Health Expenditures, Time to Death, and Age:

A Study of Individual-Level, Longitudinal Data to Identify the Combined Role of Age and Mortality in Determining Health Utilization of the Elderly

by

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A thesis submitted in conformity with the requirements for the degree of Doctor of Philosophy
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Abstract

While there is great concern about the potential impact of aging populations on health care systems in the developed world, evidence from recent decades has shown at best a weak relationship between population aging and health expenditures at the aggregate level. This thesis explores the literature that frames the relationship between age and health care utilization in the context of reduced mortality and shorter periods of morbidity at the end of life. We add to this literature with an empirical study of individual health expenditures of the British Columbia senior population in the years 1991-2001 in the categories of hospital services, continuing care, doctor billings, and pharmaceutical prescriptions. Expenditures for decedent and survivors of the same age are compared and are fitted to a model using age and time-to-death as explanatory factors. The partial derivative of the model with respect to age is analyzed for empirical estimates of the effect of age after controlling for time-to-death. Results show that decedent
costs rose over the study period while costs for survivors fell, particularly in continuing care, so that the relative cost of dying increased. The effect of age, after controlling for time to death, was muted or negative for hospitals, doctors, and drugs, but strongly positive for continuing care and, as a result, for all services combined. Overall, these results suggest that age is not a ‘red herring’, as some researchers have suggested, with respect to forecasting future demands on health systems. While future reductions in mortality and morbidity could mitigate pressures on hospitals, aging populations will put increased pressure on long-term residential care and other forms of social care.
Acknowledgments

There are many people to thank for their help and patience in seeing this thesis through, beginning with my committee of Peter Coyte, Audrey Laporte, and David Foot, who managed to devote time and thought to my project in the midst of very busy schedules and travels. I also want to thank Raisa Deber for her contribution to my literature review and help in bringing it to publication.

I owe a special thanks to Carey Levinton who was very generous with his time, advice, hardware and software in helping me through some of the modeling challenges I confronted with the final chapter.

I believe the clean and comprehensive data I received from BC adds to the value of my research. I want to express my gratitude to the custodians at the British Columbia Ministry of Health and the people at UBC’s Centre for Health and Policy Research for helping me prepare my data access request and then providing advice and context as I began to work with the data.

In addition to those directly involved with BCLHD, I want to thank Kim McGrail for helping provide me with the historical background of health care policy in British Columbia during my study period and for sharing some SAS code with me. Thanks, too, to Stephen Lee and Paul Gillan at the BC Ministry of Health, for providing input to the costing process for hospital and continuing care data, respectively.

Finally, thanks to Deanna Wong for her unwavering support and patience, and to my daughter Thalia and Rhea who always help me keep things in perspective.
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1 Introduction

This doctoral thesis is concerned with the effects of aging populations on health expenditures. The passage of the developed world’s baby boom generation into retirement age has long been anticipated, and is set to begin officially in 2011, when those born in 1946 turn 65. Over the subsequent 30 years, the percentage of the population over 65 years old in OECD nations is expected to rise from 15% to 23% (OECD 2006). The potential effects of such a dramatic shift in the age structure of the population are many, including labour supply issues; the effect on asset markets and the potential for shortfalls in pension incomes; and, probably most closely associated with aging, the potential pressures on already burgeoning health care systems. In the United States, Social Security and Medicare are often referred to as ‘twin crises’ that will bankrupt the government with population aging.

The aging population is caused not only by the passage of the baby boom into old age, but also by the combination of longer life expectancies and fertility and net migration rates that are stable or slightly declining (OECD 2006). Longer life expectancies, while increasing the rate of general population aging, may have different effects on the twin crises of pensions and health care for the elderly. If life expectancy continues the growth it experienced in the past century, the ability to support standards of living for longer periods of unproductive retirement (at least in the sense of paid employment) in a rapidly growing cohort at the same time as labour supply is dwindling may be even further curtailed. Yet the effect on health care expenditures could be more benign. Although longer life expectancies imply larger cohorts of elderly with their associated high rates of consumption of health care services, they also imply improving health status, which could mitigate this effect. While better health status may not directly imply lower health care utilization, there is some evidence suggesting that aging populations have not yet had a major effect on health spending aggregates. Cross-sectional studies of aggregate
national spending levels in several countries have found the percentage of the population over age 65 is at best a weak predictor of expenditures (Gerdtham 1992; Gerdtham et al. 1992; Getzen 1992; Hopkins and MacDonald 2000; Reinhardt, Hussey and Anderson 2002). And Barer et al. (1989; 2004) estimated the effect of population aging on annual service utilization growth in British Columbia between 1969 and 1996 at less than 0.5%, while the 65+ population proportion grew from 9.3% to 12.6% (BC Stat Tables (Ministry of Labour and Children’s Services) 2007). If health care spending is going to bankrupt developed world governments, population aging may not be the primary reason, at least based on this evidence.

