital stay. Clustering on individual identifier was applied to account

for any serial correlation that still existed because multiple observations (CISs) can come from the same individual.

6.4.3 Results - probability of HC utilisation

Regression results for the first part of the model, the probability of hospital utilisation, are presented in Table 6.3. Column (1) shows the resulting coefficient (probit) and column (2) the related standard error. Up to the 15th quarter before death, TTD has a highly statistically significant and positive association with the probability of being admitted to hospital ($p<0.01$). The size of the effect is largest for the last quarter before death and generally increases as people approach death. Estimates for TTD are compared with the quarter furthest away from death (20th quarter before death).

Regression results for the association between age and the probability of utilising acute inpatient services reveal a significant effect only for the three oldest age groups, where the effect is positive. The size of the effect is largest for the second oldest age group and slightly smaller for the oldest ages. These estimates are compared with the youngest age group (<65 years). Age effects are also influenced by TTD as can be seen from the regression results for interactions between TTD and age at death (Table 6.4). Significant interaction effects can especially be found for the older age groups and up until the 12th quarter before death. A likelihood ratio test showed that a model including TTD and age interactions terms was better specified than a model excluding these interactions ($p<0.01$). Figure 6.12 shows the interactions between TTD and age in terms of the probability of utilising HC services graphically and confirms that interactions can mainly be observed for the older ages and up until about the 12th quarter before death as shown through the unparallel lines. A steeper gradient (i.e. a larger effect of TTD) can be observed for the younger age groups and a slightly flatter gradient is found for the two oldest age groups.

Table 6-3 Regression results - probability of hospital utilisation

N= 1,124,537 (60,436)	Coefficient	SE
Column	**(1)**	**(2)**
Variable		
TTD=1	2.045***	(0.038)
TTD=2	1.030***	(0.037)
TTD=3	0.820***	(0.038)
TTD=4	0.685***	(0.037)
TTD=5	0.610***	(0.037)
TTD=6	0.455***	(0.038)
TTD=7	0.400***	(0.038)
TTD=8	0.318***	(0.038)
TTD=9	0.302***	(0.038)
TTD=10	0.220***	(0.038)
TTD=11	0.230***	(0.038)
TTD=12	0.170***	(0.038)
TTD=13	0.128***	(0.038)
TTD=14	0.133***	(0.038)
TTD=15	0.092**	(0.038)
TTD=16	0.047	(0.038)
TTD=17	0.069*	(0.037)
TTD=18	0.011	(0.037)
TTD=19	0.017	(0.036)
Age 65-69= (2)	-0.030	(0.036)
Age 70-74= (3)	-0.009	(0.033)
Age 75-79=(4)	0.023	(0.031)
Age 80-84=(5)	0.063**	(0.030)
Age 85-89=(6)	0.122***	(0.028)
Age > 90= (7)	0.120***	(0.028)
TTD x Age	Table 6.4 & Figure 6.12	-
Dep Quintile 2	0.032	(0.024)
Dep Quintile 3	0.014	(0.024)
Dep Quintile 4	0.047*	(0.025)
Dep Quintile 5	0.028	(0.026)
TTD x Dep Quintile	Table 6.5 & Figure 6.13	-
LTI	0.165***	(0.006)
Male	-0.045***	(0.007)
1991-1995	0.185***	(0.010)
1996-2000	0.295***	(0.010)
2001-2005	0.331***	(0.011)
2006-2010	0.284***	(0.118)
Constant	-1.650***	(0.032)
LR test TTD*Age	LR chi2(114)= 7369.91	p<0.01
LR test TTD*Dep Quintile	LR chi2(76)= 111.86	p<0.01

*** p<0.01; **p<0.05, *p<0.1; Robust standard errors in parentheses; Deprivation quintile 1 (most affluent) serves as the reference category; Age category 1 (<65) serves as the reference category; TTD=20 serves as the reference category; the most historic time period<1991 serves as the reference category

Table 6-4 Interaction terms TTD and age groups (Probability)

TTD	65-69	70-74 years	75-79 years	80-84 years	85-89 years	>= 90 years
1	0.064	0.036	-0.062	-0.240***	-0.813***	-1.203***
2	0.006	-0.090	-0.196***	-0.335***	-0.586***	-0.830***
3	-0.058	-0.118***	-0.226***	-0.348***	-0.545***	-0.740***
4	-0.065	-0.105***	-0.192***	-0.310***	-0.457***	-0.628***
5	-0.082*	-0.119***	-0.221***	-0.289***	-0.410***	-0.558***
6	-0.040	-0.053	-0.100**	-0.221***	-0.282***	-0.408***
7	-0.017	-0.062	-0.120***	-0.210***	-0.280***	-0.378***
8	-0.024	-0.044	-0.088**	-0.129***	-0.201***	-0.291***
9	-0.037	-0.060	-0.108***	-0.140***	-0.213***	-0.276***
10	-0.009	-0.006	-0.073*	-0.111***	-0.173***	-0.189***
11	-0.065	-0.031	-0.064	-0.090*	-0.152***	-0.177***
12	0.005	0.026	0.012	-0.043	-0.112***	-0.115***
13	0.038	0.004	-0.016	-0.047	-0.067**	-0.067*
14	-0.004	-0.016	-0.047	-0.050	-0.069**	-0.081**
15	0.017	0.006	-0.050	-0.026	-0.054	-0.042
16	0.050	0.046	0.029	0.026	-0.003	-0.043
17	0.036	0.017	0.011	-0.040	-0.038	-0.068
18	0.021	-0.010	0.030	0.013	-0.019	0.005
19	0.036	0.044	0.048	0.019	0.019	0.016

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

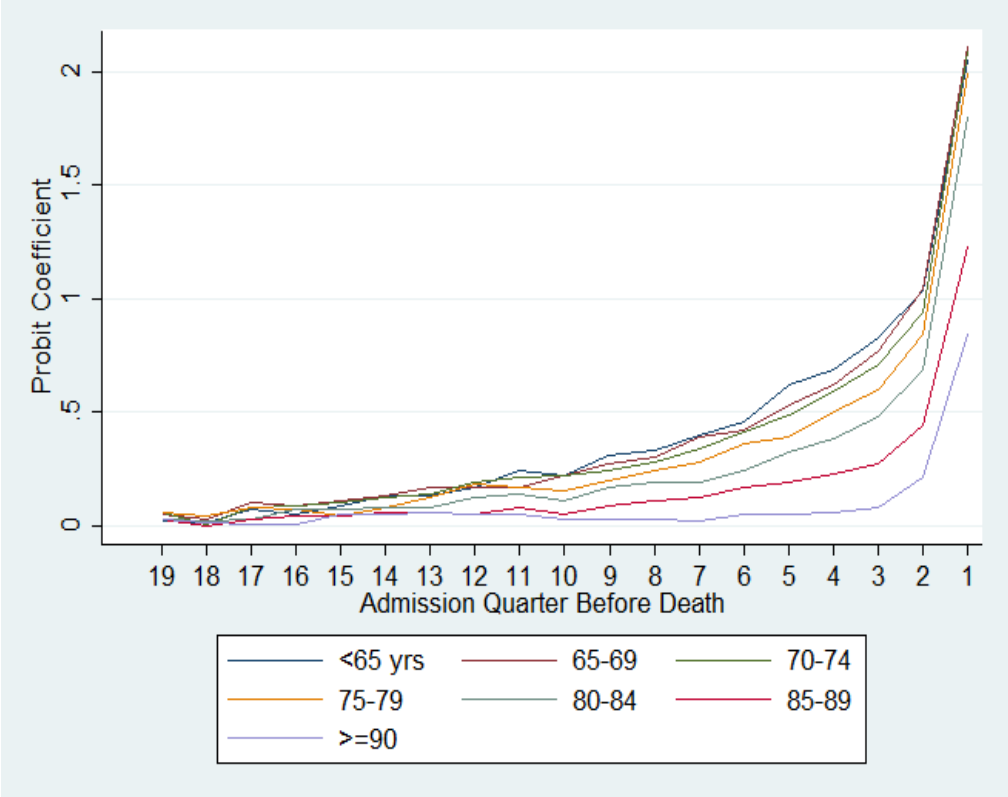

Figure 6-12 TTD and age interaction terms

Regression results in Table 6.3 also show that individuals' socio-economic status does not have an impact on their probability of utilising hospital services. Similar to the effect that age has on the probability of utilising HC, these main effects can not be interpreted directly and results for the interaction terms between TTD and deprivation score quintiles (Table 6.5) reveal that any effect that the socio-economic status has on the probability of accessing HC services is also influenced by TTD. This can be observed especially for the last quarter of life, where the association is highly significant and negative. As individuals approach death, those living in more deprived areas are less likely to reach hospital than those individuals living in the most affluent areas. This is a very important finding, highlighting the importance of the inclusion of these interactions, something that could have been missed if only main effects for deprivation score quintiles were included.

Table 6-5 Interaction terms TTD and deprivation score quintiles (Probability)

TTD	Deprivation Score Quintile =2	Deprivation Score Quintile=3	Deprivation Score Quintile =4	Deprivation Score Quintile =5
1	-0.099***	-0.092***	-0.104***	-0.136***
2	-0.084***	-0.042	-0.087***	-0.090***
3	-0.081**	-0.045	-0.072**	-0.046
4	-0.073**	-0.026	-0.073**	-0.057*
5	-0.066**	-0.035	-0.083**	-0.063*
6	-0.049	-0.044	-0.049	-0.020
7	-0.062*	-0.033	-0.047	0.011
8	-0.036	-0.018	-0.067**	-0.008
9	-0.010	-0.010	-0.045	0.009
10	0.000	0.014	0.007	0.013
11	-0.057*	-0.014	-0.033	0.007
12	-0.043	-0.023	-0.030	-0.010
13	-0.027	-0.007	-0.021	0.010
14	-0.039	-0.038	-0.030	-0.009
15	-0.037	-0.014	-0.011	-0.001
16	-0.045	-0.016	-0.016	0.004
17	-0.019	-0.005	-0.048	0.006
18	0.022	0.000	-0.006	0.022
19	-0.039	-0.042	-0.014	-0.011

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

Figure 6.13 shows the interaction terms between deprivation score quintile and TTD graphically.

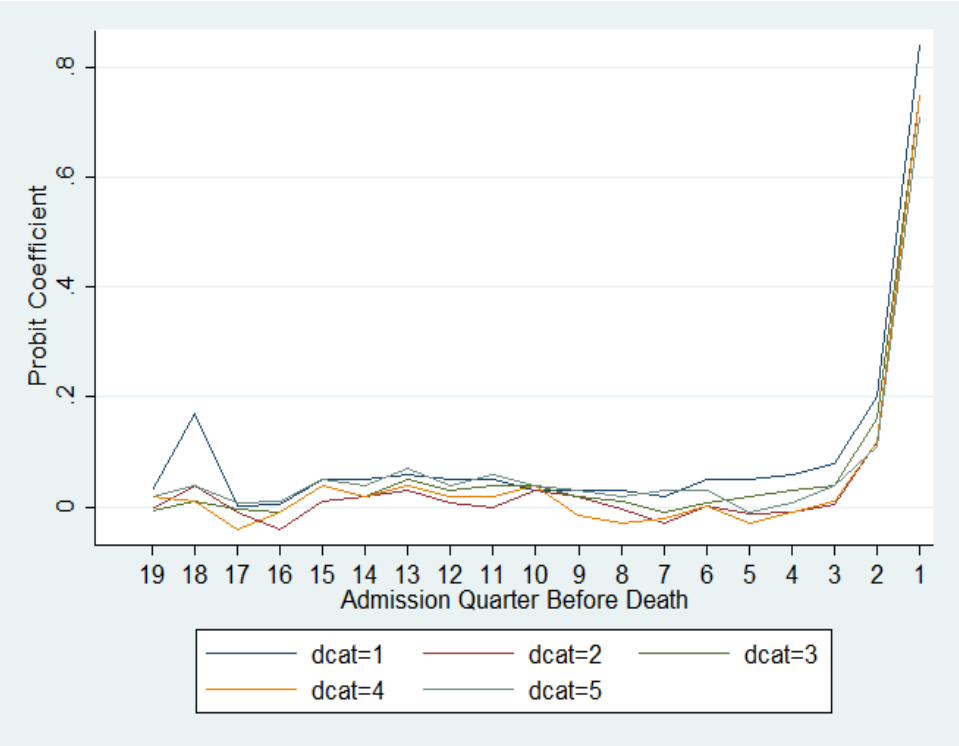

Figure 6-13 TTD and socio-economic status interaction terms

Estimation results in Table 6.3 further reveal that male SLS members are significantly less likely to access hospital care than their female counterparts ($p<0.01$). Individuals, who had stated that they suffered from a long-term illness are shown to have a higher probability of being admitted to hospital ($p<0.01$) compared with those who do not suffer from an LTI.

The year of admission that was included in six year bands in order to account for advances in medical technology is shown to have a positive and highly significant association with the probability of accessing hospital care. Compared to the most historic period (1986-1990), the subsequent periods show a higher probability of accessing hospital care, apart from the ‘projected period (2011-2015), which has a

negative association with the probability of accessing hospital care, due to missing hospital records for that period for surviving sample members.

6.4.4 Results - cost estimation

Regression results (cost ratios and corresponding standard errors) for the 2nd modelling part estimating costs given positive HC utilisation and applying the English Tariff (columns (1) and (2)) and the SNT (columns (3) and (4)) are presented in Table 6.6. The recommended distributional family was gamma and the recommended link function was a log link (Goodness of fit test results can be found in Appendix IX). Estimates presented in the table have been retransformed using exponentiation as they had been estimated on a log scale.

English Tariff – Table 6.6, columns (1) and (2)

Costs increase as people approach death. They are estimated to be about 85% higher in the last quarter of life compared to the 20th quarter before death. The association between TTD and costs is statistically significant up to the 4th quarter before death. Age at death is a significant predictor for mean quarterly costs for all but the second youngest age group. Compared to the youngest age group, costs incurred by the oldest age group are estimated to be about 50% higher. However, the effect that age has on costs is not influenced by TTD to the same extent as in the first modelling part as shown in Table 6.7. A statistically significant effect of the interaction between TTD and age is only observed for the last quarter of life and the two oldest age groups.

Table 6-6 Regression results - cost estimation

	English Tariff		**SNT**	
Observations	**N= 101,422 (39,079)**		**N= 124,117 (42,553)**	
Column	(1)	(2)	(3)	(4)
Variable	Cost Ratio	SE	Cost Ratio	SE
TTD=1	1.859***	(0.091)	1.515***	(0.059)
TTD=2	1.386***	(0.087)	1.329***	(0.063)
TTD=3	1.372***	(0.093)	1.324***	(0.064)
TTD=4	1.244**	(0.094)	1.299***	(0.066)
TTD=5	1.120	(0.089)	1.280***	(0.068)
TTD=6	1.153	(0.093)	1.222***	(0.067)
TTD=7	1.190*	(0.100)	1.253***	(0.068)
TTD=8	1.162	(0.101)	1.228***	(0.070)
TTD=9	1.033	(0.097)	1.209***	(0.071)
TTD=10	1.075	(0.097)	1.153**	(0.072)
TTD=11	1.105	(0.098)	1.143**	(0.070)
TTD=12	1.230*	(0.103)	1.169**	(0.073)
TTD=13	1.086	(0.103)	1.108	(0.075)
TTD=14	1.990	(0.430)	1.085	(0.075)
TTD=15	1.087	(0.105)	1.047	(0.075)
TTD=16	0.983	(0.100)	1.062	(0.074)
TTD=17	1.028	(0.104)	1.131	(0.084)
TTD=18	1.075	(0.105)	1.068	(0.078)
TTD=19	1.017	(0.108)	1.025	(0.077)
Age 65-69= (2)	1.100	(0.090)	0.989	(0.073)
Age 70-74= (3)	1.125*	(0.067)	1.054	(0.061)
Age 75-79=(4)	1.186***	(0.065)	1.120**	(0.056)
Age 80-84=(5)	1.259***	(0.074)	1.062	(0.054)
Age 85-89=(6)	1.391***	(0.061)	1.136***	(0.053)
Age > 90= (7)	1.481***	(0.061)	1.123***	(0.052)
TTD x Age	See Table 6.7		See Table 6.9	
Dep Quintile 2	0.911	(0.073)	0.931	(0.044)
Dep Quintile 3	0.942	(0.076)	0.975	(0.046)
Dep Quintile 4	0.910	(0.075)	0.955	(0.045)
Dep Quintile 5	0.996	(0.075)	1.057	(0.047)
TTD x Dep Quintile	See Table 6.8		See Table 6.10	
LTI	1.065***	(0.008)	1.004	(0.005)
Male	1.111***	(0.008)	1.079***	(0.005)
1991-1995	0.921***	(0.018)	0.979***	(0.005)
1996-2000	0.900***	(0.017)	1.128***	(0.011)
2001-2005	0.887***	(0.017)	1.123***	(0.011)
2006-2010	0.888***	(0.019)	1.141***	(0.011)
Constant	1542.915***	(0.080)	1814.777***	(0.058)
LR test TTD*Age	LR chi2(114)= 256.56, p<0.01		LR chi2(114)= 98.80, p=0.8438	
LR test TTD*Dep Quintile	LR chi2(76) = 117.82, p<0.01		LR chi2(76)=52.92, p=0.9798	

*** p<0.01; **p<0.05, *p<0.1
Robust standard errors in parentheses
Deprivation Score Quintile 1 (most affluent) serves as the reference category
Age category 1 (<65) serves as the reference category
TTD=20 serves as the reference category
The most historic time period<1991 serves as the reference category

Table 6-7 Interaction terms TTD and age groups - English Tariff (Cost Ratios)

TTD	65-69	70-74 years	75-79 years	80-84 years	85-89 years	>= 90 years
1	0.891	0.926	0.905	0.906	0.808***	0.779***
2	0.931	1.046	0.978	1.066	1.058	1.058
3	0.854	0.925	0.934	0.914	0.915	1.007
4	0.837	0.938	0.891	0.866	0.891	1.024
5	0.978	1.005	1.050	1.117	1.048	1.015
6	0.872	1.015	1.028	1.019	0.950	1.019
7	0.887	0.921	0.927	1.030	0.856*	0.953
8	0.937	0.997	0.968	1.054	0.965	1.044
9	0.988	1.046	1.041	1.005	1.008	1.063
10	0.935	1.032	1.025	1.045	1.016	1.016
11	0.882	0.988	0.957	0.961	0.906	0.977
12	0.929	0.920	0.904	0.912	0.896	0.956
13	0.832	1.141	0.893	0.913	0.943	0.941
14	0.634	0.663	0.668	0.729	0.620*	0.688
15	0.852	0.872	0.882	0.963	0.974	0.976
16	0.927	0.951	0.955	1.012	1.047	1.101
17	0.952	0.876	0.918	1.018	0.960	1.045
18	1.030	1.001	0.979	1.016	1.006	1.060
19	1.006	0.967	1.054	0.937	0.949	0.991

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

Figure 6.14 shows the interaction terms graphically. Individuals in the two oldest age groups (85-89 years and 90 years and older) seem to incur lower costs in their last quarter of life compared to their younger counterparts. This figure also shows that TTD does not only have an effect on the probability of reaching hospital, but also seems to impact on costs, given that individuals have reached hospital.