An important motivating factor for this thesis, and for much of the background literature in the field, is to support a move away from relatively crude age-based forecasts of future health care spending. The assumption of constant real levels of age-specific per capita health care utilization has been fairly common in public policy making (Dang, Antolin and Oxley 2001; Miller 2001; Coyte, Laporte and Stewart 2001), and misses the potential effects of relatively stable and predictable trends like the ongoing improvement in mortality and life expectancy. Taking improved mortality alone into account, and modeling based on a combination of time-to-death and age instead of age alone, researchers have found that expenditure projections can be overstated by between 10% and 60%, depending on the changes in mortality assumed and the services and period of time for which projections are made (Miller 2001; Madsen, Serup-Hansen and Kristiansen 2002; Stearns and Norton 2004; Seshamani and Gray 2002). With respect to changing morbidity, Singer and Manton (1998) argue that if the 1.5% annual decline rate observed in US age-specific disability rates towards the end of the 20th century were to continue through 2070, it could be sufficient to fully offset the expected economic burden of population aging on Medicare costs. Coyte et al. (2002, two of the authors are members of this thesis committee) found that assuming declines in age-specific morbidity could lower the requirement for additional nursing home beds planned in Ontario by more than half (and Ontario did in fact experience a problem with elevated vacancy levels in nursing homes for several years after the planned expansion went ahead).
In addition to the above papers describing the effect of incorporating mortality and morbidity declines into expenditure forecasts, there are two seminal works that set the backdrop for this thesis. First is J.F. Fries’s 1980 paper which provides a framework for understanding end-of-life morbidity. The concept of compression of morbidity, elucidated in more detail in the literature review in Chapter 2 of this thesis, is that as age-specific mortality rates are declining, so too are age-specific morbidity rates, and at a faster rate so that the severity and duration of morbidity experienced at the end of life is on average shrinking. Compression of morbidity was one of the concepts used in Coyte et al. (2002) to predict lower nursing home bed requirements, an example of the impact it could have on health care services planning. Fries’s work suggests that, in addition to missing expenditure reductions due to lower mortality, simple age-based models may further miss potential reduced utilization that could be driven by even greater declines in morbidity. Our thesis will explore end-of-life morbidity in the Chapter 2, looking for empirical evidence of compression. We also intend to use our own modeling to glean insights into how morbidity, or at least end-of-life expenditure patterns as a proxy for morbidity, changed over time in our study period.

The second influential work underlying this thesis is an empirical study modeling individual-level health expenditures from a Swiss Sick Fund as a function of time-to-death and age (Zwiefel, Felder and Meiers 1999). While several later studies followed a similar path, expanded the body of knowledge, and augmented the methodology, Zwiefel, Felder and Meiers’ paper was the first, and its provocative title (Aging of Population and Health Care Expenditure: A Red Herring?) set the tone for subsequent debate. The concept of age as a ‘red herring’ is that age has no effect on health expenditures after changes in mortality and/or morbidity are taken into account. The desire to move away from age-based models is a reflection of the suspicion that age alone is insufficient to predict health expenditures and that mortality and morbidity projections need to be added to forecasting models. A major theme of this thesis is to explore the different ways in which age influences health expenditures, including but not limited to through mortality
and morbidity rates that increase with age. We intend to add a model to the literature and use this as a basis for supporting or refuting the ‘red herring’ thesis.

The thesis is organized into three major chapters, bookended by this introduction and a conclusion. Chapter 2 is a review of the literature, some of which is cited above. The literature review is organized in a progression that reflects the broader progression of the thesis in its subsequent chapters. It begins with an exploration of the relationship between mortality and morbidity at the end of life, anchored by Fries’s original paper. The second section compares studies in the literature that measure the relative cost of dying, where costs for decedents are compared to those for survivors of the same age. The third and final section of the review covers a more recent body of studies that expand on the cost of dying calculations to develop full statistical models of health expenditures as a function of age and time to death. The questions we seek to address in the review include the following:

1. To what extent have lower mortality rates been associated with correspondingly lower morbidity rates at older ages?
2. What is the empirical evidence for compression of morbidity in the literature and what methodological issues, if any, arise in comparing population trends in morbidity and mortality?
3. Is there evidence that lower mortality and lower morbidity correspond to lower health care utilization?
4. What are the differences and similarities among cost-of-dying studies and time-to-death models over different jurisdictions, different time periods, and for different health care service categories?
5. Is there any evidence of changes over time in the relative cost of dying or the effect of time to death?
6. How have empirical studies of the cost of dying and time-to-death models been used to change our understanding of the effects of aging populations?
Chapters 3 and 4 mirror the second and third sections of the literature review. We use our data to calculate relative cost-of-dying ratios and build models of health expenditure as a function of age and time to death. Our empirical work is based on a dataset covering the years 1991-2001 from the province of British Columbia. The data include individual level utilization of health care services from four different provider categories: hospital inpatient and outpatient services; continuing care, including home care and long-term residential care; physician billings; and claims for prescription drugs, which are covered by the government for all residents 65 or more years old. We have comprehensive data from the British Columbia Ministry of Health that includes records for all individuals served. Since British Columbia runs a government-sponsored universal health care insurance system, nearly the entire population of individuals aged 65 or over is represented in our data.

Chapter 3 is a descriptive analysis of our data and calculations of average expenditures for decedents and survivors for all ages and spending categories (in our study decedents are defined as those in their last year of life, while survivors are the remaining population; this is the most common definition in precedent studies however our literature review finds that other definitions – and time periods – have been used). In this chapter the data source is described in greater detail. We describe the process and assumptions with which costs were assigned to utilization figures, how inflation was taken into account in cost estimates, and how expenditures were grouped into annual periods based on the month of death for decedents. We also review the major developments in health care policy in British Columbia for the study period to provide some context for our results. Our data analysis primarily compares decedent and survivor expenditures estimates for individuals of the same age. The resulting decedent / survivor cost ratios provide estimates of the relative cost of dying. The methodology is similar to that used in the literature, and our discussion compares our results with those of earlier studies.
The descriptive analysis and segmentation of the population into decedents and survivors provides the means for other analyses beyond the cost-of-dying ratios. We look at how the average share of total individual spending among service categories differs between decedents and survivors by age group. In addition, we combine the decedent / survivor cost estimates with population figures and death rates to estimate the proportion of total spending allocated to decedents for each age group and service category. Conducting such an analysis over an extended time period can shed some light on how systemic care patterns might have shifted between preventive, curative, and palliative applications. Finally, we are able to use our data to perform an allocation of health care spending changes in British Columbia between 1991 and 2001 for the 65-and-older population. Specifically, we isolate the effects of population growth, medical inflation, change in age distribution, change in death rates, and changes in decedent and survivor per capita real expenditure rates. The results of this analysis can be compared with the aforementioned literature showing weak links between population aging and health expenditure aggregates. By breaking down the various ways that aging and per capita spending patterns affect aggregate health spending levels in greater detail, more insight could be gained into why aging has had less of an effect than commonly anticipated.

Chapter 4 returns to the second influential paper discussed earlier, the ‘red herring’ argument of Zweifel, Felder, and Meiers. Before building our own time-to-death model, we explore theoretical frameworks for understanding how individual age can influence utilization of health care services. The ‘red herring’ argument is that age only influences health care utilization through increased incidence of mortality and morbidity. If this is true, then models that include mortality and morbidity (in this case using proximity to death as a proxy) would show no residual effect of age. We review two theoretical economic utility maximization frameworks that each hypothesize other ways in which age might influence demand for health care services. In particular, willingness to pay and/or undergo the other costs associated with treatment (e.g. time, risk, invasiveness, recovery) may decline as the returns to healthy time or the length of life to be gained decrease. To these theoretical frameworks we add a qualitative context suggesting
numerous ways in which the desire or ability to access health care services might change with age. We use this theoretical backdrop to generate hypotheses of our own as to how the influence of age – controlled for time to death – might differ among the four service categories in our analysis.

The remainder of the Chapter 4 consists of our time-to-death model of individual health expenditures. We incorporate up to three years of time to death in the model using dummy variables. The remaining population is all those known to survive at least three years from the time at which expenditures are measured. Our focus is on the effect of age in the model. With the time-to-death dummies accounting for late-stage morbidity and mortality, we can look for residual effects of age to support or refute the ‘red herring’ thesis of Zweifel, Felder and Meiers. We also look at the four service categories separately to support or refute our own hypotheses. Finally, we break the data into two separate datasets covering 1991-1994 and 1996-1999 and analyze changes in the effects of age and time to death between the two time periods. Our interest in these temporal changes is to determine the stability of the relationships we have measured and to compare to a precedent study that undertook a similar analysis (Seshamani and Gray 2004b).

To summarize, our aim with this thesis is to add insight into the relationship between population age and health expenditures and to add a contribution to the body of research that measures the relative cost of dying and models health care expenditure as a function of time to death. The novel contributions we anticipate from this thesis are the following:

1. A comprehensive literature review linking the concepts of compression of morbidity and epidemiological transition with empirical data on recent trends in mortality and morbidity and with cost-of-dying and time-to-death analyses.
2. Estimates of the cost of dying and time-to-death models using a population-wide government data source from a jurisdiction with universal health insurance coverage.
3. A detailed attribution of the ways in which population aging affects aggregate health expenditures.

4. A review of theoretical and qualitative models exploring the relationship between age and health care expenditures.

5. An analysis of temporal change in cost-of-dying ratios and the effect of age and time to death on expenditures across different service categories.

It is hoped that this thesis will help decision makers in health care and public sector finance to better understand how different scenarios for population morbidity and mortality could change the way aging influences demand for health care services. If individuals dying at older ages use different service categories in different quantities than their younger counterparts, changing life expectancies could change balance of demand for these services at the aggregate level. Changing life expectancies will also change crude population death rates, either mitigating or exacerbating the rise in crude death rates brought on by population aging. Understanding the costs of dying and influence of time to death at the individual level should help put these developments into context, and to quantify their effects on macro budgets.
2 Literature Review

2.1 Introduction

The impact of population aging on health care expenditures is a topic of growing interest in academic and policy circles as the largest population cohorts in most developed countries approach the age of 65. The potential economic stakes of the coming demographic transition are substantial. The expenditure implications of demographic trends are a function of: the number of people in high use categories, the length of time that they remain in that category, and the cost of the health services they use. Older persons use more health care; in OECD nations, average per capita expenditures for persons age 65 and over are 2-8 times those for the working-age population, with the multiple steadily increasing with age (Mayhew 2000; Freund and Smeeding 2002; CMS 2006). With the proportion of OECD populations in these higher-spending cohorts projected to grow from 13.0% in 2000 to 20.9% in 2030 (OECD 2006), projections that assume age-specific spending distributions remain fixed argue that expenditures as a proportion of GDP will grow by as much as three percentage points in the first half of the 21st century in both the US (Dang 2001) and the EU (EPC 2003; Bains and Oxley 2004), placing the sustainability of health care systems into doubt.

Yet these assumptions may not prove accurate. Predictions of rapid growth in expenditures due to growing elderly cohorts are not reflected in the data. For example, in the US, the proportion of the population over age 65 grew from 9.8% in 1970 to 12.4% in 2000 (OECD 2006), yet by one estimate the shift in population age distribution accounted for only 0.2 percentage points of the 4.3% inflation-adjusted annual growth in expenditures (Meara, White and Cutler 2004). Similar results have been observed in other OECD nations. Analyzing individual health services utilization, Barer et al. (1989; 2004) estimate the effect of population aging on annual service utilization growth in the
Candian province of British Columbia between 1969 and 1996 at less than 0.5%, while the 65+ population proportion grew from 9.3% to 12.6% (BC Stat Tables 2007). Cross-sectional studies of aggregate national spending levels in several countries have found the percentage of the population over age 65 is at best a weak predictor of expenditures (Gerdtham 1992; Gerdtham et al. 1992; Getzen 1992; Hopkins and MacDonald 2000; Reinhardt, Hussey and Anderson 2002).

Population aging is only one among a number of drivers of health care expenditures, and the effects of the relatively slow pace of change in population age structure may be overwhelmed by other factors such as population growth (Denton and Spencer 1995; Denton, Gafani and Spencer 2002); the introduction of new technologies and treatments (McClellan and Newhouse 1997; McClellan 1996; Meara, White and Cutler 2004), increased utilization (e.g., of drugs, diagnostic tests), and price inflation, particularly given tight labour markets in health care (Jacobzone 1998; Goetghebeur, Forrest and Hay 2003; Hay 2003; Koenig et al. 2003). Nevertheless, with the most rapid growth in elderly cohorts still to come, it is important to clarify how their relative spending patterns in old age are likely to compare to those of recent generations to determine whether population aging remains a toothless tiger or starts to have a bite.