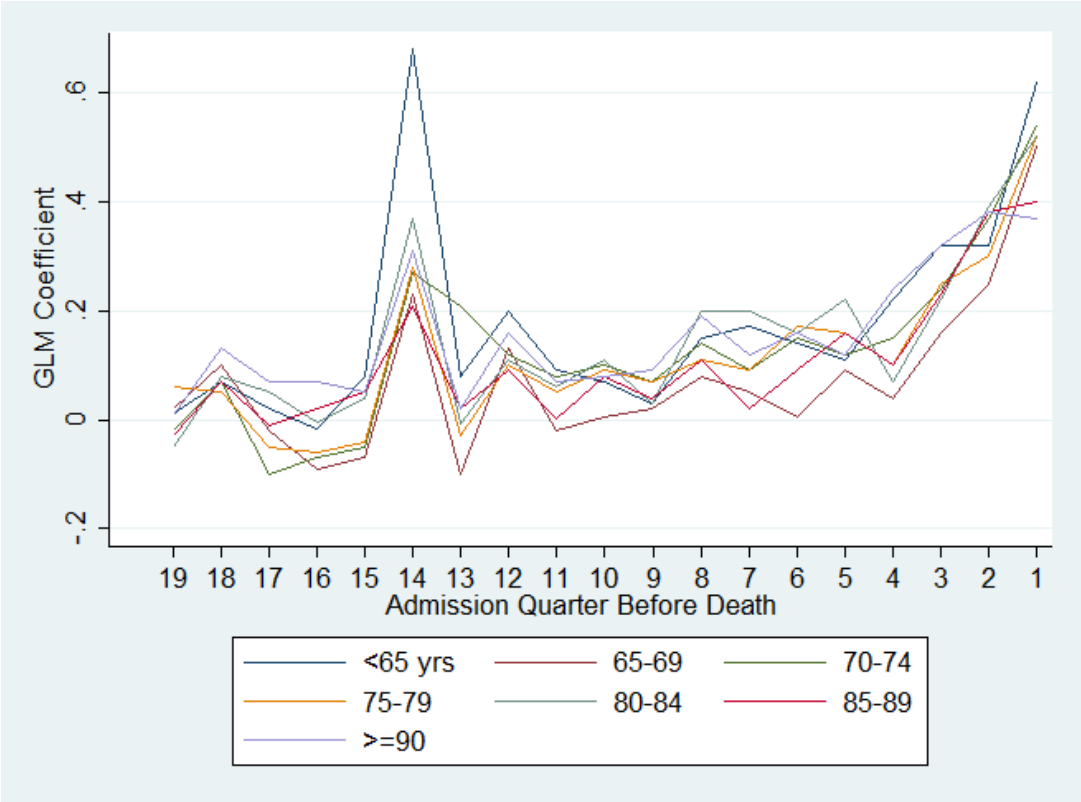

Figure 6-14 TTD and age interaction terms, Cost estimation

The socio-economic status has a negative impact on costs for those individuals living in the 2nd, 3rd, 4th or 5th quintile compared to individuals living in the most affluent quintile, however, this effect is not statistically significant. In order to investigate whether the effect that the socio-economic status has on costs is influenced by TTD, the interaction effects are presented in Table 6.8. Results only show very small effects for some quarters without any recognisable pattern. Interaction effects are presented graphically in Figure 6.15.

Table 6-8 Interaction terms TTD and deprivation - English Tariff (Cost Ratios)

TTD	Deprivation Score Quintile =2	Deprivation Score Quintile=3	Deprivation Score Quintile =4	Deprivation Score Quintile =5
1	1.117	1.069	1.098	1.018
2	1.139	1.050	1.119	1.041
3	1.129	1.083	1.119	1.039
4	1.159*	1.223**	1.276***	1.154
5	1.216**	1.055	1.160	1.041
6	1.158*	1.129	1.154	1.058
7	1.118	1.043	1.129	1.061
8	1.126	1.109	1.080	1.003**
9	1.256	1.141	1.221*	1.060
10	1.208*	1.120	1.137	1.066
11	1.145	1.129	1.168*	1.110
12	1.014	1.017	1.040	1.015
13	1.119	1.168	1.203**	0.971
14	0.840	0.760	0.839	0.744
15	1.189*	1.191*	1.176*	1.049
16	1.193*	1.088	1.172*	1.065
17	1.160	1.196*	1.154	1.085
18	1.089	1.039	1.057	0.947
19	1.167	1.055	1.159	0.992

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

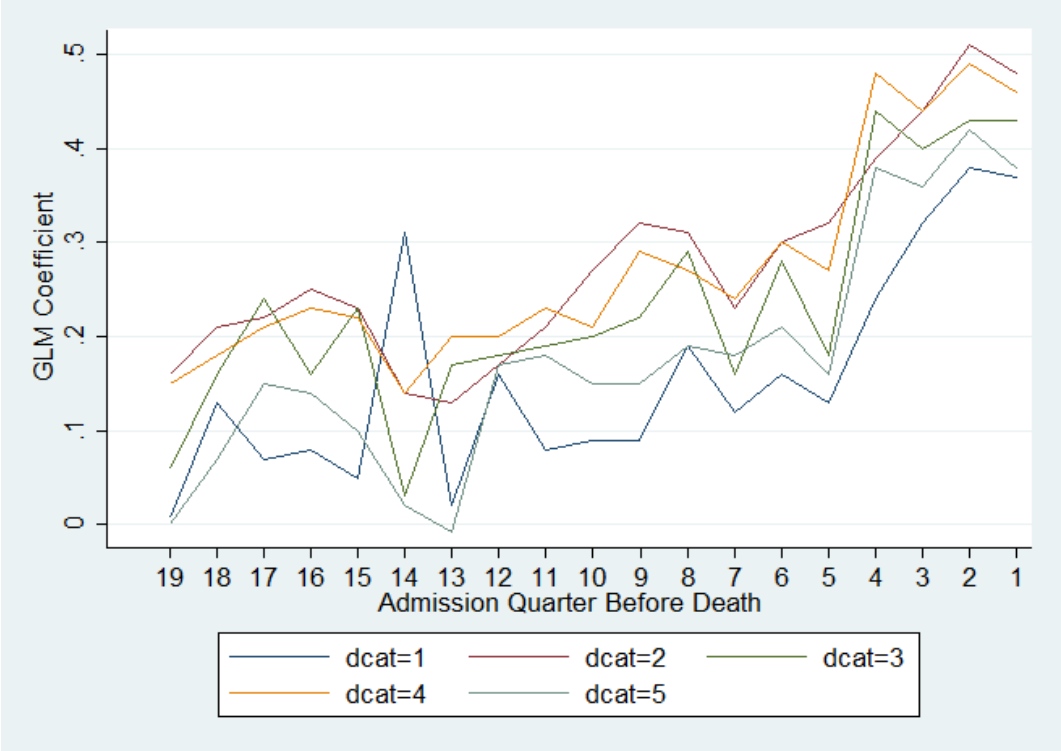

Figure 6-15 TTD and deprivation quintile interaction terms, Cost estimation

Results in Table 6.6 also show that on average, male individuals incur significantly higher costs than females (~11%) and individuals, who reported a limiting long-term illness, incur significantly higher costs compared to those without any long-term illnesses (6%).

SNT – Table 6.6, columns (3) and (4)

Similar to regression results obtained from the application of the English Tariff, the association between TTD and costs is highly significant (columns (3) and (4) in Table 6.6). However, unlike employing the English Tariff, this effect can be observed up until the 12th quarter before death when using the SNT. Costs in the last quarter of life are estimated to be about 52% higher than in the 20th quarter before death. This is considerably lower than estimates obtained from applying the English Tariff. Table 6.6 also shows that, similar to employing the English Tariff, male individuals incur significantly higher costs than females (~8%). Contrary to using the English Tariff, however, having a long-term illness does not seem to have an effect on costs incurred in the last 20 quarters of life when using the SNT.

Age at death only appears to be a significant predictor for costs for the two oldest age groups and the 4th youngest age group. Again, estimates are lower compared to the English Tariff. The oldest age groups are estimated to incur costs that are only 13% higher on average than those incurred by the youngest age group. Interaction terms between TTD and age show a highly significant association with costs up until the seventh quarter before death and mainly for the two oldest age groups (Table 6.9).

Table 6-9 Interaction terms TTD and age groups - SNT (Cost Ratios)

TTD	65-69	70-74 years	75-79 years	80-84 years	85-89 years	>= 90 years
1	1.016	1.005	0.924	0.986	0.924	0.949
2	0.958	0.983	0.842***	0.940	0.926	0.913
3	0.949	0.899	0.851***	0.895*	0.815***	0.878**
4	0.903	0.916	0.853**	0.841***	0.830***	0.887*
5	0.938	0.899	0.870**	0.897*	0.852**	0.864**
6	0.928	0.958	0.923	0.891*	0.894*	0.950
7	0.913	0.947	0.908	0.939	0.834***	0.913
8	1.002	0.974	0.883*	0.921	0.885*	0.945
9	0.961	0.952	0.909	0.941	0.926	0.960
10	0.987	0.997	0.942	1.011	0.950	1.020
11	0.951	0.947	0.899	0.938	0.895*	0.951
12	1.036	0.884	0.905	0.936	0.879*	0.975
13	0.889	0.962	0.912	0.950	0.885*	0.951
14	0.975	0.929	0.954	0.998	0.882	1.004
15	0.916	0.962	0.939	0.982	0.953	0.963
16	1.039	0.927	0.966	1.002	0.931	1.005
17	0.937	0.852	0.863*	0.974	0.914	0.978
18	1.037	1.001	0.943	1.025	0.967	1.037
19	1.059	0.964	1.037	1.029	0.967	1.021

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

Table 6-10 Interaction terms TTD and deprivation - SNT (Cost Ratios)

TTD	Deprivation Score Quintile =2	Deprivation Score Quintile=3	Deprivation Score Quintile =4	Deprivation Score Quintile =5
1	1.059	1.009	1.023	0.907**
2	1.032	0.974	0.995	0.888**
3	1.074	1.001	0.994	0.883**
4	1.073	1.012	1.066	0.878**
5	1.112*	1.003	0.949	0.867**
6	1.073	1.023	0.988	0.895*
7	1.027	0.977	0.989	0.892*
8	0.999	0.988	0.939	0.858**
9	1.037	0.976	1.014	0.874**
10	1.037	0.984	1.007	0.896*
11	1.067	1.004	1.015	0.920
12	1.048	0.969	1.014	0.919
13	1.084	1.017	1.069	0.877**
14	1.055	0.984	1.057	0.900*
15	1.154**	1.076	1.076	0.958
16	1.033	1.055	1.046	0.904
17	1.072	1.006	1.039	0.894*
18	1.027	0.996	0.988	0.895*
19	1.057	0.987	1.034	0.914

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

The socio-economic status seems to have a negligible effect on costs towards the end of life and no significant association could be observed. The inclusion of interaction terms between TTD and deprivation score quintiles however reveals a highly significant association ($p<0.05$) that can be observed for the most deprived quintile (5) and quarters 1-9 before death (Table 6.10). Individuals living in the most deprived areas seem to incur significantly lower costs compared to people from the most affluent areas.

Predicted costs by socio-economic status

Average cost estimates by deprivation score quintile and admission quarter before death for the English Tariff and the SNT are presented in Table 6.11. These were obtained from multiplying the first part of the model (probability of hospitalisation) and the second modelling part (costs incurred given positive utilisation), as outlined in Equation 6.3. Estimates vary between £1,960 (SD=587) for the least deprived quintile and £2,054 (SD=521) for the most deprived quintile in the last quarter of life (English Tariff). This shows that in the last quarter of life nearly £100 more is spent on individuals from the most deprived areas compared to people from the most affluent areas.

A less pronounced difference between deprivation score quintiles is found for the application of the SNT in the last quarter of life. Differences in costs between socio-economic groups become less marked the further away from death an individual is. The same comparison is made in Figure 6.16 which visualises the differences between employing the English Tariff and the SNT looking at different times away from death by deprivation score quintile. As already described for Table 6.11, some differences can be observed for the quarter closest to death between the two costing methods however, these seem to be very small. In the preceding analyses in this chapter it is therefore considered only to apply the English Tariff, as this is in line with the analysis in Chapter 5 and also the recommendations from Chapter 4.

Table 6-11 Predicted costs in GBP (SD) [CI] by deprivation score quintile

Admission quarter before death	Deprivation Quintile 1	Deprivation Quintile 2	Deprivation Quintile 3	Deprivation Quintile 4	Deprivation Quintile 5
English Tariff					
1	1,960 (587)	1,947 (592)	1,948 (578)	1,998 (558)	2,054 (521)
	[1,946; 1,974]	[1,936; 1,957]	[1,938; 1,958]	[1,988; 2,009]	[2,044; 2,065]
2	724 (205)	714 (203)	714 (195)	738 (194)	760 (184)
	[719; 728]	[710; 717]	[711; 717]	[734; 742]	[757; 764]
10	255 (70)	298 (79)	287 (76)	292 (75)	294 (75)
	[253; 257]	[297; 299]	[285; 288]	[291; 294]	[292; 295]
20	192 (68)	185 (64)	187 (65)	188 (66)	195 (69)
	[190; 193]	[184; 186]	[186; 188]	[187; 190]	[194; 197]
SNT					
1	1,992 (691)	1,910 (672)	1,926 (659)	1,984 (649)	1,975 (590)
	[1,976; 2,008]	[1,898; 1,922]	[1,914; 1937]	[1,972; 1996]	[1,964; 1,987]
2	718 (287)	654 (261)	680 (262)	693 (261)	704 (250)
	[711; 725]	[650; 659]	[675; 684]	[688; 698]	[700; 709]
10	287 (88)	294 (88)	295 (87)	310 (91)	302 (87)
	[285; 289]	[293; 296]	[293; 296]	[308; 312]	[301; 304]
20	200 (73)	198 (72)	204 (73)	211 (76)	224 (81)
	[199; 202]	[197; 199]	[203; 205]	[209; 212]	[223; 226]

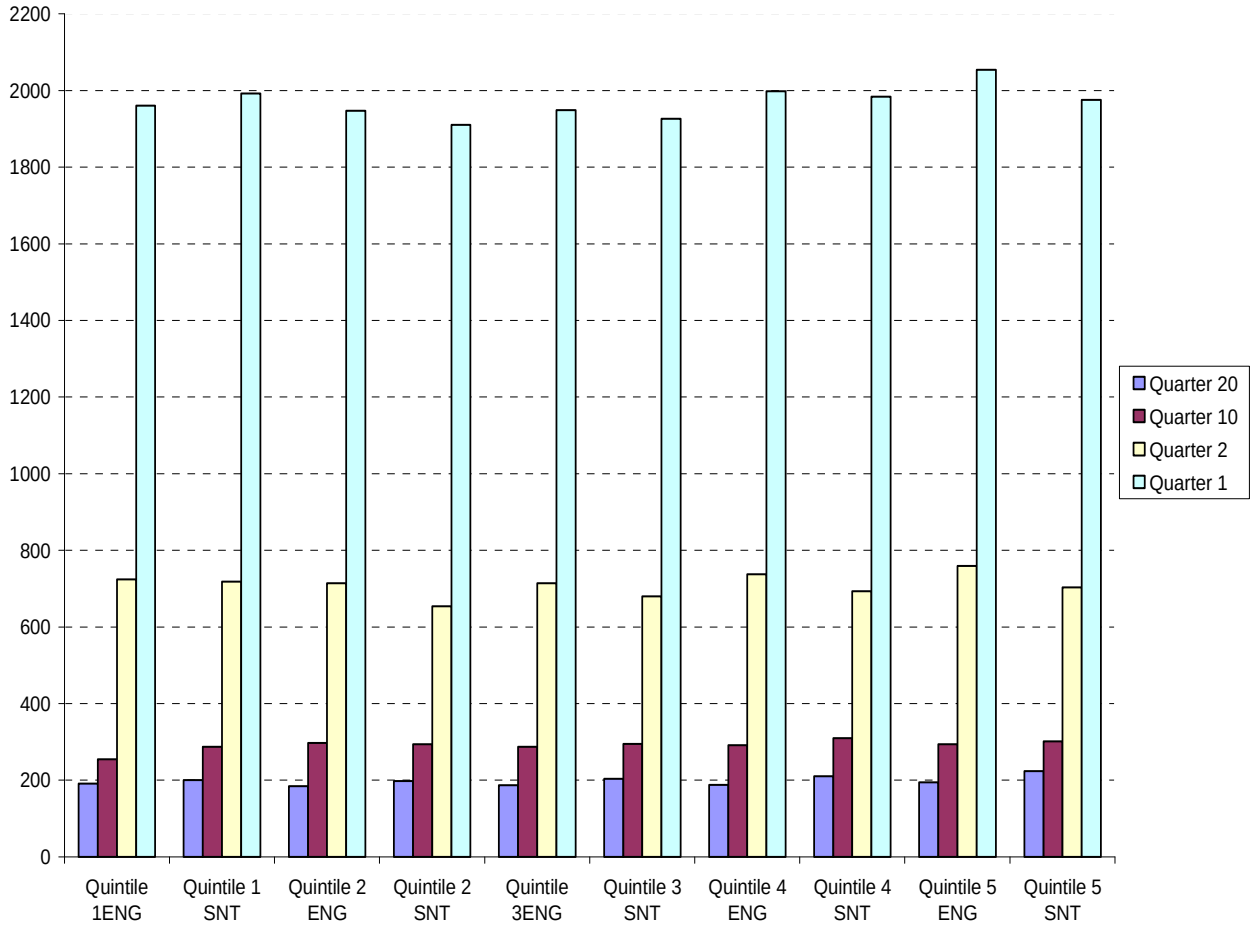

Figure 6-16 Effect of socio-economic status on costs (English Tariff and SNT)

Predicted costs by age group

As a final step, cost predictions are obtained stratified by age group, TTD and also gender. Costs were aggregated into annual costs using quarterly costs as obtained from the regression model; for example costs for quarters 1, 2, 3 and 4 were added up to represent costs for the last year of life etc. Results are presented in Table 6.12. The English Tariff is used here to obtain cost predictions as an illustrative example and also because there were only small differences that could be found between the SNT and the English Tariff in both, descriptive analysis and regression analysis.

Results show that male individuals, aged 65-69 who are in their last year of life incurred £4,028 on average, whereas males aged >=90 years in their last year of life only incurred £2,341 on average. This confirms the earlier observation of costs for the eldest age group being lower towards the end of their life compared to younger ages.

Table 6-12 Predicted costs in £ by TTD, age and gender

Male	Age	Year 1	Year 2	Year 3	Year 4	Year 5
	<65	4,183	1,354	952	787	573
	65-69	4,028	1,259	915	694	637
	70-74	4,298	1,370	1,051	805	640
	75-79	4,150	1,388	1,074	800	752
	80-84	4,026	1,402	1,081	905	785
	85-89	2,827	1,190	1,056	990	898
	>=90	2,341	1,289	1,309	1,256	1,169
Female						
	<65	4,492	1,410	985	811	590
	65-69	4,290	1,294	934	703	645
	70-74	4,565	1,401	1,068	813	645
	75-79	4,460	1,447	1,116	826	774
	80-84	4,437	1,565	1,218	1,026	881
	85-89	3,361	1,409	1,200	1,090	972
	>=90	2,336	1,274	1,248	1,190	1,108

Figure 6.17 shows how mean predicted costs, applying the English Tariff, that have been aggregated to represent years rather than quarters before death, are distributed over age groups. This is presented for males only, since the distribution for females is similar and only the scale will differ by the magnitude of the explanatory variable ‘Male’ that was estimated in regression analysis. Costs are estimated to be highest in the last year of life, with costs decreasing the further away from death an individual is. This pattern can be observed for all age groups. Costs in the last year of life seem to be highest for ages 70-84 at death and lowest for the two oldest age categories. Differences in costs between different times away from death are less pronounced for the two oldest age groups than they are for the younger ages. This figure clearly shows the interaction effects between age and TTD.

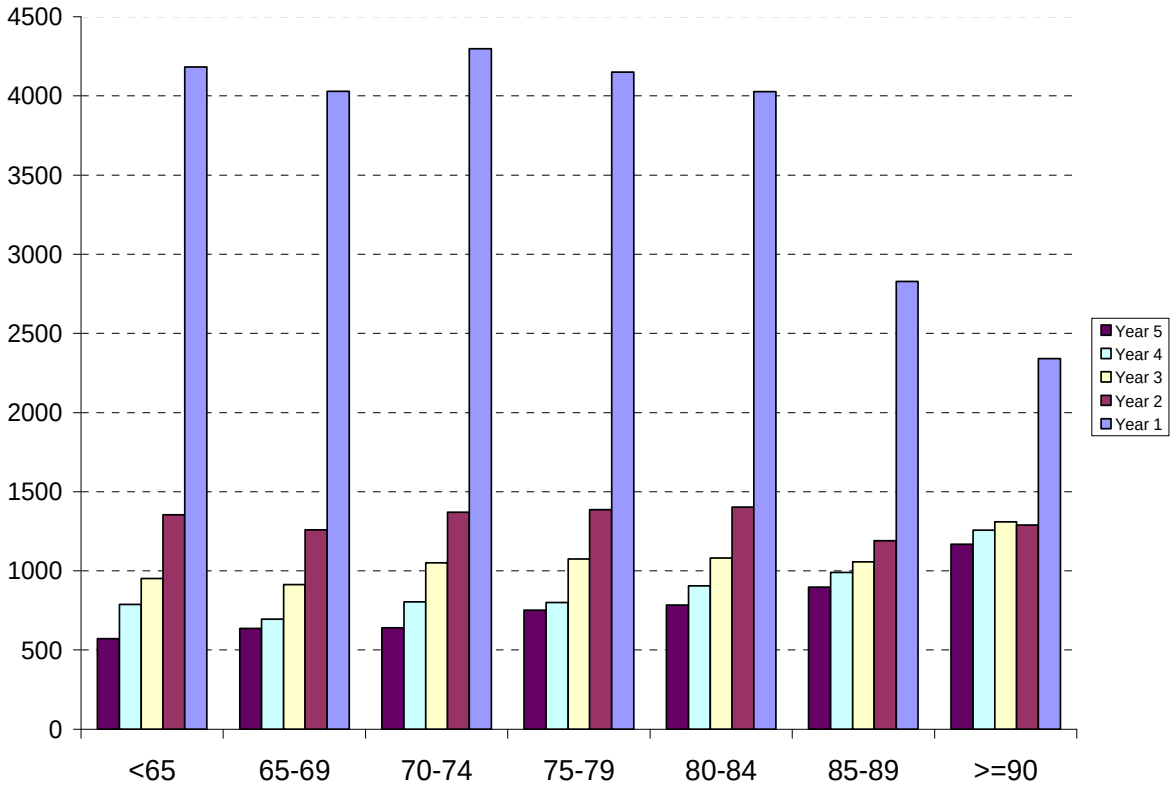

Figure 6-17 Predicted costs by age and year before death, males

Figure 6.18 (males) shows the mean predicted costs on a quarterly level, for the last year of life only. A similar pattern can be found of how costs are distributed over age groups, with the two oldest age groups incurring lower costs than the remaining, younger ages in all four quarters before death. Costs in the last quarter of life are substantially higher for all age groups compared to the second, third and fourth quarter before death. Costs in the last quarter of life can be observed to be markedly lower for the two oldest age groups and lowest for the eldest (>= 90 years). The difference in predicted costs between quarter 1, quarter 2, quarter 3 and quarter 4 before death is less pronounced for the two oldest age groups than the younger ages.

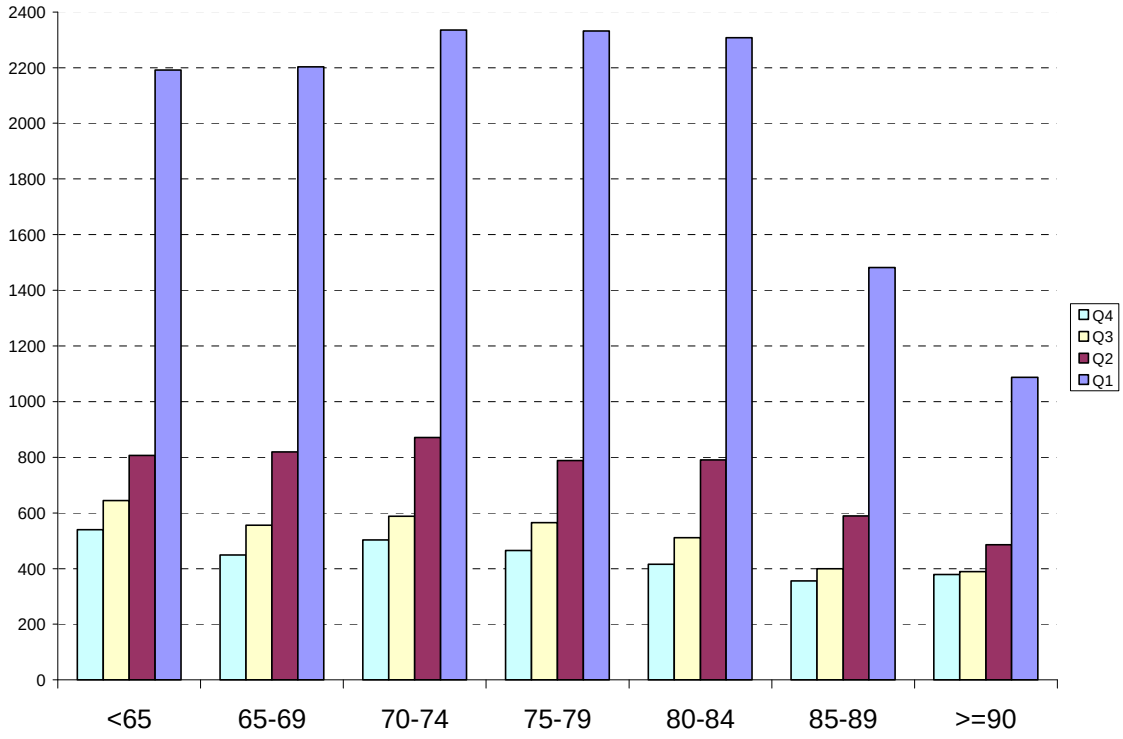

Figure 6-18 Predicted costs by age and quarter before death, last year of life, males

6.5 HC expenditure projections

The following section analyses two different approaches of generating HC expenditure projections for Scotland and so addresses the issue of an overestimation of future HC expenditure if a purely demographic approach was applied, as outlined in Section 3.8.1. The analysis in this section tests whether similar results to those from other published studies can be found for a sample of the Scottish population. If results from this chapter should confirm previous results of an overestimation of future HC costs when employing a purely demographic approach, this chapter also seeks to provide an estimate of the magnitude of any such overestimation of future HC costs. The first approach presented here predicts HC expenditure only accounting for demographic changes in the

population and the second approach extends the first approach by controlling for remaining TTD.

In a first step population estimates are obtained for both methods. In a second step these estimates are multiplied by cost estimates using the purely demographic approach and the TTD approach.

6.5.1 Population estimates - demographic approach

For both approaches, HC expenditure projections are based on 2008 population estimates provided by National Records of Scotland, formerly GROS, which were the latest projections available (GROS, 2011). These estimates provide information on the total number of people projected to be living in Scotland up until the year 2033. Population estimates for the year 2011 are utilised as the base year, representing an index of 100. Projected costs are obtained for four future time points (2016, 2021, 2026 and 2028). Since population estimates are only available until 2033 and since it is required for the TTD approach to be able to calculate the proportion of the population in year one to five before death, the last estimate can be obtained for the year 2028.

Although, this results in unequal time intervals, it was judged that it adds additional information on future HC costs and has therefore been added to the analysis. Results from both modelling approaches are finally compared.

For population estimates, all persons usually resident in Scotland are covered regardless of their nationality (GROS, 2011). Projecting population numbers into the future very likely has an increasing level of uncertainty the further away these projections are. However, information on the high and low variants of population projections were not available from NRS and the precision of population projections for Scotland is of minor importance here, as the aim of this study is to highlight the differences in projected future HC expenditure under two different approaches.

Population projections are available for each specific age (up to and including individuals aged 101) and by gender. The time horizon for these projections is also available for individual calendar years and up to the year 2033. Since the aim of this thesis is to analyse an ageing populations' impact on HC expenditure, projections for that part of the population aged 65 and older are analysed.

The simplified scenario of assuming constant age-expenditure profiles, the 'demographic approach' and projecting HC expenditure is used to obtain a comparator for the TTD approach in order to quantify the extent to which both approaches diverge from each other. Using population projections from NRS as outlined above, the total number of the projected population is utilised and stratification is carried out for age group and sex.

Observed annual HC expenditure is obtained for the entire SLS sample and not only those individuals in their last five years of life as described in the regression modelling section. Since the SLS is a representative sample of the Scottish population it can be assumed that any HC expenditures incurred are also representative for HC costs incurred on average by the Scottish population. HC expenditure is observed for three consecutive years (2006, 2007 and 2008) for which the average is calculated. Observation of HC expenditure is undertaken stratified by gender as well as by age groups.

2006/2007 was also the price year that had been used throughout Chapters 4 and 5. The derived average annual HC expenditures are then multiplied by population estimates, stratified by age group and gender for the years 2011, 2016, 2021, 2026 and 2028. Finally, costs are aggregated over all age groups and both genders and the resulting cost provides a projection under a simplified scenario, which only accounts for demographic changes in the population.

6.5.2 Population estimates - TTD approach

In addition to stratifying projected population numbers by age group and gender as outlined above, the TTD approach also takes into account the number of people in each of these groups who are in their last five years of life. Again, information provided by NRS on the projected population in Scotland is initially utilised to obtain the necessary population numbers. In addition to the procedure described earlier, each single age is now also stratified by TTD in years, so that an estimate of the population in each calendar year that is in their last year of life, penultimate year of life, third year before death, fourth year before death and fifth year before death can be obtained. This is achieved by using projections of the number of deaths, which are available from NRS on request.

Similar to projected population numbers, projected numbers of death are available for individual ages (up to and including the age of 125) and individual calendar years (up to and including the year 2033). The following calculations were used in order to get an estimate of the number of individuals projected to be in a particular year before death. The year 2011 is used here as an example.

$TTD_1 = Deaths_{age/sex2012}$ Equation (6.4)

$TTD_2 = Deaths_{age/sex2013}$ Equation (6.5)

$TTD_3 = Deaths_{age/sex2014}$ Equation (6.6)

$TTD_4 = Deaths_{age/sex2015}$ Equation (6.7)

$TTD_5 = Deaths_{age/sex2016}$ Equation (6.8)

Where $TTD_{1\text{-}5}$ is the number of the population projected to be in particular year before death; Deaths $_{age/sex}$ is the projected number of deaths by age and sex.