In this respect, one key issue is the extent to which higher health care costs at older ages are associated with aging, with death, or with some combination of the two. Population aging, expressed as growth in the percentage of individuals over the age of 65, is driven by both inflow (a function of fertility and immigration rates), and outflow (death rates and out-migration). To the extent that aging is driven by the former, larger cohort sizes at higher-spending ages might be expected to lead to higher expenditures. However, the effect on expenditures of aging due to lower death rates is less clear. Again cohort sizes increase, yet the improvement in mortality implies an improvement in health, possibly leading to lower expenditures.
In the last two decades of the 20th century, age-specific death rates in the US decreased, leading to a net decline in the overall population mortality rate of 2.5% (CDC 2006). If mortality rates continue to fall, the effect of growing elderly cohorts on future expenditures could be mitigated. In contrast, to the extent expenditures are associated with age independent of life expectancy, these lower mortality rates would mean more elderly people and higher expenditures.

One approach to analyzing trajectories of health expenditures and morbidity developments at the end of life is to begin with death and work backwards. Researchers are employing mortality-based analyses to answer such questions as: If individuals are dying on average at older ages, how do health expenditures in the last years of life change with age at death? How does aging affect health expenditures for those individuals still many years from death? Are mortality changes paralleled by similar changes in the health status of individuals still living? How quickly do individuals in different age groups deteriorate from good health to death? And, critically, are these age-death-expenditure relationships changing over time?

This chapter reviews contributions from the literature concerning age, mortality, morbidity, and expenditures in answering these questions, with particular emphasis on use of time-to-death as a variable for modeling individual health expenditures. As opposed to strictly age-based models, time-to-death models count backwards from the fixed reference point (a known date of death), and measure expenditures against this backwards count. This approach enables the separate effects of mortality and age to be identified and modeled with greater specificity. With the effects of mortality controlled, the estimated relationship between age and expenditures can capture more subtle aspects of the aging process, such as how the utilization of services changes with age, and hence offers the potential for more accurate forecasts of future expenditures.
The review is organized into three principal sections. First, in Section 2.2, we present an analytical framework for understanding the relationship between mortality and morbidity at the end of life, and how this relationship might change both over time and with age at death. The framework derives from the ‘epidemiological transition’ debate about whether morbidity is compressing, expanding, or staying the same. We then survey empirical studies of morbidity prevalence to determine the degree of support for these competing theories.

In Section 2.3 we review the literature that uses individual-level data to measure the ‘cost of dying’. These studies generally compare the health care costs for a given age group of people who died (‘decedents’) to those still living (‘survivors’). Differences in decedent versus survivor costs for different ages reflect the ‘intensity of care’, and changes in age-specific intensity over time in conjunction with demographic forecasts suggest possible future scenarios for aging and expenditures.

Section 2.4 brings in the relatively new and growing body of literature that uses individual-level data to develop empirical models of the relationship between expenditures and time-to-death. These studies are a natural extension of the cost of dying literature reviewed in the second section, but add more quantitative rigour and analyze larger and more complex datasets. They move beyond the binary comparison of decedents versus survivors to a more continuous measure of how expenditures change as death is approached. Finally, the contribution of such models to clarify the relationship between age, mortality, and morbidity among the elderly and to provide more accurate expenditure forecasts is examined.
2.2 Analytical Framework: Relationships between Mortality and End-of-Life Morbidity

As Figure 2.1 shows, US data demonstrate a close relationship between per capita expenditures and death rates, which both rise steadily with age (CMS 2006, CDC 2006). The literature suggests a direct association between high expenditures and death: in the American Medicare program the 5% of beneficiaries age 65 and over who die in a given year have accounted for 25%-30% of total expenditures (Lubitz and Riley 1993; Hoover et al. 2002). Similarly, in the Canadian province of Manitoba, the 1% of the adult population that died in 2000/2001 accounted for 21% of expenditures (Menec et al., 2004). Yet it is not the death event itself that drives expenditures but the morbidity that precedes and may eventually lead to death.

Figure 2.1: U.S. Per Capita Health Expenditures and Death Rates by Age

Sources: CDC 2006; CMS 2006
Cutler and Sheiner (1998) provide a useful framework for analyzing expenditures at the aggregate level. In this framework, expenditures are conceived as the sum over all ages of the product of: 1) the number of people alive in each age group; 2) the average health status at each age; and 3) the per capita medical spending conditional on health status, which also varies according to age. Note that this framework looks only at averages and ignores the considerable skewing of health status, and costs, within each age group (Deber, Forget and Roos 2004); sick people (of whatever age) are likely to be expensive, while most people (in all age cohorts) incur relatively few costs.

Most demographic-based predictions of future health care spending have focused on numbers of people, assuming that the average health status remains constant and per capita spending grows at rates equal to the rate of inflation, either in the general economy or in health care specifically (Dang 2001; Miller 2001). However, as we note in the introduction, increasing numbers at older ages is at least partially due to lower mortality rates. If age-specific mortality rates fall, it is plausible that health status defined in terms of disability or illness – Cutler and Sheiner’s second factor – will also improve. In that case, forecasts of future expenditures may be overestimated since they take into account the larger numbers of people alive at older ages due to mortality reductions, but not the potential improvement in health status and lower need for health care that might be associated with the lower mortality. In contrast, if mortality reductions are associated with increased morbidity in the newly surviving population, forecasts may be underestimated. Empirical data are required.

### 2.2.1 Epidemiological Transition: The Theory

Considerable theoretical and empirical research has addressed the morbidity-mortality relationship. The empirical work typically measures the prevalence of morbidity and enters these rates into mortality-based life tables to calculate health-adjusted life expectancies (HALE). Life expectancies are then segmented into a healthy period
(assumed to be low morbidity) and a period of high morbidity at the end of life. Depending on the measure of morbidity taken, HALE is also variously characterized as disability-free life expectancy (e.g. Crimmins, Saito and Reynolds 1997; Freedman et al. 2004; Sagardui-Villamor et al. 2005) and disease-free life expectancy (e.g. Mathers et al. 2001; Mathers et al. 2004; Mathers, Iburg and Begg 2006).