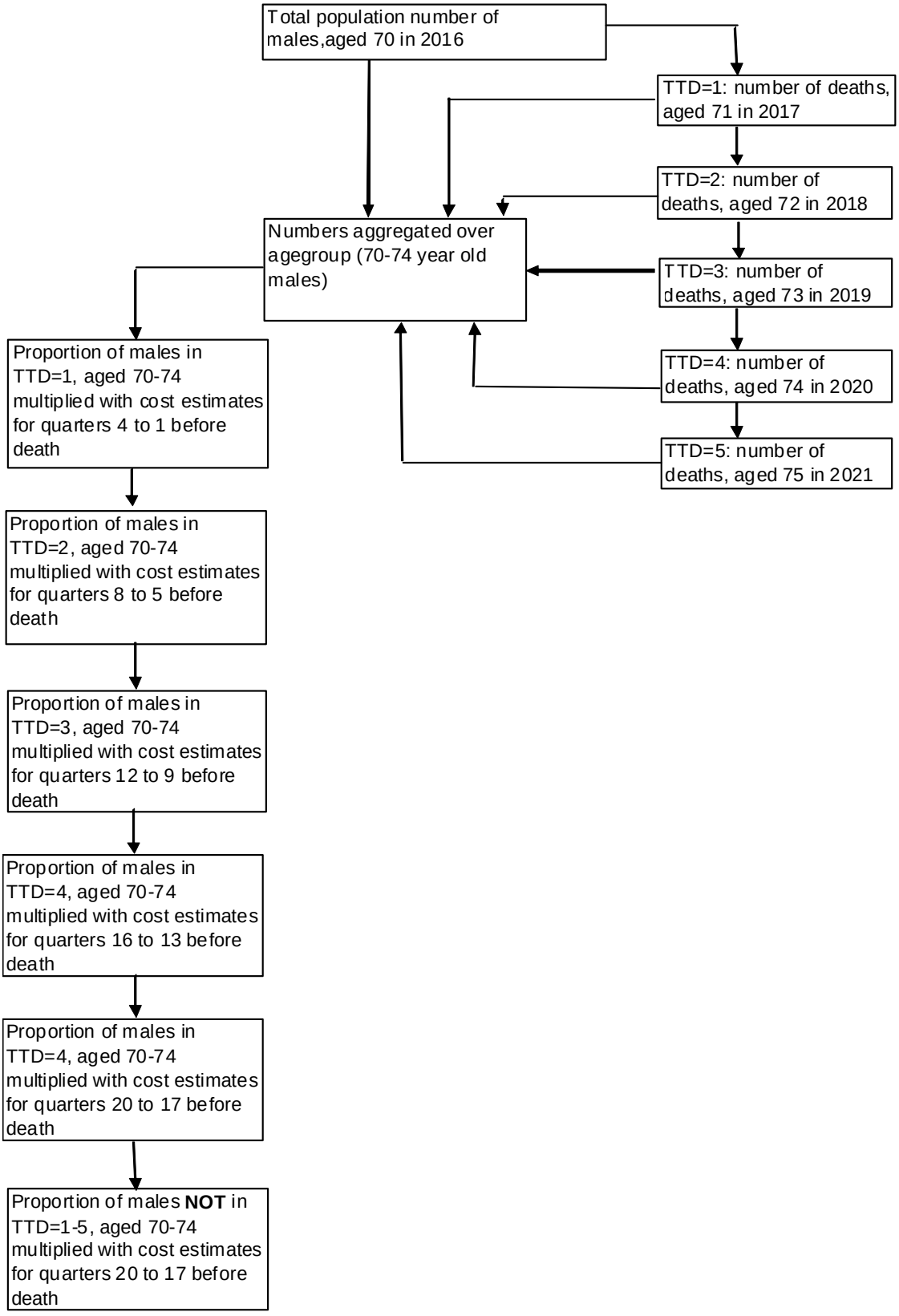

Figure 6-19 Example- obtaining population numbers by TTD

Figure 6.19 shows an example using the projected population number for males, aged 70 in 2016 and the corresponding projected number of deaths. To calculate the number of males aged 70 in their last year of life in 2011, the number of 71 year old males, who are projected to die in 2017 is utilised. In order to calculate the number of 70 year old men who are in their penultimate year of life, the projected number of deaths for males aged 72 in 2018 is applied etc. These calculations are repeated for all ages (by gender and for individuals aged 65 and older) for the time points specified above (2011, 2016, 2021, 2026 and 2028). This provides an estimate of the number of people expected to be in year 1 to 5 before death. It also provides an estimate of the number of individuals, who are not within their last five years of life. This is achieved through subtracting those in year 1, 2, 3, 4 and 5 before death from the total number of the projected population in each age group.

The next step is to summarise single ages of the projected number of the population in their last, 2^{nd}, 3^{rd}, 4^{th} and 5^{th} year before death into age groups to align with those age groups used in regression analysis. As explained earlier, projections are only calculated for that part of the population aged 65 and older.

Cost estimates per capita are obtained from the econometric model presented in Section 6.4.2. Contrary to the procedure described of obtaining cost estimates under a purely demographic approach, for this TTD approach, predicted costs are obtained after fitting the two-part model and multiplying estimates from the probability part with estimates from the part that estimated costs conditional on having incurred positive HC expenditure. These predicted costs are then obtained stratified by age group, by gender and also remaining TTD. Cost estimates derived from the regression model represent quarterly costs. These are aggregated to represent annual costs, so that:

$$TTD_{quarter1} + TTD_{quarter2} + TTD_{quarter3} + TTD_{quarter4} = TTD_{year1} \quad \text{Equation (6.9)}$$

For those individuals in the Scottish population, whose death is further away than five years as obtained from projected population and deaths numbers, cost estimates for the fifth year before death, are applied. This method is deemed feasible given that the resulting curves for observed and predicted costs are basically flat for quarters 10 to 20 before death (see Figure 6.2). The assumption here is that annual costs beyond the fifth year before death are constant. Further evidence for this method is given by the insignificant association between TTD and incurred costs, given positive utilisation from about the 13th quarter before death, indicating that TTD will not have an impact on costs from that point in time onwards.

Finally, costs for each stratum are multiplied by the respective population estimates for each age group, gender and TTD stratum and are aggregated over TTD, age group and gender to provide HC expenditure projections for the years 2011, 2016, 2021, 2026 and 2028 that have been adjusted for remaining TTD.

The year 2011 serves as the base year for HC expenditure projections and costs from the demographic approach and the TTD approach for that year are set to 100. All subsequent analyses consider any deviation from this indexed level. A comparison of the growth rate of costs from 2011 onwards between the demographic approach and the TTD approach is undertaken to show whether a simplified approach overestimates future HC costs and if that is the case, the magnitude of the overestimation.

6.5.3 Results - population projections

Figures 6.20 and Figure 6.21 show, how the projected number of the entire Scottish population develops over the next two decades. The presentation is done separately for males (Figure 6.20) and females (Figure 6.21) and represents age groups for the ages 65 and older. A constant increase can be observed, for both males and females and for all age groups.

The slope of the graph for female age groups seems to be somewhat steeper than the slope for the graphs representing age groups for males. This suggests that the already higher proportion of females in each age group in Scotland continues to rise faster than the number of males in each age group.

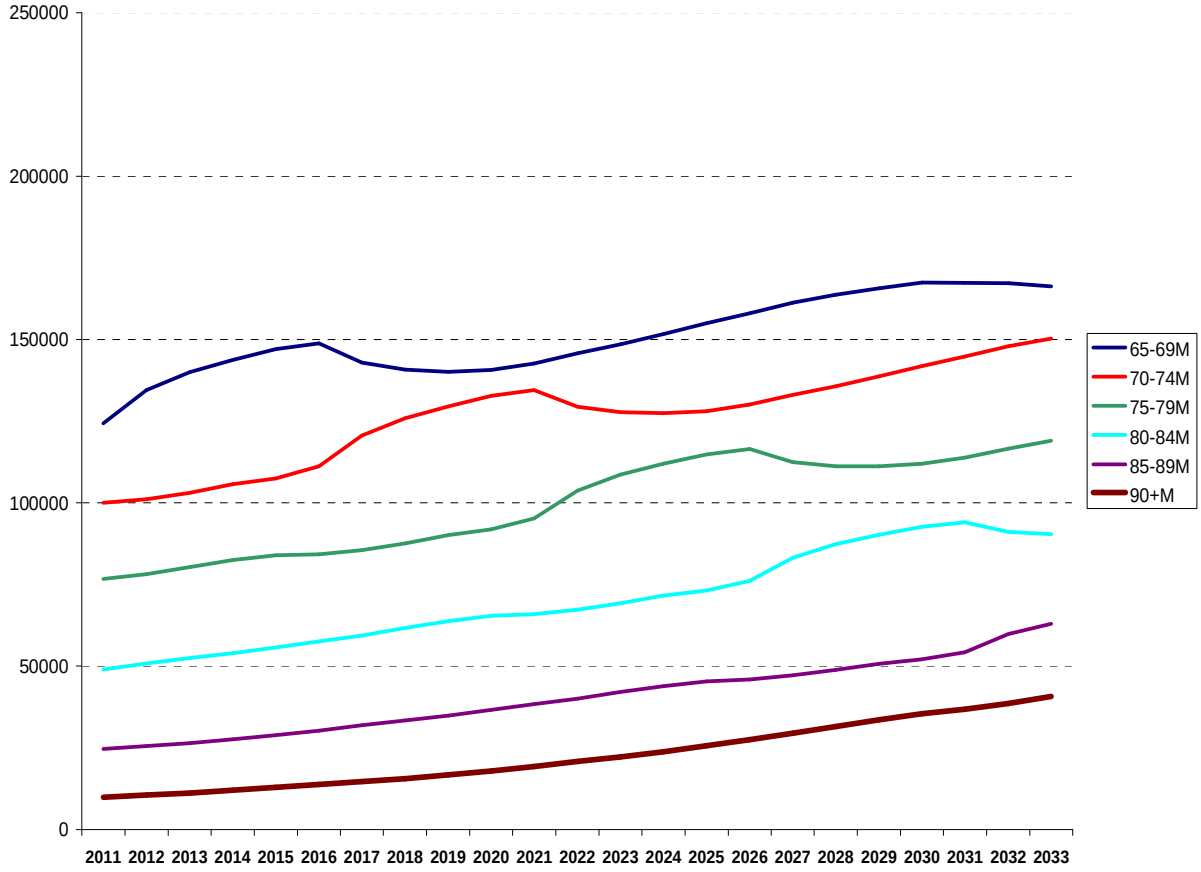

Figure 6-20 Projected number of males (65+)

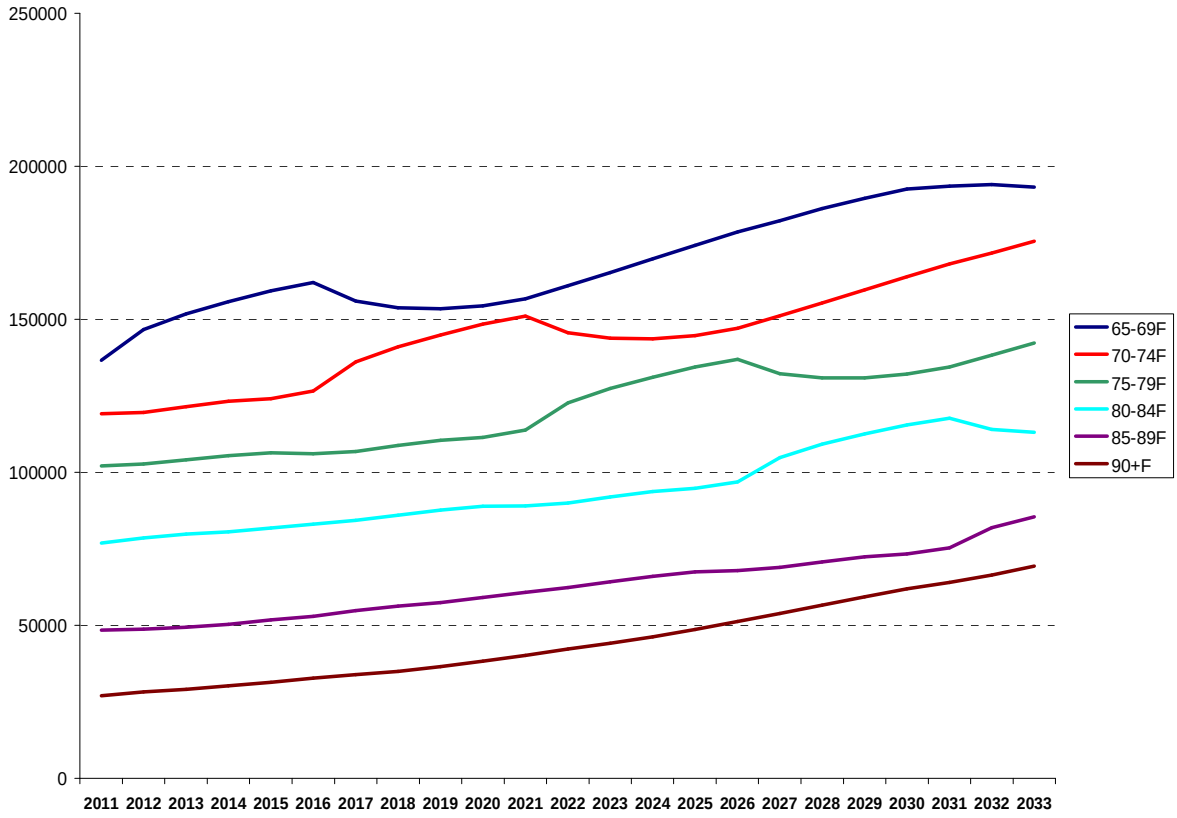

Figure 6-21 Projected number of females (65+)

Figure 6.22 combines Figures 6.20 and 6.21 and shows, how the projected number of the entire Scottish population develops over the next two decades aggregated over all age groups. A constant increase can be observed, for both males and females, with the number of females remaining about 100,000 higher than the number of males in the 65+ population.

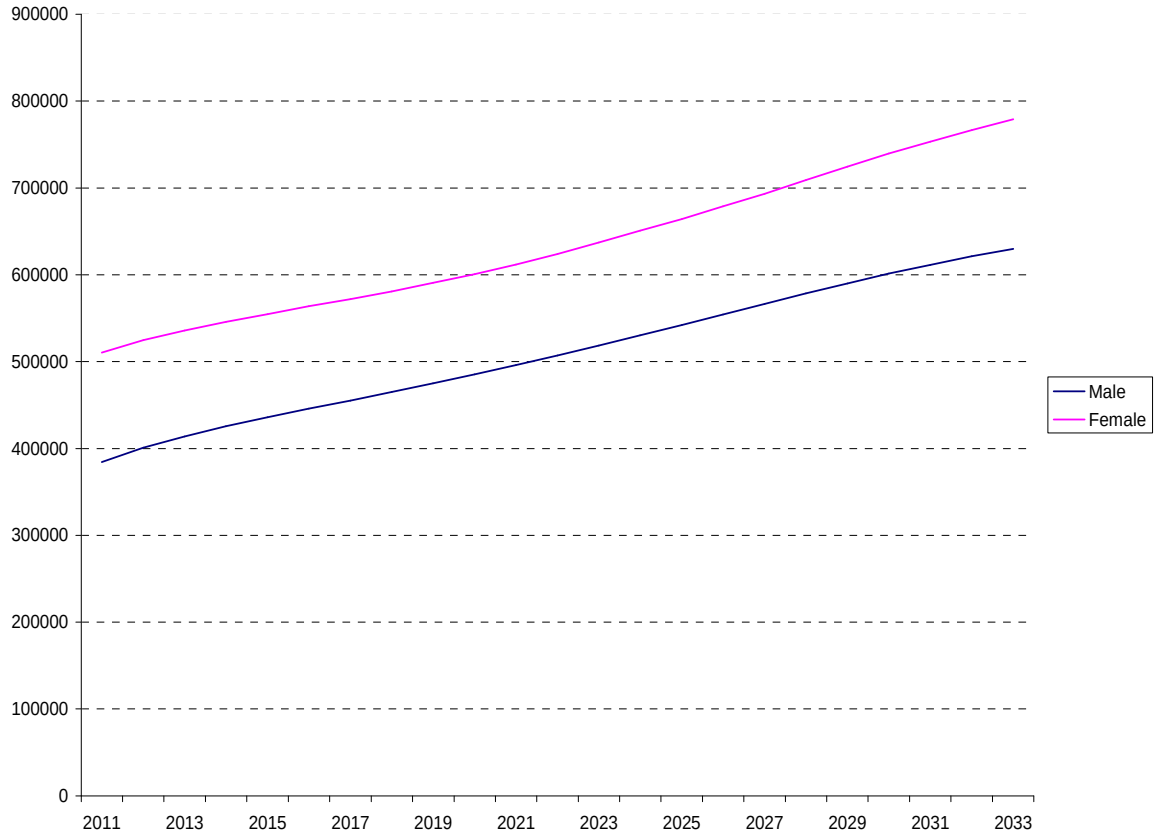

Figure 6-22 Aggregated number of males and females in Scotland (65+)

The projected numbers of deaths for males and females from 2011 until 2033 for individuals aged 65 and older are presented in Figure 6.23 (males) and Figure 6.24 (females). Both figures are based on population estimates obtained from NRS and represent the entire population of Scotland aged 65 and older. Comparing the number of deaths for males and females it can be observed that more females are dying. This is mainly caused by the fact that more females are alive at the age of 65 and above compared to males, as could be seen from Figure 6.20 and Figure 6.21 above.

For males a slight increase in the number of deaths can be observed for the three oldest age groups, whereas the number of deaths for the three youngest age groups seems to fluctuate over the next decades, keeping relatively stable.

For females either a slight downward shift or a stable development of the absolute number of deaths can be observed for almost all age groups, apart from the eldest. For women aged 90 and older a steep increase in the number of deaths is observed for the next couple of decades.

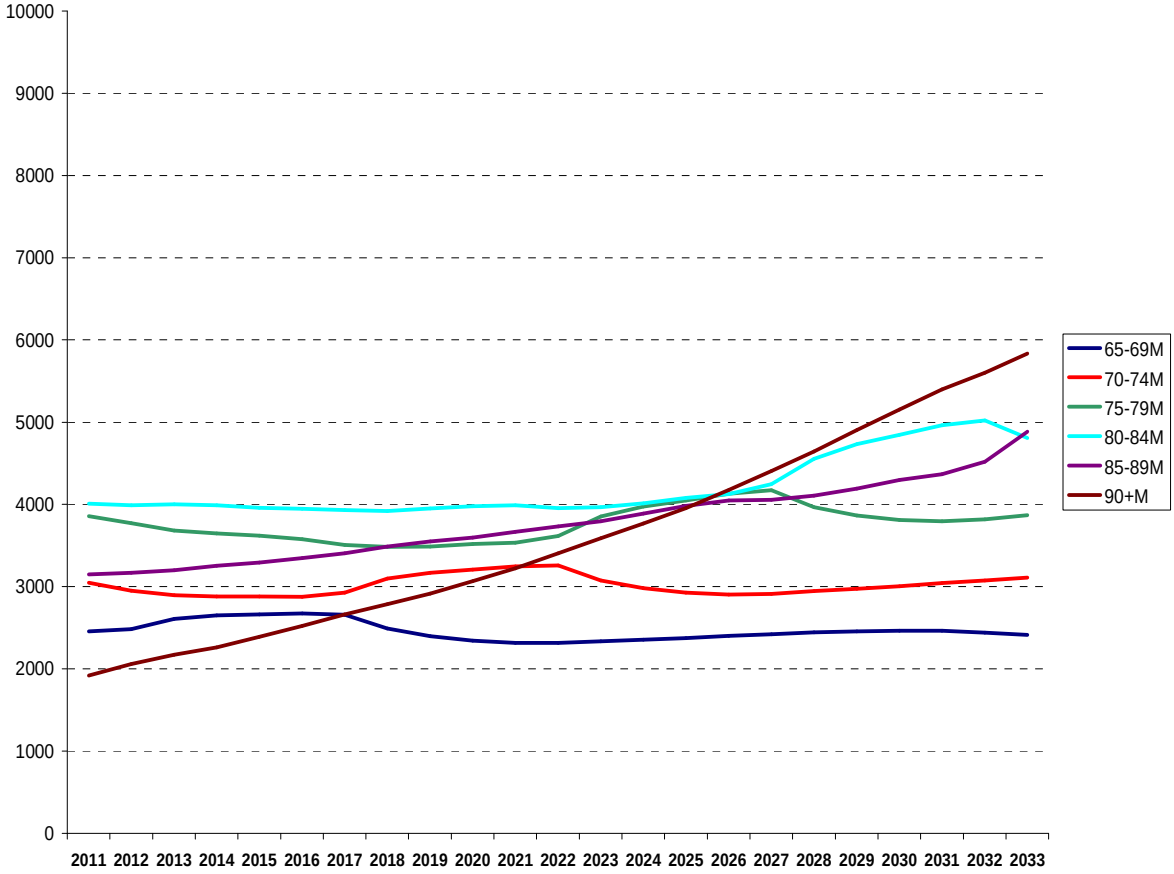

Figure 6-23 Projected number of deaths in Scotland, males (65+)

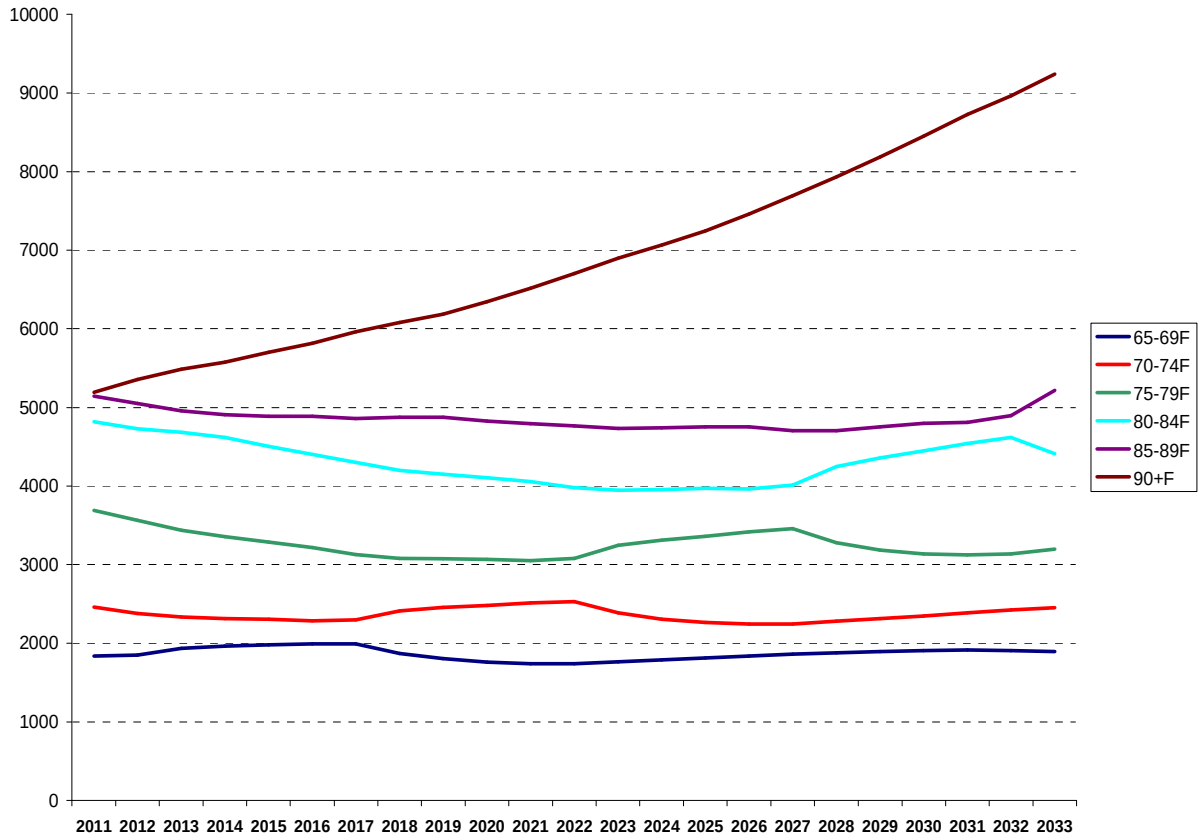

Figure 6-24 Projected number of deaths in Scotland, females (65+)

Figure 6.25 combines Figure 6.23 and Figure 6.24 and shows the aggregated number of deaths over all age groups and presents differences in the number of deaths for males and females. For females a slight downward shift in the absolute number of deaths is observed until 2020 after which deaths are projected to rise. For males a slight increase in the number of deaths can be observed up until 2017, followed by a slightly more pronounced increase. The difference in the absolute number of deaths between males and females seems to narrow over time, confirming overall, that people are projected to die at older ages.

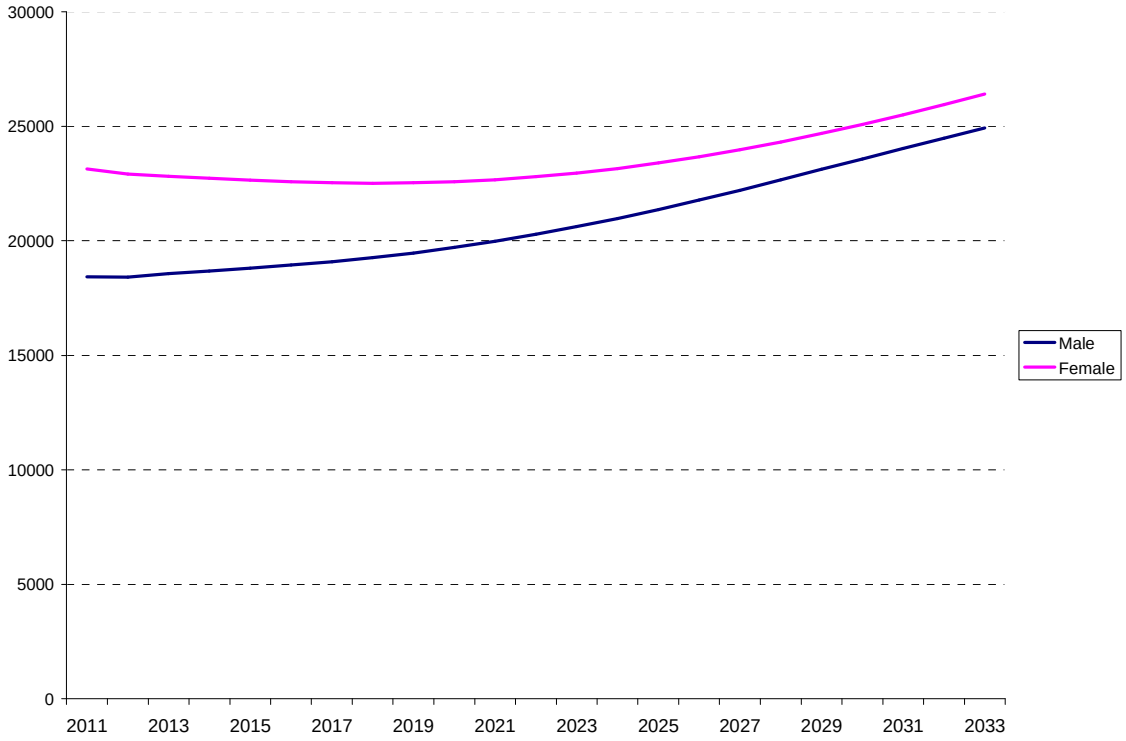

Figure 6-25 Aggregated number of deaths, males and females (65+)

6.5.4 Results - HC expenditure projections

Results obtained from HC expenditure projection for both, the demographic approach and the TTD approach are presented in Table 6.13. These results are for that part of the sample aged 65 and older and for acute inpatient care expenditure, which will account for a substantial part of the total HC expenditure, but not for all of it. Results should therefore be interpreted with these limitations in mind.

Table 6-13 HC expenditure projections (acute inpatient care) for those aged 65+

Year	TTD Approach	Demographic Approach
2011	100	100
2016	110.2	112.7
2021	120.2	124.8
2026	132.3	139.9
2028	139.6	146.5

The growth rate observed for the TTD approach is projected to be lower than the growth rate that would be obtained when applying a simplified approach and only accounting for demographic changes in the population. This can be observed for all years for which a projection was carried out. Overall, the gap between a growth rate obtained under the demographic approach and a growth rate obtained under a TTD approach seems to widen slightly over time. Results in Table 6.13 show that in 15 to 17 years time the difference between projected HC expenditures will be about 7%.

Figure 6.26 shows, how the projected HC expenditure is expected to be distributed in year 2011 (base year), 2016, 2021, 2026, and 2028. Both, Table 6.13 and Figure 6.26 show an overestimation of future HC expenditure on the over 65s for acute inpatient care under the demographic approach. The magnitude of the overestimation is observed to be between 2% in 2016 and 7% in the year 2028.

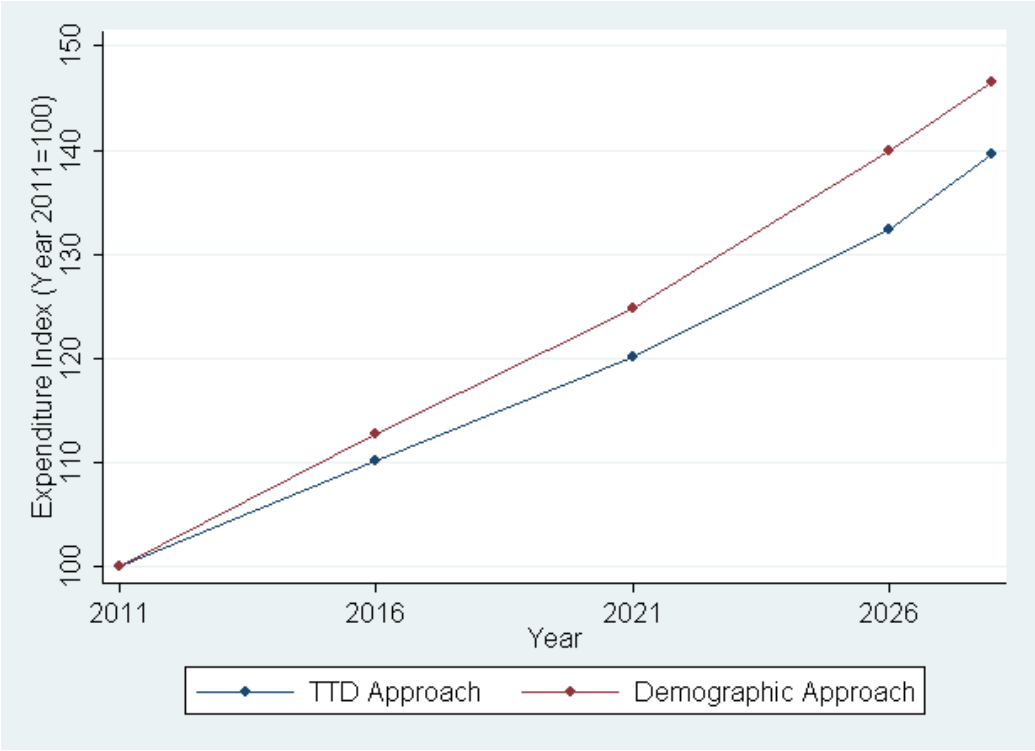

Figure 6-26 Projection of HC expenditure for acute inpatient care (65+)

6.6 Discussion

Using a representative sample for the Scottish population, the SLS, the analysis in this chapter has shown that TTD, age at death and the interaction between these two have a significant effect on HC costs and so confirms findings from other previous research as well as findings in Chapter 5. This is very important, since other national studies might not have been able to utilise data that was representative of the population the study was undertaken in. The analysis also showed that TTD influences HC expenditure differently for different age groups and deprivation score quintiles.

The analysis of the effect that TTD in general had on costs provided similar findings to those obtained in Chapter 5. Using HRG costing and the English Tariff as one costing approach also showed TTD to be a significant predictor of costs towards the end of life. Comparing the magnitude of the effect between the last quarter of life in the Renfrew/Paisley sample and the SLS sample showed that costs for the Renfrew/Paisley sample were about 100% higher than in the 12th quarter before death, whereas they were about 85% higher for the SLS sample compared to the quarter furthest away from death (20th quarter). TTD in the SLS sample showed an effect that steadily increased as people approached death, whereas a 'spike' in costs for the Renfrew/Paisley sample could be observed for quarters seven and eight before death. Although similar, it might be that these results can not be compared directly since they have been obtained using two different samples of the Scottish population.

The analysis in this chapter focused on three main issues, all of which are discussed in detail below. First of all, this study sought to test whether findings from other research that showed differences in HC utilisation and costs by socio-economic status (Cookson and Laudicella, 2011) also translates into differences in costs incurred towards the end of life given evidence that 'poorer' people seem to die prematurely (Chalmers and Capewell, 2001). This analysis was motivated by findings from the analysis in Chapter 5, where individuals from more deprived areas seemed to cost less at the end of life. A second issue that was investigated was the application of two different cost variables to provide further evidence for the importance of choosing a method to cost hospital stays and so to underpin the analysis undertaken in Chapter 4 in this thesis. One final and very important issue the analysis in this chapter concentrated on was the comparison of projected HC expenditure under two different modelling approaches, including and excluding remaining TTD, in order to obtain an estimate of the over/under-estimation of future costs if TTD were excluded from a projection model.

6.6.1 Socio-economic status

The impact of individuals' socio-economic status on the probability of accessing hospital care seems to be influenced by TTD, as can be seen from interaction effect results obtained from the first part of the model (Table 6.5). As people approach death, those living in more deprived areas are less likely to reach hospital compared to those living in the most affluent deprivation score quintile. These findings confirm previous research undertaken in Scotland that looked at out-of-hospital cardiac deaths by socio-economic status and found that mortality rates out-of-hospital were much higher in deprived socio-economic groups (Capewell *et al*, 2001).

Further results for the second modelling part (costs incurred, given positive utilisation) revealed that the type of costing method seems to influence the effect that the socio-economic status has on estimated hospital costs at the end of life. This could be seen in regression results for TTD and deprivation interactions (Table 6.8 (English Tariff) and Table 6.10 (SNT)). When applying the SNT to cost hospital stays a significant association between costs and the interactions between socio-economic status and TTD could be observed for the most deprived quintile. Applying the English Tariff however, reveals a much less pronounced (or possibly no) interaction effect between TTD and socio-economic status. It was already pointed out that these findings seem to be contrary to findings from previous research (which notably used English HRGs) that suggested that 'the poor cost more' (Cookson and Laudicella, 2011). This thesis has found a reverse effect, with 'poorer' people costing less in their last five years of life.

One possible explanation is that the difference between costing methods mainly lies in the fact that the SNT does not offer a means to account for very long stays through the application of additional per diem costs and so places less weight on very long stays. People from more deprived areas are known to have longer stays at hospital, often due to a lack of available care in their own homes. Therefore, any deprivation category effect that might be present could have been modified by giving more weight to LOS in the set-

up of the cost variable when using the English Tariff, but not when using the SNT. An alternative explanation could be that more is spent on individuals from more deprived areas during their life time, but not immediately before their death.