The theoretical framework places trends in elderly mortality and morbidity in the context of the epidemiological transition. First introduced by Abdel Omran (1971/2005), the concept of the epidemiological transition characterizes the way in which social, environmental, and health factors combine to change life expectancies, the most common causes of death, and rates of disease prevalence among successive population cohorts. Medical and social advances that drastically reduced the rates of mortality due to infectious diseases and heart disease, to take two examples, have significantly changed the size and composition of the cohorts surviving into old age (Cutler and Richardson 1997; Mathers et al. 2001). As cohorts that might have died earlier before these advances age, rates of disease prevalence and morbidity are likely to also change.

Researchers contemplating the interaction of these cohort effects, medical advances, and socioeconomic factors have reached a wide range of conclusions with respect to the likely implications for morbidity at the end of life. Fries (1980) popularized the concept of ‘compression of morbidity’, predicting that the period of morbidity preceding death among the elderly would shrink over time. He argued that gains in life expectancy would slow to the extent that premature deaths due to disease approached zero. Further reductions in mortality would thus have to occur mainly among the elderly, where past decreases have been relatively minor. Fries theorized that at some point medicine would be unable to mitigate the process of natural aging and that human longevity would approach a natural limit. However, improvements in lifestyle, socioeconomic conditions, and medicine could reduce chronic conditions within that relatively fixed lifespan, and
thus would lead to a compression of the period of infirmity preceding death. The next cohorts of elderly would be healthier than in the past.

In a counter-argument to Fries’s compression hypothesis, Olshansky et al. (1991) present a theory of expansion of morbidity. While the authors generally agree with Fries with respect to limits to longevity (Olshansky, Carnes and Cassel 1990), they suggest that even minimal mortality reductions at old ages would lead to increasing morbidity associated with people surviving for longer periods with non-fatal chronic conditions.

Figure 2.2 provides a graphical representation of the competing theories of end-of-life morbidity. Three pairs of horizontal bars are depicted, with each pair representing the lifetime experience of population cohorts separated in time and experiencing different rates of both mortality and morbidity. In all cases life expectancy is assumed to increase. In the first pair (2a), reductions in age-specific mortality rates (leading to increases in life expectancy) have exceeded reductions in the age-specific rate of morbidity incidence. As a consequence the period of chronic end-of-life morbidity expands, as represented by the growth in the shaded area of the bar. In the second depiction (2b), the combination of a decrease in age-specific morbidity incidence and an increase in life expectancy leads to a roughly equal postponement of both death and the onset of chronic morbidity. In this scenario, morbidity neither expands nor compresses; the length of the period of chronic end-of-life morbidity remains relatively unchanged. In the final depiction (2c), the relationship between changes in life expectancy and age-specific morbidity is reversed, with morbidity incidence now falling faster than mortality. This is Fries’ compression of morbidity scenario.

It should be noted that similar models could be derived for constant, or even falling, life expectancy, depending on the relative growth rates in age-specific morbidity. Furthermore, as Robine and Michel (2004) note, different models can co-exist in different sub-populations. For example, compression of morbidity can take place among the more
educated while the less educated experience expansion (Crimmins and Saito 2001), or males and females within a given age group may have different patterns (Jagger, Barberger-Gateau and Robine 2005). The duration of end-of-life morbidity is also likely to vary with age at death.

Figure 2.2: Illustration of Expansion, Postponement, and Compression of Morbidity Theories

2.2a: Expansion of morbidity. In expansion, the change in life expectancy, represented by the difference between life spans $O'D'$ and $OD$, exceeds the change in morbidity-free life expectancy, $(O'M' - OM)$. The result is an expansion in the length of morbidity at the end of life (hatched portion of bars) - i.e. $D'M' > D - M$

\[
\begin{array}{c}
\text{O} \\
\text{M} \\
\text{D} \\
\text{O'} \\
\text{M'} \\
\text{D'}
\end{array}
\]

2.2b: Postponement of morbidity. In postponement, the shifts $DD'$ and $MM'$ are equal in magnitude so that there is no difference in the length of end-of-life morbidity between periods

\[
\begin{array}{c}
\text{O} \\
\text{M} \\
\text{D} \\
\text{O'} \\
\text{M'} \\
\text{D'}
\end{array}
\]

2.2c: Compression of morbidity. In compression, the shift in onset of end-of-life morbidity, $MM'$ exceeds the change in life expectancy, $DD'$, resulting in a compression of end-of-life morbidity

\[
\begin{array}{c}
\text{O} \\
\text{M} \\
\text{D} \\
\text{O'} \\
\text{M'} \\
\text{D'}
\end{array}
\]

Legend: O = beginning of life, M = onset of end-of-life morbidity, D = death
The shift from the upper to lower bar in each pair (i.e. from OD to O'D') represents a change in population health and life expectancies experienced over a period of calendar time.
2.2.2 Epidemiological Transition: The Evidence

The shaded area of the bars in Figure 2.2 can be understood as the difference between total and health-adjusted life expectancy. The compression of morbidity theory predicts that this difference will shrink, either in absolute terms, or as a percentage of total life expectancy. The expansion of morbidity theory holds the opposite.