6.6.2 Costing method

In addition to the different results obtained for TTD and deprivation interaction terms, the costing method also influenced the remaining results of included explanatory variables. In terms of the size of the effect, the TTD effect is much more pronounced for the English Tariff than it is for the SNT (that is the coefficients are larger). However a highly statistically significant association of TTD with costs can be found as far back as 12 quarters before death for the SNT, whereas statistical significance of TTD for the English Tariff is only found up until the fourth quarter before death.[19] The smaller effect that can be found especially in the last quarter of life might entirely be attributable to missing extra per diem costs[20], so that as a consequence, costs estimates will be lower than for the English Tariff.

No effect of having an LTI could be found for the SNT. A possible explanation might be that individuals with an LTI would be expected to have longer stays at hospital and not accounting for extra per diem costs in the set-up of the SNT might not reflect this underlying reason for incurring higher costs.

6.6.3 Population and HC expenditure projections

As shown in Figure 6.17 and Figure 6.18, HC expenditure for acute inpatient care seems to be concentrated in the last year of life, and in particular the time immediately before death, i.e. the last quarter of life. Death is being postponed into older ages leading to an increased longevity as confirmed by Figure 6.23 and 6.24, where an

[19] For quarters 7 and 12 before death only a marginally statistically significant effect is found.

[20] Extra per diem costs are applied to those hospital stays, were the LOS exceeds a so called trim-point, which marks the expected LOS for each HRG and the SNT does not offer means to apply extra per diem costs for very long stays.

increase in the number of projected deaths over the next decades could be observed for the oldest age groups, when no such increase could be observed for the younger age groups. The two approaches of projecting HC expenditure demonstrated that costs do not rise as quickly if factors, such as TTD and increasing longevity and also the postponement of diseases into older ages were accounted for.

These findings are in line, although at the lower end of the scale, with other research that has found future HC expenditure at risk of being overestimated if TTD is not accounted for and estimates of an overestimation varied between 3.4% and 18.5% (Breyer and Felder, 2006, Hakkinen et al., 2008, Polder et al., 2006, Serup-Hansen et al., 2002, Stearns and Norton, 2004).

The analysis in this chapter showed that if deaths are postponed into older ages, and a compression of morbidity is present as put forward by Fries (1980), which was later confirmed by other researchers (Christensen et al., 2009, Payne et al., 2007), HC expenditure (and HC budgets) would not increase to the same extent than it would were these factors ignored. These factors would be ignored if, when that part of the population that is in their last year(s) of life would not be taken into consideration by obtaining separate cost estimates for the time immediately before death. The analysis in Chapter 6 found future HC costs in Scotland under a purely demographic approach to be overestimated by about 7% in 2028 thus confirming results from the wider international literature.

The fact that the estimates for an overestimation of future HC expenditure are at the lower end of the scale compared to other, international results could be explained by the selection of the sample and the HC system that has been analysed. It could be speculated that there are national differences in terms of the extent of care that is delivered to people close to death. If this is the case this would have an impact on cost estimates obtained stratified by TTD which are subsequently used in order to project

future HC expenditure under a TTD approach. When interpreting these results it should be noted that HC expenditure projections have been calculated for that part of the population aged 65 and older and for acute inpatient care only. Although this might constitute a large proportion of the entire expenditure, it does not provide a complete picture of the entire HC system and its associated costs.

Another important factor that will contribute to differences in findings will be each country's demographic structure. Differences found for HC expenditure projections using a demographic and a TTD approach will be larger if demographic changes occur more rapidly. If the number of deaths in each age group would remain constant over time then no differences would be found between projection approaches.

7 MAIN FINDINGS, POLICY IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

7.1 Introduction

The empirical analyses undertaken in the three preceding chapters has, based on the critical assessment of the literature in Chapter 3, presented issues in the research field that have either not been addressed to date, or have been dealt with using a variety of methods resulting in different, sometimes conflicting findings. This thesis has also, for the first time in Scotland, employed advanced econometric methods and a representative sample of the Scottish population to estimate the effect that population ageing and remaining TTD have on HC expenditure in an acute inpatient care setting.

This final chapter summarises the main findings of this thesis in Section 7.2. In Section 7.3 potential policy implications are outlined, followed by a discussion of possible limitations of the analyses in this thesis in Section 7.4. Section 7.5 provides a presentation of how this work could be taken forward in the future.

7.2 Main findings

7.2.1 Comparison of alternative costing methods

Chapter 4 provided an overview of alternative costing methods. The analysis in this chapter was motivated by the fact that researchers can, and do, apply different methods of costing hospital stays, i.e. there is no gold standard. The research question of ‘How do different methods to cost inpatient hospital stays affect cost estimates and also the marginal effect that explanatory variables have?’ was examined. It was vital to address

this issue before proceeding with the main empirical analyses in Chapters 5 and 6 since the availability of alternative costing methods for acute inpatient hospital stays required a decision on which method to use in order to inform analyses in the subsequent chapters.

Ideally the costing method reflects the nature of a hospital stay, which is characterised by a fixed and variable cost component. It should also reflect the diagnosis and any procedure undertaken. Costing methods vary in the level of precision with which these pre-requisites are reflected in the actual unit cost that is assigned. Per diem costing, for instance, assumes that the first day in hospital is as expensive as each subsequent day. Specialty specific per episode costing is insensitive to the diagnosis and procedure. Costing methods that reflect case-mix (HRGs) are difficult to implement in Scotland as these either require the assignment of English Tariff, a fact that could be argued not to be appropriate for Scottish hospital episode statistics, or they require the assignment of the SNT, which is still being developed and currently only used for cross-boundary flows of payments between different health boards in Scotland.

In order to assess differences in results, both on an absolute scale, but more importantly in terms of the marginal effect that a set of explanatory variables has on costs, five methods of assigning unit costs to acute inpatient care episodes were compared. These included, in addition to the methods mentioned above, a novel method that has to date not been used in any costing exercise and was based on research done by NRAC (Bishop et al., 2006). While it is recognised that the chosen costing approach should be mainly determined by the research question, Chapter 4 highlighted important issues that arise from the application of alternative methods.

A comparison of HRG and per diem costing as the two most commonly used methods (Anandan et al., 2009, Lorgelly et al., 2010, Maheshwari et al., 2010, Poole et al., 2010, Gray et al., 2001, Stewart et al., 2002, Christensen and Munro, 2008, Harjola et al.,

2009, Ringborg et al., 2009, Liu et al., 2002, Walker et al., 2003, Miller et al., 2009), revealed substantial scale differences and some difference in the size of the effects that explanatory variables have on costs. Chapter 4 also concluded that studies that employ a per diem costing approach neglect the nature of a hospital stay, which is characterised by fixed costs being independent of LOS and variable costs varying with LOS, and thereby might be in danger of overestimating costs. Although general conclusions in terms of sub group analysis, i.e. males are less costly than females, did not seem to be influenced by the type of costing, the magnitude of the effect was.

The analysis of alternative costing methods emphasised that any inference made from econometric modelling of costs, where the marginal effect of explanatory variables is assessed, is substantially influenced by the costing method. It also revealed that the marginal effect of explanatory variables was influenced to a much lesser degree by the econometric modelling framework and it was concluded that this had a negligible impact on obtained estimates for HC expenditure.

This analysis of costs took into account the special characteristics of HC expenditure data for which a detailed description was provided in Section 3.4 and used the appropriate estimators to model these expenditure data. In the discussion of findings from Chapter 4 the application of the HRG costing method (method 1) was recommended as this method facilitates the inclusion of disease specific costs, incorporates a fixed and variable cost component through the application of a trim point payment (for the English Tariff) and further allows adequate costing of hospital stays that involve more than one episode of care. It was therefore concluded to be the preferred method to cost acute inpatient stays.

7.2.2 Renfrew/Paisley study

The analysis of the Renfrew/Paisley sample in Chapter 5 addressed the issue of the relationship between age, TTD and HC expenditure. Specifically Chapter 5 sought to answer three questions:

1. What is the independent effect of TTD and age on expenditure for acute inpatient care in Scotland?

2. How do previously unconsidered explanatory variables, such as health risks and health status measures impact on HC expenditure as the population ages and approaches death?

3. How does sample selection, in particular the inclusion/exclusion of surviving sample members due to right censoring, impact on estimated costs?

In order to answer these research questions, Chapter 5 firstly utilised findings from Chapter 4 in its empirical analysis of the cost of ageing and the cost of dying. The methods employed in Chapter 5 were novel as they compared for the first time the difference in estimated costs, when accounting for age and remaining TTD for different sample scenarios. The analysis and the development of the methods were motivated by findings from the literature that revealed that no consistent and robust methods were in place to account for right censoring of the surviving proportion of the sample population. The review of the literature highlighted a variety of methods that have been employed in the past and outlined limitations that could arise from sample selection (Zweifel et al., 1999, Felder et al., 2000, Moorin and Holman, 2008, Seshamani and Gray, 2004c) or inappropriate assumptions for survivors and their TTD (Stearns and Norton, 2004, Breyer and Felder, 2006).

The empirical analysis of this present study facilitated a comparison of the impact on estimated costs as people approach death for different sample scenarios: the inclusion of decedents only (scenario A), the inclusion of decedents and survivors, using the censoring date as the date of death for survivors (scenario C), and the inclusion of decedents and survivors, using a predicted TTD for survivors (scenario D) in econometric modelling. As an additional guidance of how deceased or survivor status impact costs, scenario B was added, which included surviving sample members only.

For the novel method, scenario D, the predicted TTD was obtained through the application of survival analysis and extrapolation of additional predicted years of life for that part of the sample population that was alive at the end of the study period, i.e. censored. The quarters before death and their associated observed costs for survivors could then be adjusted accordingly. Estimated costs showed a £491 difference on average in the last quarter of life between the decedent group (scenario A) and the group using the censoring date (scenario C) and a £12 difference between the decedent group (scenario A) and the group using a predicted TTD (scenario D). These results confirmed the initial hypothesis of an overestimation of costs, particularly in the last quarter of life if survivors are excluded from the analysis and provided an estimate of costs in order to answer research question three above.

In addition to exploring a robust method of accounting for survivors' right censoring the main findings of the analysis undertaken in Chapter 5 were that TTD, age and the interactions between these two factors were significant predictors for HC expenditure in the last 12 quarters of life. These results confirmed findings from other national research (Zweifel et al., 1999, Seshamani and Gray, 2004b). On average, the two youngest age groups (<65 and 65-69 years) were found to incur higher costs than the older age groups, confirming in part the 'red herring' argument put forward by Zweifel and colleagues in 1999. However, age was still found to be an important predictor for HC

expenditure and that TTD influenced costs differently for different age groups as shown through the inclusion of interactions between TTD and age.

The strength of this analysis is also expressed through the excellent linked data with very low attrition rates and minimum missing data that comprise the Renfrew/Paisley study. Clinical measurements that were taken at baseline allowed the inclusion of previously unconsidered explanatory variables (Graham and Normand, 2001, Lowe, 2005). This facilitated investigation of how important these baseline factors were in explaining HC expenditure as people aged and approached death.

Some perhaps surprising results were obtained for two of the health status indicators: SBP and cholesterol level, where individuals with a measure within healthy limits were more likely to access hospital services. This result might be explained with the 'worried well' who may be seeking medical attention earlier than other people. This seems partly confirmed by a significant effect that a normal SBP has on costs incurred in the second part of the estimation, where these individuals, although more likely to access hospital services, were shown to incur lower costs. There might also be a lower risk for adverse events and subsequent related costs for individuals with a normal SBP. For the cholesterol level, which had a significant association with the probability of accessing hospital services, this significant association almost entirely disappears in the second part of the regression modelling. Only for the sample that includes decedents (scenario A) a marginally significant effect ($p<0.1$) could be found that suggested that individuals with a healthy level of cholesterol incur higher costs.

Another explanation for these surprising results could be provided through the time of this study. An inverse association between the cholesterol level and the socio-economic status was found in previous research (Smith *et al*, 1998; Hawthorne et al, 1995), i.e. individuals from more affluent areas had a higher reading. The study took place at a time, when public knowledge of the harmful effects of cholesterol was limited. People

from more affluent areas could afford eating red meat and may have consequently had a higher cholesterol level. In turn, people with a healthy cholesterol level may have had unhealthy readings for other health status measures (Smith *et al*, 1998; Hawthorne et al, 1995; Hart C, personal communication). In general, health status indicators that have previously not been included in the analyses were found to be significant predictors for costs in the future and the inclusion of such measures, where the available data allow to do so, is recommended here.

Results from this present study confirm conclusions from other research such as studies on the issue of rationing health care by age. Williams (1997) puts forward the 'fair innings' argument, which argued that limited resources should be devoted to those that would benefit most, i.e. more should be done to enable younger people to survive than should be done to enable older people to survive (Williams, 1997). Results from the analysis in this thesis seem to confirm this, as costs at the end of life that were obtained for the eldest ages seemed to be consistently lower than those for younger age groups.

7.2.3 Scottish Longitudinal Study

Chapter 6 extended the analysis of the association between TTD, age and costs undertaken in Chapter 5, but using a representative sample of the Scottish population. It was necessary to consider a representative sample as the two remaining research questions this thesis set out to answer required the results to be generalisable for the entire Scottish population:

1. What is the association between socio-economic status and HC expenditure at the end of life?

2. How are HC expenditure projections influenced when using a model accounting for TTD versus a model that only accounts for the increasing proportion of elderly individuals?

The analysis was performed using a similar modelling and costing approach as undertaken in Chapter 5 which provided a means to validate the methods employed using the Renfrew/Paisley sample. The representative sample consisted of SLS sample members, enumerated at either the 1991 or 2001 census.

In order to explore the impact that the socio-economic status has on costs, a measure representing deprivation score quintiles was included. Previous research has shown that people living in more deprived areas incurred higher costs in general (Cookson and Laudicella, 2011, Lemstra et al., 2009). Other research, undertaken in Scotland shows a clear association between pre-mature death and socio-economic status (Chalmers and Capewell, 2001). This thesis sought to ascertain whether differences between socio-economic status and death and socio-economic status and costs also translated into differences between socio-economic status and the costs incurred towards the end of life.

Estimated average costs in the last quarter of life seemed to differ between individuals from the most affluent quintile and individuals from the most deprived quintile. It was found that TTD influenced costs differently for different deprivation score quintiles. Differences were detected for the effect that the interaction terms between the socio-economic status and TTD had on costs between the two different methods of costing hospital stays (the English Tariff and the SNT). When applying the English Tariff only marginally statistically significant associations could be observed. The model that employed the SNT however, revealed a significant association with costs for the most deprived quintile (5) and quarters 1 to 9 before death. Differences were most likely caused by not being able to assign extra per diem costs when using the SNT.

Findings from this analysis contradict previous research (Cookson and Laudicella, 2011, Lemstra et al., 2009) as results show that there is only a very small effect that the socio-economic status has on costs at the end of life, which suggested that poor people might

cost less, that is have less spent on them. It should be noted, however, that Lemstra *et al* (2009) have used income as a proxy for socio-economic status in their analysis which might explain some of these different findings. Cookson and Laudicella (2011) have used a specific disease area (hip replacement) which could also serve as an explanation for different results. Another explanation for these different findings is that costs are most likely driven by the probability of reaching hospital, which was shown to be lower for individuals from more deprived areas. This is in agreement with results from other studies undertaken in Scotland (Capewell *et al*, 2001).

The second research question explored in Chapter 6, was the extent to which future HC expenditure (for acute inpatient care, as the most expensive sector in the NHS) might be overestimated if a simple approach of applying constant age-expenditure profiles to future population numbers was used compared to an approach that takes into account the changing pattern of morbidity via the inclusion of remaining TTD as a measure of morbidity.

The analysis in Chapter 6 found future HC costs in Scotland in the year 2028 under a purely demographic approach to be overestimated by about 7%, thus confirming results from the wider international literature. The discussion in Chapter 6 highlighted that results for any overestimation of costs between the two different approaches of projecting HC expenditure are found to be at the lower end of the scale compared to other research. It was concluded that the fact that studies were carried out in a variety of countries, with differences in how HC was organised, paid for and delivered must necessarily lead to different cost estimates for the TTD approach as this mainly depends on the amount of money spent on individuals in their last years of life. It was also concluded that the speed of the demographic change will have an impact on the difference found between the two approaches.

7.3 Policy implications

Chapter 2 provided a summary regarding how TTD had been examined by NRAC to decide whether it should be included in the current resource allocation formula. That chapter also outlined the current adjustments that are made in the resource allocation formula, which are for the age and sex structure of the population, remoteness and MLC. NRAC argue that these factors ensure that resources are allocated according to need, yet the formula does not currently account for TTD.

Section 2.4.3 examined the reasons for the exclusion of the factor TTD in resource allocation in Scotland. The decision not to include TTD was partly based on the research that has to date been undertaken in Scotland (Lowe, 2005, Graham and Normand, 2001). NRAC acknowledged that this was preliminary research and that further analyses were necessary to fully inform future reviews of the resource allocation formula. This thesis provides the requested extensive research, both a comprehensive cohort (Renfrew/Paisley study) and a representative sample (SLS) linked to Scottish acute inpatient care records, are employed in models which use advanced econometric techniques, it showed how TTD influences costs.

One important issue for any policy maker is equity. This thesis thoroughly investigated how the socio-economic status impacts on costs towards the end of life and found poorer people to incur less costs, which might mainly be caused by the fact that they also seemed to be less likely to access hospital services. This finding certainly deserves further analysis as to the factors that cause this relationship between socio-economic status, access to HC and associated costs.

In addition, a method was presented to obtain estimates of the proportion of the population projected to be in a particular year before death. These proportions can be calculated for each single year of age and separately for males and females. Projected

numbers of the total population and the number of deaths are available from NRS and can easily be implemented to calculate the proportion of the population projected to be in their last, second last, etc. year of life. This extension is something previous research in Scotland did not address and therefore was consequently unable to provide an estimate of future cost projections with and without TTD.

With death as the main contributing factor to HC costs, a lower number of deaths in the future will lead to decreasing costs of dying and hence to lower HC projections. It is therefore, at least partially, counteracting the effect that an increasing proportion of elderly people might have on HC expenditure. However, as the diagnostic techniques and management of diseases are changing and a higher amount is probably spent on avoiding disease rather than curing it, a shift from expenditure on acute inpatient care towards HC sectors that are concerned with preventative care (i.e. primary care) might be observed in the future.

In addition to the implications this research has for resource allocation, there are other factors that are important, especially for HC planning and budgeting. As shown, future HC expenditure is at risk of overestimation if TTD is neglected in the modelling process. Resources that would have been directed to finance acute inpatient care could be re-allocated to different public sectors.

7.4 Limitations

One main and general limitation that applies to the analyses in all empirical chapters is that of only being able to analyse the acute inpatient care sector. It was argued that this might be the most important sector as it is characterised by very high costs compared to other HC sectors, however it is not possible to draw an overall complete picture of how

population ageing and TTD influence the entire HC sector or even the LTC sector. This is further complicated by the fact that LTC in Scotland does not fall within the remit of the NHS, but is the responsibility of local councils. Several studies that have also or only analysed how population ageing and TTD affect costs for LTC found a reversed effect to the one that is usually found for acute inpatient care (de Meijer et al., 2011, McGrail et al., 2000, Spillman and Lubitz, 2000). It is therefore important to distinguish between HC sectors when interpreting results and to be aware of possible differences in the effect that population ageing has, mainly caused by different pattern of utilisation at different ages. Specific limitations that concern each of the empirical chapters are presented below.

7.4.1 Costing methods

Limitations arising from the analysis of alternative costing methods can mainly be attributed to the fact that inpatient stays were considerably longer on average in the past than they are now. This raises the question of how to adequately account for this without over-estimating recent costs or under-estimating historic costs. Employing data from a cohort, which ages over time, may mean that the two effects, a) LOS decreases over time and b) LOS increases with age, might cancel each other out. Without access to full historic costs this problem is difficult to overcome. This leads to another limitation, which is the use of the trim point LOS in HRG based costing applying English costs. 2006/2007 was chosen as the reference year with respective tariffs and trim point information. But the trim point can change over time, such that applying the same trim point value for all time periods observed may have also introduced bias, but full historical data on trim points was not available.

Another point of criticism that could be raised is that the explanatory variables included in the model in Chapter 4 do not fully explain costs and this model is likely to suffer from omitted variable bias. However, it should be noted that the chosen explanatory variables are mainly to facilitate comparison of methods rather than to fully explain hospital costs.

Limitations that arise from the analysis of alternative costing methods ultimately affect the analyses in Chapters 5 and 6 as these have used the costing methods presented in Chapter 4.

7.4.2 Renfrew/Paisley study

Although the analysis in Chapter 5 using the Renfrew/Paisley sample is novel for Scotland and provides some important insights into the mechanism of how TTD, population ageing and costs interact, like many empirical analyses using longitudinal cohort data, it also has limitations. One limitation that has already been explained is the nature of inpatient stays and how these have changed over time, especially in terms of LOS.

One problem that frequently characterises time series data is serial correlation, i.e. observations for the same observational unit (an individual) are not independent. There are two layers to this issue: firstly, hospital episodes are not independent. One approach that partly accounts for serial correlation is the use of a CIS and the aggregation of costs into quarterly costs. However, this leaves a second issue: the potential correlation between quarters before death per individual. In order to derive correct standard errors clustering on patient identifier was applied. One final limitation is concerned with the fact that clinical measurements were only taken at baseline and therefore could not be followed up over time.

Results for the analysis of different sample scenarios that excluded and included the surviving part of the sample and recommended survival analysis in order to account for right censoring, will very much depend on the proportion of the sample that is alive at censoring and also on their age. If there is only a very small proportion that is right censored, it might be unlikely that results will alter substantially between various sample scenarios.

7.4.3 Scottish Longitudinal Study

The analysis in Chapter 6 also potentially suffers from a number of limitations in addition to those highlighted from arising from the costing of hospital episodes over a long period of time. The analysis also used the method of undertaking survival analysis in order to account for right censoring of survivors in the SLS. Contrary to the Renfrew/Paisley sample the SLS sample consisted of a much larger proportion of survivors mainly caused by a younger average age of sample members. It could be argued that for the survival analysis to provide useful predictions of additional years of life, actual death should not be too far in the future. This is because observed costs for quarters before death are adjusted according to results from survival analysis. If the analysis looks at the last five years of life but the predicted date of death seems to be 10 or 15 years away from the censoring date, these observations might not be as useful as those, whose death is only two years away from the censoring date.

Despite these limitations, the application of a more advanced method of including survivors when employing econometric modelling of costs towards the end of life has obvious advantages. It increases the sample size and thereby the statistical power; and it mitigates the problem of sample selection bias.

7.5 Future research

Evidence in this thesis and from previous research has shown that population ageing does not lead to an increase in future HC expenditure to the extent that might have been previously anticipated. This thesis is the first extensive empirical study in that research area in Scotland that has used linked data. However, further important research questions remain that can be answered utilising the excellent linked data that Scotland has available, such as how do geographical inequalities impact on HC costs towards the

end of life? Scotland is characterised by large geographical areas that are either accessible rural areas or very remote areas. These areas face major challenges in terms of access to HC services. Research has shown that for instance for acute MI the distance between hospital and home can predict mortality, which tends to be higher in these rural areas (Wei *et al*, 2008). Rural areas in Scotland are also characterised by a larger proportion of elderly people, either because younger people tend to leave these areas or because of a retiree emigration into these parts of Scotland. In addition, LOS in hospital tends to be longer in rural areas on average because of a lack of nursing homes or informal care at home.

These different patterns of utilisation of HC and LTC in remote areas will have an impact on how TTD affects HC expenditure. On the other hand, rural areas tend to have better socio-economic indicators as they face lower unemployment and are generally less deprived than urban areas. Such an analysis might therefore be able to revisit the issue of the impact that socio-economic status has on costs at the end of life.

An important aspect of future research in this area would therefore be to inform budgeting as to the mechanism of how the different factors described above impact on HC expenditure. Can results from research that did not take into account spatial dependencies be confirmed when including geographical location? Such an analysis might also be able to revisit the issue of the impact that socio-economic status has on costs at the end of life which may well be influenced by geographical location.

The analyses in this thesis assumed exogeneity between TTD and HC expenditure, similar to many other studies that have been undertaken in this field. However, the possible endogeneity between these two variables is an issue that has not been solved entirely to date. Future methodological research could explore further avenues to purge TTD off its endogeneity, such as using predicted TTD instead of observed values. Further methodological work worthwhile undertaking could be concerned with the

inclusion of measures of uncertainty around HC expenditure, TTD and population estimates as well as the application of a random effects model. This would allow us to ascertain whether there is any correlation between error terms (u_i) that are obtained from the first and the second part of the model. This might also provide a better understanding as to whether those individuals, who are more likely to use HC services, also incur higher costs.

In addition, other HC sectors would need to be analysed. As pointed out throughout this thesis, the sector of acute inpatient care might be very different in terms of the effect that TTD and age will have on future costs. It was mentioned that an analysis of the LTC sector might provide very different results. To gain an overall understanding of the financial impact of an ageing population it would be highly informative to be able to analyse a broader spectrum of HC services.

Appendices

Appendix I: Literature search strategy

Medline 1950-2009; 24th Feb 2009

1. (health care cost* or healthcare cost*).tw.
2. "Cost of Illness"/
3. Models, Econometric/
4. Population Dynamics/
5. health care costs/ or hospital costs/ or health expenditures/
6. aging/ or longevity/
7. aged/ or "aged, 80 and over"/ or frail elderly/
8. (aged or elder* or ageing or aging or "over 65").ti.
9. 8 or 6 or 7
10. (cost* or expenditure or spend*).ti.
11. ((healthcare or health care or hospital*) and (cost* or expenditure or spend*)).tw.
12. 11 or 2 or 5
13. 4 and 9 and 12
14. limit 13 to english language
15. proximity to death.tw.
16. "time to death".tw.
17. "last year* of life".tw.
18. 16 or 17 or 15
19. 18 and 12
20. limit 19 to english language
21. Long-Term Care/
22. social care.mp.
23. Nursing Homes/ or Homes for the Aged/
24. care home*.mp.
25. 22 or 21 or 24 or 23
26. 25 and 10
27. 4 and 26 and 9
28. 25 and 4 and 9
29. limit 28 to english language
30. 3 and 14
31. 3 and 29
32. 25 and 18 and 10

Appendix II: Composition of specialty groups

Specialty Group	Specialty	Specialty Group	Specialty
Accident & Emergency	Accident & Emergency	Medical Other	Allergy
Acute Other	Chiropody		Clinical Pharmacology & Therapeutics
	Surgical Podiatry		Endocrinology
Adolescent Psychiatry	Adolescent Psychiatry		Genito-Urinary Medicine
Cardiac Surgery	Cardiac Surgery		Homoeopathy
Cardiology	Cardiology		Immunology
Child Psychiatry	Child Psychiatry		Nuclear Medicine
Clinical Oncology	Clinical Oncology		Palliative Medicine
Communicable Diseases	Communicable Diseases	Medical Paediatrics	Medical Paediatrics
Coronary Care Unit	Coronary Care Unit (Significant Facility)	Nephrology	Nephrology
Dental	Orthodontics	Neurology	Neurology
	Paediatric Dentistry	Neurosurgery	Neurosurgery
	Restorative Dentistry	Obstetrics GP	GP Obstetrics
	Community Dental Practice	Obstetrics Specialist	Obstetrics Ante-Natal
	General Dental Practice		Obstetrics
Dermatology	Dermatology		Post-Natal
Ear Nose & Throat	Ear Nose & Throat		Obstetrics
Gastroenterology	Gastroenterology		Midwifery
General Medicine	General Medicine		Community Midwifery
General Practice	General Practice (excluding Obstetrics)	Ophthalmology	Ophthalmology
General Psychiatry	Forensic Psychiatry	Oral Surgery & Medicine	Oral Surgery
	General Psychiatry		Oral Medicine
	Psychotherapy	Orthopaedics	Orthopaedics
General Surgery (excluding Vascular)	General Surgery (excluding Vascular)	Plastic Surgery & Burns	Plastic Surgery
Geriatric Assessment	Geriatric Medicine	Rehabilitation Medicine	Rehabilitation Medicine
Geriatric Long Stay	Geriatric Medicine	Respiratory Medicine	Respiratory Medicine
Geriatric Psychiatry	Psychiatry of old age	Rheumatology	Rheumatology
Gynaecology	Gynaecology	Special Care Baby Unit	Special Care Baby Unit (Significant Facility)
Haematology	Haematology	Spinal Paralysis	Spinal Paralysis
High Dependency Unit	High Dependency Unit (Significant Facility)	Surgical Paediatrics	Surgical Paediatrics
Intensive Care Unit	Intensive Care Unit (Significant Facility)	Thoracic Surgery	Thoracic Surgery
Learning Disabilities	Learning Disabilities	Urology	Urology
Medical Oncology	Medical Oncology	Vascular Surgery	Vascular Surgery
		Young Chronic Sick	Younger Physically Disabled (Significant Facility)

Appendix III: Fixed and variable cost split[21]

Specialty	%fixed	%variable
SCBU	0.0	100.0
ICU	0.0	100.0
CCU	21.0	79.0
Spinal Paralysis	0.0	100.0
General Medicine	55.5	44.5
Communicable Diseases	54.7	45.3
Dermatology	7.8	92.2
Geriatric Medicine	0.0	100.0
Medical Paediatrics	44.2	55.8
Nephrology	40.1	59.9
Neurology	0.0	100.0
Acute Other?	0.0	100.0
Rehabilitation Medicine	0.0	100.0
Respiratory Medicine	10.7	89.3
Rheumatology	33.8	66.2
General Surgery	66.7	33.3
Accident & Emergency	0.0	100.0
Cardiothoracic Surgery	70.4	29.6
Ear, Nose & Throat	78.7	21.3
Neurosurgery	68.5	31.5
Ophthalmology	81.1	18.9
Orthopaedics	68.2	31.8
Plastic Surgery	68.1	31.9
Surgical Paediatrics	55.4	44.6
Urology	65.3	34.7
Oral Surgery	84.6	15.4
Community Dental Practice	93.5	6.5
Obstetrics	60.0	40.0
GP Obstetrics	67.2	32.8
GP Other Than Obstetrics	38.9	61.1
Gynaecology	71.8	28.2
Haematology	44.5	55.5
Clinical Oncology	0.0	100.0

[21] These values were obtained through personal communication with the NHS Resource Programme, Health Finance Information Team at ISD Scotland.

Appendix IV: Interaction terms TTD*Age: Sample Scenarios A, B, C and D (c.f. Table 5.3)