The evidence compiled in the literature generally favours the compression theory. Most measures of morbidity among the elderly have declined in recent years in a broad spectrum of developed countries (Manton, Stallard and Liu 1993; Manton, Stallard and Corder 1995; Jacobzone, Cambois and Robine 2000; Doblhammer and Kytir 2001; Crimmins 2004; Robine and Michel 2004; Spillman 2004; Jagger, Barberger-Gateau and Robine 2005; Sagardui-Villamor et al. 2005) after a period of relatively stagnant morbidity in the 1970s and early 1980s (Crimmins, Saito and Reynolds 1997; Crimmins 2004, CDC 2007). Prevalence of functional disabilities with activities of daily living (ADL) such as eating and toileting and instrumental activities of daily living (IADL) such as homemaking declined among the elderly at an annual rate of 1.5%-2% in the 1990s and into the 2000s (Crimmins, Saito and Reynolds 1997; Singer and Manton 1998; Fries 2003; Jacobzone, Cambois and Robine 2000; CDC 2007). Improvements of a similar magnitude have been observed in self-reported ratings of health status (Doblhammer and Kytir 2001; Jagger, Barberger-Gateau and Robine 2005, Crimmins 2004; CDC 2007). Although prevalence of many chronic diseases such as arthritis, diabetes, and cancer has increased (Robine and Michel 2004; Robine, Mormiche and Sermet 1998; Cutler and Richardson 1997, CDC 2007), theory (Manton 1982) and evidence (Robine, Mormiche and Sermet 1998; Crimmins 2004; Mathers et al. 2004; Mathers, Iburg and Begg 2006) indicate that the average severity of these diseases is declining, so that increased disease prevalence is consistent with falling levels of disability.
To estimate whether compression or expansion of morbidity has occurred, morbidity trends need to be compared to developments in mortality. The limit to longevity predicted by Fries and Olshansky has not yet been reached (Jacobzone, Cambois and Robine 2000; Wilmoth 2000; Fries 2003). Decreases in age-specific mortality continue, particularly at older ages: mortality for ages 75 and older in the U.S. fell 1.2% annually between 1980 and 2003 (CDC 2006). However, since age-specific disability declined at an even faster rate (1.5% or higher), the proportion of life characterized as ‘disability-free’ has increased (Manton 1988; Crimmins, Hayward and Saito 1994; Crimmins, Saito and Reynolds 1997; Singer and Manton 1998; Crimmins 2004; Mathers et al. 2004; Jagger, Barberger-Gateau and Robine 2005). For example, Crimmins, Saito, and Ingegneri (1997) estimate that the portion of life after 65 expected to be free of disability rose from 49% in 1980 to 51% in 1990. Sagaudui-Villamor et al. (2005) estimate substantially larger gains in Spain between 1986 and 1999, with the disability free portion growing by 20 percentage points for both sexes.

The combination of morbidity prevalence data and mortality incidence data into one calculation raises potential issues concerning timing and cohort effects (Murray, Solomon and Mathers 2000; Barendregt, Bonneux and Van der Maas 1994; Mathers and Robine 1997). The simplification of life into a three-stage model – healthy, pre-death morbidity, death – does not allow for transitions back and forth between the healthy and morbidity states, or for gradations of morbidity. Researchers have introduced multi-state models that address this concern by incorporating rates of incidence and remission from states of morbidity (e.g. Manton and Stallard 1996, Mathers and Robine 1997, Crimmins, Saito, and Reynolds 1997; Buckley et al. 2004), but empirical applications of this adaptation result in relatively little change from base estimates (Murray, Solomon and Mathers 2000). As a result the simpler life table methods using morbidity prevalence continue to represent the majority of the literature.
It is tempting to conclude that the compression of morbidity evident in the estimations of increasing disability-free life expectancy should translate to reduced health care expenditures. As a first approximation, one can link the epidemiological transition to expenditure trends, where costs in the shaded portions of the bars will be relatively high, and costs in the remainder relatively low. In that case, a compression of cost scenario would predict a relatively short period of high expenditures (often in the period before death), whereas an expansion scenario would predict a relatively long period of high expenditure associated with longer survival with chronic disease.

For example, Singer and Manton (1998) argue that if the 1.5% annual decline rate observed in US disability rates were to continue through 2070, it could be sufficient to fully offset the expected economic burden of population aging; the support ratio (the number of economically active persons 20-64 relative to chronically disabled persons 65 and older) could be maintained at 1994 levels. If there were no further morbidity declines, however, this ratio would fall by over 60%. Jacobzone et al. (2000) reach similar conclusions from a broad survey of OECD disability and demographic data, projecting that growth in long-term care spending as a share of GDP could be completely eliminated by improved disability trends in the United States and substantially reduced even in OECD countries with lower projected growth in the working-age population.

Jacobzone et al. (2000) sound a note of caution in linking disability trends to developments in health expenditures. Apparent declines in population morbidity may be due to one or a combination of increased usage of the health care system, more effective health care, or healthier lifestyles. Different combinations of these variables carry different implications for expenditures. In some studies, improved independence among the elderly parallels increased usage of technology and personal aids, suggesting that better – and more expensive – management of symptoms may be more responsible for the observed improvement than better individual health (Manton, Stallard and Corder 1995; Freedman et al. 2004; Spillman 2004).
As health care services may be used in prevention and symptom mitigation, the declines in disability and poor self-rated health cannot directly be linked to reduced consumption of care without further research. The evidence from this section on morbidity and mortality trends describes developments in age-specific health status – the second factor in Cutler and Sheiner’s decomposition of health expenditures. To complete the picture, evidence is required for the third factor: medical spending given health status. The remaining sections of this chapter review the literature that undertakes this investigation through the direct examination of expenditure data in the context of mortality.

2.3 The Cost of Dying

Cost-of-dying studies fall into two broad categories. *Decedents only* studies count “lifetime costs” (often from eligibility for US Medicare at age 65 to death) of known decedents, plot these against time-to-death, and compare total costs and share of total costs incurred in the last year(s) of life for decedents of different ages. *Decedents vs. survivors* studies compare the health care expenditures of individuals dying in a given period to ‘survivors’ in the same age cohort who continue to live; results are often expressed as decedent/survivor cost ratios. The second method has been employed by a broader range of studies, allowing comparison across different sectors of the health care system, jurisdictions, and age groups. With health status approximated by proximity to death, cost-of-dying estimates can provide an estimate of Cutler and Sheiner’s third factor: the intensity of care given health status.

2.3.1 Decedent Costs and Age

The relationship between health care expenditures and death changes significantly with the age at death. However, it is important to take note of which health care sectors are
included in the expenditure measurement. For services covered by US Medicare 30%-50% less is spent in the last year(s) of life on decedents at ages older than 85 versus those in the 65-75 age range (Lubitz and Prihoda 1984; Lubitz and Riley 1993; Lubitz, Beebe and Baker 1995; Miller 2001; Hoover et al. 2002; Yang, Norton and Stearns 2003, Levinsky et al. 2001), with the decline in decedent costs with age more pronounced for hospital costs. Hospital costs for decedents 85 and older are estimated to be 50% lower than for 65-69 year-olds in the US (Yang, Norton and Stearns 2003) and as much as 70% lower in Denmark (Madsen, Serup-Hansen and Kristiansen 2002).