	Scenario A		Scenario B		Scenario C		Scenario D	
	β	**SE**	**β**	**SE**	**β**	**SE**	**β**	**SE**
TTD1*Age2	-0.003	0.142			-0.003	0.142	-0.004	0.142
TTD1*Age3	-0.062	0.131			-0.062	0.131	-0.060	0.131
TTD1*Age4	-0.227*	0.125			-0.462***	0.123	-0.222*	0.125
TTD1*Age5	-0.354***	0.125	-0.212	0.131	-0.915***	0.121	-0.352***	0.124
TTD1*Age6	-0.521***	0.132	-0.311**	0.141	-1.058***	0.125	-0.459***	0.127
TTD1*Age7	-0.564***	0.156	-0.399**	0.173	-1.141***	0.139	-0.686***	0.142
TTD2*Age2	-0.154	0.148			-0.153	0.148	-0.154	0.148
TTD2*Age3	-0.060	0.135			-0.059	0.135	-0.058	0.135
TTD2*Age4	-0.195	0.130			-0.280**	0.128	-0.190	0.130
TTD2*Age5	-0.264*	0.130	-0.013	0.130	-0.450***	0.126	-0.262**	0.128
TTD2*Age6	-0.402***	0.137	-0.080	0.139	-0.572***	0.130	-0.365***	0.132
TTD2*Age7	-0.505***	0.158	-0.058	0.162	-0.637***	0.143	-0.591***	0.145
TTD3*Age2	-0.105	0.150			-0.104	0.150	-0.105	0.150
TTD3*Age3	-0.169	0.139			-0.168	0.139	-0.167	0.139
TTD3*Age4	-0.179	0.133			-0.235*	0.131	-0.174	0.133
TTD3*Age5	-0.347***	0.134	-0.051	0.126	-0.434***	0.130	-0.346***	0.132
TTD3*Age6	-0.486***	0.142	-0.210	0.136	-0.585***	0.135	-0.473***	0.137
TTD3*Age7	-0.521***	0.166	-0.364**	0.164	-0.675***	0.148	-0.607***	0.150
TTD4*Age2	-0.176	0.152			-0.175	0.152	-0.176	0.152
TTD4*Age3	-0.133	0.139			-0.132	0.139	-0.131	0.139
TTD4*Age4	-0.245*	0.133			-0.275**	0.132	-0.240*	0.133
TTD4*Age5	-0.338**	0.134	0.105	0.129	-0.322**	0.129	-0.342***	0.132
TTD4*Age6	-0.331**	0.140	-0.127	0.138	-0.419***	0.133	-0.336**	0.135
TTD4*Age7	-0.491***	0.165	0.016	0.160	-0.440***	0.147	-0.453***	0.147
TTD5*Age2	-0.038	0.156			-0.037	0.156	-0.038	0.156
TTD5*Age3	0.079	0.139			0.080	0.139	0.081	0.139
TTD5*Age4	0.004	0.134			-0.009	0.132	0.009	0.134
TTD5*Age5	-0.124	0.134	-0.157	0.128	-0.163	0.130	-0.130	0.132
TTD5*Age6	-0.176	0.142	-0.209	0.136	-0.218	0.134	-0.147	0.136
TTD5*Age7	-0.289*	0.164	-0.220	0.156	-0.284*	0.146	-0.205	0.146
TTD6*Age2	-0.274*	0.160			-0.273*	0.160	-0.275*	0.160
TTD6*Age3	-0.215	0.145			-0.213	0.145	-0.214	0.145
TTD6*Age4	-0.222	0.139			-0.230*	0.137	-0.218	0.139
TTD6*Age5	-0.267*	0.139	-0.094	0.128	-0.303**	0.135	-0.288**	0.137
TTD6*Age6	-0.316**	0.146	-0.154	0.136	-0.359***	0.139	-0.348**	0.140
TTD6*Age7	-0.263	0.166	-0.221	0.163	-0.362**	0.151	-0.324**	0.150
TTD7*Age2	-0.306	0.161			-0.304	0.161	-0.306*	0.161
TTD7*Age3	-0.009	0.141			-0.007	0.141	-0.007	0.141
TTD7*Age4	-0.121	0.136			-0.144	0.134	-0.117	0.136
TTD7*Age5	-0.176	0.136	0.046	0.130	-0.187	0.132	-0.210	0.134
TTD7*Age6	-0.157	0.142	0.004	0.136	-0.196	0.135	-0.177	0.136
TTD7*Age7	-0.172	0.164	-0.135	0.163	-0.270*	0.148	-0.210	0.147
TTD8*Age2	0.045	0.176			0.047	0.176	0.045	0.176
TTD8*Age3	0.172	0.160			0.174	0.160	0.174	0.160
TTD8*Age4	0.131	0.155			0.125	0.153	0.134	0.155
TTD8*Age5	0.094	0.155	-0.056	0.130	0.072	0.151	0.052	0.153
TTD8*Age6	0.068	0.160	-0.144	0.140	0.017	0.154	0.079	0.154
TTD8*Age7	-0.062	0.181	-0.035	0.157	0.003	0.164	-0.028	0.164
TTD9*Age2	-0.056	0.169			-0.055	0.170	-0.057	0.169
TTD9*Age3	-0.049	0.156			-0.047	0.156	-0.048	0.156
TTD9*Age4	-0.190	0.150			-0.160	0.149	-0.189	0.150
TTD9*Age5	-0.137	0.150	-0.101	0.130	-0.143	0.146	-0.183	0.148
TTD9*Age6	-0.160	0.156	-0.219	0.139	-0.208	0.150	-0.186	0.150
TTD9*Age7	-0.191	0.175	-0.227	0.167	-0.230	0.162	-0.175	0.160
TTD10*Age2	-0.016	0.164			-0.015	0.164	-0.016	0.164
TTD10*Age3	-0.069	0.151			-0.068	0.151	-0.069	0.151
TTD10*Age4	-0.029	0.145			-0.039	0.143	-0.029	0.145
TTD10*Age5	-0.031	0.145	0.032	0.129	-0.039	0.141	-0.047	0.143
TTD10*Age6	-0.112	0.151	-0.111	0.138	-0.150	0.145	-0.126	0.144
TTD10*Age7	-0.032	0.173	-0.142	0.159	-0.122	0.156	-0.041	0.155
TTD11*Age2	-0.044	0.156			-0.043	0.156	-0.043	0.156
TTD11*Age3	-0.098	0.140			-0.097	0.140	-0.097	0.140
TTD11*Age4	-0.099	0.135			-0.112	0.132	-0.098	0.135
TTD11*Age5	-0.143	0.134	0.026	0.131	-0.142	0.129	-0.133	0.131
TTD11*Age6	-0.117	0.142	-0.061	0.139	-0.168	0.134	-0.153	0.133
TTD11*Age7	-0.141	0.163	-0.131	0.167	-0.215	0.147	-0.105	0.145

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

Appendix V: Interaction terms TTD*Age: Sample Scenarios A, B, C and D (c.f. Table 5.4)

	Scenario A		Scenario B		Scenario C		Scenario D	
	Cost Ratio	SE	Cost Ratio	SE	Cost Ratio	SE	Cost Ratio	SE
TTD1*Age2	1.332	0.180			1.341	0.179	1.329	0.180
TTD1*Age3	0.779	0.201			0.782	0.198	0.785	0.201
TTD1*Age4	0.766	0.181			0.774	0.171	0.758	0.183
TTD1*Age5	0.763	0.168	0.640*	0.238	0.757*	0.156	0.786	0.161
TTD1*Age6	0.766	0.171	0.629*	0.241	0.733*	0.159	0.911	0.163
TTD1*Age7	0.769	0.219	0.562	0.376	0.651**	0.216	0.712	0.244
TTD2*Age2	1.164	0.220			1.158	0.219	1.155	0.221
TTD2*Age3	0.686	0.230			0.686*	0.228	0.687	0.230
TTD2*Age4	0.649**	0.218			0.639**	0.209	0.636**	0.221
TTD2*Age5	0.662**	0.204	1.068	0.232	0.652**	0.193	0.678*	0.199
TTD2*Age6	0.725	0.210	0.964	0.236	0.652**	0.198	0.843	0.205
TTD2*Age7	0.742	0.257	1.378	0.365	0.739	0.252	0.685	0.278
TTD3*Age2	0.903	0.254			0.909	0.252	0.906	0.253
TTD3*Age3	0.661	0.267			0.662	0.263	0.667	0.264
TTD3*Age4	0.730	0.263			0.724	0.249	0.725	0.262
TTD3*Age5	0.660	0.253	1.019	0.223	0.691	0.234	0.680	0.246
TTD3*Age6	0.708	0.247	0.789	0.226	0.647*	0.233	0.819	0.238
TTD3*Age7	0.743	0.295	0.621	0.346	0.592*	0.281	0.642	0.307
TTD4*Age2	0.906	0.237			0.916	0.238	0.899	0.238
TTD4*Age3	0.686	0.259			0.679	0.258	0.680	0.258
TTD4*Age4	0.515***	0.217			0.541***	0.212	0.509***	0.220
TTD4*Age5	0.700*	0.215	0.951	0.265	0.663**	0.199	0.720	0.210
TTD4*Age6	0.682*	0.223	1.064	0.305	0.685*	0.213	0.782	0.215
TTD4*Age7	0.798	0.285	0.833	0.377	0.670	0.258	0.673	0.291
TTD5*Age2	1.135	0.293			1.113	0.299	1.132	0.296
TTD5*Age3	0.775	0.299			0.751	0.307	0.777	0.302
TTD5*Age4	0.621*	0.267			0.618*	0.268	0.611*	0.272
TTD5*Age5	0.617*	0.263	1.056	0.217	0.653*	0.257	0.633*	0.260
TTD5*Age6	0.540**	0.259	1.074	0.240	0.617*	0.264	0.618*	0.255
TTD5*Age7	0.751	0.306	0.995	0.368	0.724	0.312	0.635	0.322
TTD6*Age2	1.340	0.444			1.377	0.462	1.329	0.448
TTD6*Age3	0.744	0.426			0.743	0.430	0.738	0.422
TTD6*Age4	0.519**	0.284			0.510**	0.272	0.508**	0.286
TTD6*Age5	0.405***	0.259	1.046	0.234	0.460***	0.248	0.402***	0.255
TTD6*Age6	0.524**	0.266	0.918	0.245	0.490***	0.252	0.586**	0.258
TTD6*Age7	0.619	0.315	0.806	0.353	0.506**	0.297	0.497**	0.323
TTD7*Age2	0.419	0.602			0.421	0.605	0.420	0.602
TTD7*Age3	0.314**	0.586			0.313**	0.589	0.318*	0.587
TTD7*Age4	0.240**	0.580			0.255**	0.579	0.238**	0.581
TTD7*Age5	0.355*	0.582	1.263	0.203	0.387*	0.577	0.361*	0.580
TTD7*Age6	0.397	0.587	0.992	0.202	0.357*	0.578	0.436	0.581
TTD7*Age7	0.350*	0.595	0.899	0.385	0.317*	0.601	0.299**	0.604
TTD8*Age2	0.859	0.484			0.870	0.477	0.864	0.482
TTD8*Age3	0.430*	0.464			0.436*	0.454	0.439*	0.461
TTD8*Age4	0.432*	0.479			0.444*	0.457	0.426*	0.474
TTD8*Age5	0.330**	0.440	0.907	0.223	0.367**	0.426	0.347**	0.434
TTD8*Age6	0.397**	0.453	0.719	0.228	0.364**	0.431	0.421**	0.440
TTD8*Age7	0.426*	0.477	0.609	0.341	0.334**	0.454	0.380**	0.481
TTD9*Age2	1.908	0.529			1.991	0.545	1.938	0.541
TTD9*Age3	0.985	0.375			1.020	0.391	0.994	0.378
TTD9*Age4	0.678	0.256			0.733	0.247	0.673	0.258
TTD9*Age5	0.724	0.262	1.022	0.237	0.823	0.246	0.745	0.252
TTD9*Age6	0.696	0.257	0.890	0.225	0.739	0.240	0.787	0.256
TTD9*Age7	0.631	0.287	0.884	0.359	0.722	0.291	0.583*	0.308
TTD10*Age2	1.680**	0.244			1.673**	0.240	1.686**	0.241
TTD10*Age3	1.049	0.267			1.049	0.263	1.054	0.264
TTD10*Age4	1.504	0.294			1.605*	0.258	1.490	0.294
TTD10*Age5	0.906	0.227	0.623**	0.226	1.030	0.203	0.926	0.211
TTD10*Age6	1.298	0.245	0.500***	0.236	1.094	0.212	1.283	0.221
TTD10*Age7	0.993	0.261	0.427***	0.350	0.890	0.253	0.913	0.281
TTD11*Age2	1.231	0.257			1.273	0.248	1.249	0.254
TTD11*Age3	0.836	0.281			0.855	0.271	0.852	0.277
TTD11*Age4	0.699	0.256			0.786	0.238	0.697	0.255
TTD11*Age5	1.174	0.334	1.144	0.213	1.201	0.251	1.057	0.287
TTD11*Age6	0.795	0.256	0.972	0.239	0.927	0.235	0.877	0.238
TTD11*Age7	0.864	0.290	1.377	0.422	1.248	0.341	0.767	0.300

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

Appendix VI: Diagnostic Tests (c.f. Table 5.4)

Scenario A: Decedents

```
FITTED MODEL:  Link = Log ; Family =  igaussian

Results, Modified Park Test (for Family)

   Coefficient:   3.979748

   Family, Chi2, and p-value in descending order of likelihood

     Family                              Chi2        P-value

     Inverse Gaussian or Wald:         5.6709         0.0172
     Gamma:                           23.1549         0.0000
     Poisson:                         52.4544         0.0000
     Gaussian NLLS:                   93.5695         0.0000

Results of tests of GLM Log  link

     Pearson Correlation Test:                        0.7958
     Pregibon Link Test:                              0.6395
     Modified Hosmer and Lemeshow:                    0.3882
```

Scenario B: Survivors only, using censoring date as date of death

```
FITTED MODEL:  Link = Log ; Family =  igaussian

Results, Modified Park Test (for Family)

   Coefficient:   2.894239

   Family, Chi2, and p-value in descending order of likelihood

     Family                              Chi2        P-value

     Inverse Gaussian or Wald:         0.0632         0.8016
     Gamma:                            4.5157         0.0336
     Poisson:                         20.2621         0.0000
     Gaussian NLLS:                   47.3025         0.0000

Results of tests of GLM Log  link

     Pearson Correlation Test:                        0.5163
     Pregibon Link Test:                              0.9081
     Modified Hosmer and Lemeshow:                    0.0750
```

Scenario C: Decedents and survivors, using survivors' censoring date

```
FITTED MODEL:  Link = Log ; Family =  igaussian

  Results, Modified Park Test (for Family)

     Coefficient:   3.747877

     Family, Chi2, and p-value in descending order of likelihood

       Family                              Chi2        P-value

       Inverse Gaussian or Wald:          4.2959         0.0382
       Gamma:                            23.4648         0.0000
       Poisson:                          57.9948         0.0000
       Gaussian NLLS:                   107.8860         0.0000

  Results of tests of GLM Log  link

       Pearson Correlation Test:                         0.4558
       Pregibon Link Test:                               0.0240
       Modified Hosmer and Lemeshow:                     0.0062
```

Scenario D: Decedents and survivors, using predicted date of death for survivors

```
FITTED MODEL:  Link = Log ; Family =  igaussian

  Results, Modified Park Test (for Family)

     Coefficient:   3.928224

     Family, Chi2, and p-value in descending order of likelihood

       Family                              Chi2        P-value

       Inverse Gaussian or Wald:          5.2997         0.0213
       Gamma:                            22.8699         0.0000
       Poisson:                          52.7422         0.0000
       Gaussian NLLS:                    94.9165         0.0000

  Results of tests of GLM Log  link

       Pearson Correlation Test:                         0.7229
       Pregibon Link Test:                               0.6884
       Modified Hosmer and Lemeshow:                     0.6150
```

Appendix VII: Ethics Approval Form

University of Glasgow | Faculty of Medicine

Ms Claudia Geue
University of Glasgow
Public Health and Health Policy
Room 203
1 Lilybank Gardens
Glasgow
G12 8RZ

11 January 2010

Dear Ms Geue

Medical Faculty Ethics Committee

Project Title: Population ageing: what are the implications for healthcare expenditure in Scotland?

Project No.: FM01709

The Faculty Ethics Committee has reviewed your application and has agreed that there is no objection on ethical grounds to the proposed study. They are happy therefore to approve the project, subject to the following conditions:

- The research should be carried out only on the sites, and/or with the groups defined in the application.
- Any proposed changes in the protocol should be submitted for reassessment, except when it is necessary to change the protocol to eliminate hazard to the subjects or where the change involves only the administrative aspects of the project. The Ethics Committee should be informed of any such changes.
- If the study does not start within three years of the date of this letter, the project should be resubmitted.
- You should submit a short end of study report to the Ethics Committee within 3 months of completion.

Yours sincerely

Dr Una MacLeod
Faculty Ethics Officer

Dr U MacLeod
Clinical Senior Lecturer

General Practice & Primary Care, Division of Community Based Sciences, University of Glasgow, 1 Horselethill Road, Glasgow, G12 9LX

Tel: 0141 330 8328
E-mail: u.macleod@clinmed.gla.ac.uk

Appendix VIII: SLS Project Clearance Form

SLS PROJECT CLEARANCE FORM

SLS Unit, Room 1G1,
Ladywell House,
Ladywell Road,
Edinburgh,
EH12 7TF.

2 February 2010

Dear Claudia

Your project proposal "Population Ageing: What are the implications for healthcare expenditure in Scotland?" has now been assessed by the SLS Research Board. I am pleased to inform you that the board decided that your proposal has been:

☒ Cleared as it stands

☐ Cleared as it stands, with some suggestions for change/improvement

☐ Cleared under condition there are minor changes

☐ Cleared under condition there are major changes

☐ Rejected

You may be aware that there is another current SLS project being carried out by David Bell of Stirling University. The Research Board feels that it would be useful for you to contact David (if you haven't already done so) in order to avoid any duplication of effort, and to discuss whether there is scope for collaborating on aspects of your research.

Your SLS Support Officer, Peteke Feijten, can put you in touch with David, and will be able to advise on the next steps.

With kind regards,

Claire Boag, SLS project manager

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Appendix IX: Diagnostic Tests (c.f. Table 6.6)

English Tariff

```
FITTED MODEL:  Link = Log ; Family =  Gamma

  Results, Modified Park Test (for Family)

     Coefficient:   2.860117

     Family, Chi2, and p-value in descending order of likelihood

       Family                              Chi2        P-value

       Inverse Gaussian or Wald:         0.0298         0.8630
       Gamma:                            1.1265         0.2885
       Poisson:                          5.2686         0.0217
       Gaussian NLLS:                   12.4560         0.0004

  Results of tests of GLM Log  link

       Pearson Correlation Test:                        0.6586
       Pregibon Link Test:                              0.6282
       Modified Hosmer and Lemeshow:                    0.0022
```

SNT

```
  FITTED MODEL:  Link = Log ; Family =  Gamma

  Results, Modified Park Test (for Family)

     Coefficient:   .222258

     Family, Chi2, and p-value in descending order of likelihood

       Family                              Chi2        P-value

       Gaussian NLLS:                    8.2521         0.0041
       Poisson:                        101.0475         0.0000
       Gamma:                          527.9486         0.0000
       Inverse Gaussian or Wald:      1288.9554         0.0000

  Results of tests of GLM Log  link

       Pearson Correlation Test:                        0.7250
       Pregibon Link Test:                              0.5266
       Modified Hosmer and Lemeshow:                    0.3117
```

Appendix X: SLS Output Clearance Form

SLS OUTPUT CLEARANCE FORM

SLS Unit, Room 1G1,
Ladywell House,
Ladywell Road,
Edinburgh,
EH12 7TF.

20 December 2011

Dear Claudia

Thank you for sending the SLS chapter of your thesis, the introduction and conclusion. I have suggested a few changes (tracked in your original document), to emphasise that the SLS is an anonymised dataset , and a couple of other minor points. Once you have made these changes then these three chapters can be considered cleared.

Regards

Claire Boag,

SLS project manager

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

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