These results appear to depend in part on how care is organized and financed. For example, one Canadian study (McGrail et al. 2000) finds that hospital costs decline 30%-35% between the oldest and youngest age groups. However, this is not reflected in the number of days spent in hospital; Roos, Montgomery and Roos (1987) and Menec et al. (2004) find that the number of inpatient hospital days in Manitoba peaks for decedents aged 75-84 and that there is relatively little difference between the 85+ and 65-74 age groups, implying that although the number of hospital days did not decline linearly with age, the intensity of services received per hospital day did. Lower intensity of hospital care with age is also found in the US Medicare program (Long and Marshall 2003; Levinski et al. 2001). In contrast with the Manitoba results, Busse, Krauth, and Schwarz (2002) find age-related declines of nearly 50% in decedent inpatient hospital days in Germany. These findings point to potentially significant differences in the way hospitals are used in different jurisdictions.

But hospital and Medicare costs are only part of the full health care system, and other sectors may not have the same relationship between age and decedent costs. In particular, services such as nursing homes and home care, which are not always covered by public funding, are largely used by the very old (or very ill) and may substitute for hospitals or emergency rooms (Werblow, Felder and Zweifel 2007). A key policy
question is who bears what costs, and whether financial barriers to use of certain services might affect observed expenditures.

The literature confirms that non-hospital costs-of-dying show trends that are opposite and often greater in magnitude than those for hospital and Medicare costs. Nursing home decedent costs, in particular, rise dramatically with the age at death, typically by a factor of five times or more when comparing the youngest and oldest old (Roos, Montgomery and Roos 1987; Menec et al. 2004; McGrail et al. 2000; Spillman and Lubitz 2002; Yang, Norton and Stearns 2003). Costs from sectors outside of hospitals and nursing homes are less commonly studied, but the available evidence suggests that home care and outpatient pharmaceutical costs demonstrate a similar, but somewhat weaker, increase to nursing home costs (McGrail et al. 2000; Menec et al. 2004; Spillman and Lubitz 2002; Yang, Norton and Stearns 2003). Physician costs more closely resemble hospital costs, though the decline in decedent spending with age is somewhat weaker (Menec et al. 2004; Madsen, Serup-Hansen and Kristiansen 2002). Hoover et al. (2002) find non-Medicare costs double for decedents aged 85+ versus 65-74, while Yang, Norton, and Stearns (2003) show that Medicaid costs (comprising mainly nursing homes costs at these ages) more than triple for the same age groups. It should be noted that none of the studies reviewed includes costs that are not covered under insurance plans, an omission that would likely be most significant for the nursing home and home care spending categories.

When nursing home and non-Medicare costs are combined with hospital and/or Medicare costs to obtain decedent costs for a more complete spectrum of health care services, a more stable age-cost relationship emerges. Hoover et al. (2002) and Yang, Stearns, and Norton (2003) find total decedent costs change minimally with age at death. In contrast, McGrail et al. (2000) estimate a rise of 42% in Canadian decedent costs for ages 85-87 over age 66. The difference between the American and Canadian results indicates the potential impact of service mix and the extent of public financing. Because the mix of services received changes from primarily hospital-based care for the younger old to...
primarily nursing home and home care for those 85 and older, more generous coverage for non-hospital services (as is the case in Canada) could increase the cost differential with age. Putting all costs together, higher average age at death does not reduce the economic burden to society of caring for the dying although it does reduce the acute care portion. At best, decedent costs remain stable with age. However, who bears those costs is likely to vary, with lower costs to public payers in systems which leave the costs of nursing homes and home care to private insurers and/or to individuals and their families.

Although they do not provide direct estimates of survivor expenditures, the lifetime cost studies do shed light on the important question of whether longer lifetimes entail higher cumulative expenditures. As with other findings in this literature, the difference between Medicare or hospital costs and nursing or social care is substantial. Evidence of lifetime Medicare costs indicate that cumulative costs rise at a decelerating rate with age at death to age 90 and then level off thereafter (Lubitz, Beebe and Baker 1995; Gornick, MacMillan and Lubitz 1993). Rather than add more years of expenditure, longer lifetimes are more likely to delay but not increase the years of heavy spending, not unlike scenario 2b from Figure 2. When non-Medicare expenditures are considered, however, the conclusions change (Spillman and Lubitz 2000; Spillman and Lubitz 2002). Lifetime expenditures for nursing homes and home care grow at an accelerated rate with age at death, pointing more to the expansion of morbidity of scenario 2a.

2.3.2 Survivor Costs and Age

While higher average age at death may not reduce average decedent costs, lower mortality rates will nonetheless reduce the percentage of decedents in any age group so that total decedent costs to society could still decline. This decline would only be temporary, since every cohort will eventually die off and incur the costs of dying, but continued mortality declines could help spread out what would otherwise be a rapid acceleration in expenditures as the population ages and the baby boom cohorts enter the
last phase of life. However, if the expansion of morbidity thesis holds, or if the intensity of care for survivors grows, then the growing survivor cohorts created by lower mortality rates will place heavy demands on the health care system.

Table 2.1 summarizes the cost-of-dying studies. Here, we move from the decedent-only results summarized above, to studies that compare survivors and decedents within the same age cohort, thus offering insight into the health expenditures of survivors of different ages. Similar to the case of decedent costs, nursing home and non-Medicare survivor costs rise much faster with age than costs from hospitals and the Medicare program. Nursing home costs among survivors in the younger ages near 65 are very low and as a consequence of this low base the growth rate in survivor costs to older ages is high and variable. Nursing home costs for ages over 85 are estimated to be anywhere from 12 (Roos, Montgomery and Roos 1987) to over 30 times (McGrail et al. 2000) those at age 65. Taking all non-Medicare costs into account, where survivor costs at young ages are higher than for nursing homes alone, Hoover et al. (2002) calculate a smaller multiple of 3.6 times in comparing ages 85+ to those 65-74.

Unlike the case of decedent costs, hospital and Medicare survivor costs continue to rise with age, and are 50%-70% higher for the older versus younger old (Lubitz and Riley 1993; Lubitz, Beebe and Baker 1995; Hoover et al. 2002; Madsen, Serup-Hansen and Kristiansen 2002). Again, studies that measure inpatient hospital days instead of costs estimate a higher growth rate with increasing age (Roos, Montgomery and Roos 1987; Menec et al. 2004; Busse, Krauth and Schwartz 2002), suggesting intensity of hospital care may diminish for the oldest categories. Total costs from all components of the health care system for survivors more than double from age 65-74 to age 85+ (Hoover et al. 2002) and continue to grow into older ages. McGrail et al. (2000) compare 65-year-olds to those 90-93 and find total costs for survivors in the older cohort are eight to nine times as high.
Table 2.1: Summary of Cost-of-Dying Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Year(s) of Data</th>
<th>Age Group(s) Studied</th>
<th>Sector(s) of Health Care System Included</th>
<th>Lifetime comparison?</th>
<th>Intra-cohort comparison?</th>
<th>Decedent / Survivor cut-off</th>
<th>Decedent-Age Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lubitz and Prihoda (1984)</td>
<td>1977, 1978</td>
<td>67-69, 70-74, 75-79, 80-84, 85+</td>
<td>Medicare expenditures</td>
<td>n</td>
<td>y</td>
<td>1 year compared to 2 or more years</td>
<td>Costs fall by 43% from ages 67-69 to ages 85+</td>
</tr>
<tr>
<td>Lubitz and Riley (1993)</td>
<td>1976, 1979, 1983, 1988</td>
<td>65 and higher</td>
<td>Medicare expenditures</td>
<td>n</td>
<td>y</td>
<td>Last year vs. more than one year</td>
<td>In 1976 costs fell 40% from age 65-69 to age 85+, in 1988 fell 34%</td>
</tr>
<tr>
<td>Lubitz, Reeha and Baker (1995)</td>
<td>1974-1988</td>
<td>65-101 (at death)</td>
<td>Medicare expenditures</td>
<td>y</td>
<td>n</td>
<td>Last 2 years / age 65 to last 2 years</td>
<td>Costs fall by 32% from age 70 to 90</td>
</tr>
<tr>
<td>Gornick, McMillan and Lubitz (1993)</td>
<td>1974-1988</td>
<td>80, 90, 100 (at death)</td>
<td>Medicare expenditures</td>
<td>y</td>
<td>n</td>
<td>16-years to death costs fall by 32% for death at age 100 vs. 80</td>
<td>Costs rise by 5% from age 75-79 to 80-84 and fall 40% from age 80-84 to 90+</td>
</tr>
<tr>
<td>Long and Marshall (2000)</td>
<td>Unspecified</td>
<td>75-79, 80-84, 85-89, 90+</td>
<td>Hospitals only, managed care admissions</td>
<td>n</td>
<td>y</td>
<td>Last year of life vs. more than one year</td>
<td>Costs in last year of life decline 33% between youngest and oldest ages: Hospital and ICU admissions decrease 30% and 50%, respectively. Use of ventilators and respirators down 67%</td>
</tr>
<tr>
<td>Levinsky et al. (2001)</td>
<td>1996 85+</td>
<td>65-74, 75-84, 1968</td>
<td>Hospitals only, managed care admissions</td>
<td>n</td>
<td>n</td>
<td>Last year of life, no survivors included</td>
<td>No explicit cut-off: each year can be compared</td>
</tr>
<tr>
<td>Miller (2001)</td>
<td>1974-1990</td>
<td>65+, 75, 85, 95</td>
<td>Medicare Expenditures</td>
<td>y</td>
<td>n</td>
<td>Last 18 months / age 65 to last 18 months</td>
<td>Costs fall by 48% from age 75 to 95</td>
</tr>
<tr>
<td>Van Weel and Michels (1997)</td>
<td>1991-1995</td>
<td>65+</td>
<td>Dutch acute care and primary care</td>
<td>y</td>
<td>n</td>
<td>No trend, one cohort, 8k Dfl per year</td>
<td>No trend, one cohort, 8k Dfl per year</td>
</tr>
</tbody>
</table>
Table 2.1 (continued): Summary of Cost-of-Dying Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Year(s) of Data</th>
<th>Age Group(s) Studied</th>
<th>Sector(s) of Health Care System Included</th>
<th>Lifetime comparison?</th>
<th>Intra-cohort comparison?</th>
<th>Decedent / Survivor cut-off</th>
<th>Decedent-Age Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Madsen, Serup-Hansen and Kristiansen (2002)</td>
<td>1995 All ages</td>
<td>Danish acute care and primary care</td>
<td>n</td>
<td>y</td>
<td>Last year vs. more than one year</td>
<td>Hospital costs fall by 70% from age 65 to 95+, Primary care costs fall by 33% from age 65 to 85+</td>
<td></td>
</tr>
<tr>
<td>Spillman and Lubitz (2000)</td>
<td>1974-1996</td>
<td>Medicare Expenditures, nursing home, and home care costs</td>
<td>y</td>
<td>n</td>
<td>Last 2 years / age 65 to last 2 years</td>
<td>Total costs rise by 22% from age 70 to age 90, Medicare costs fall 37%, nursing home costs rise by factor of 5x</td>
<td></td>
</tr>
<tr>
<td>Hoover et al (2002)</td>
<td>1992-1996</td>
<td>65-74, 75-84, 85+</td>
<td>Medicare Expenditures, nursing home, and home care costs</td>
<td>y</td>
<td>Last year vs. more than one year</td>
<td>Total costs stable from ages 65-74 to 85+, Medicare costs fall 35%, non-Medicare costs rise by factor of 2x</td>
<td></td>
</tr>
<tr>
<td>Roos, Montgomery and Roos (1987)</td>
<td>1973-1982</td>
<td>45-64, 65-74, 75-84, 85+</td>
<td>Canadian acute care, nursing home, and primary care</td>
<td>n</td>
<td>Each of last four years vs. eight years or more</td>
<td>Last four years hospital days rise 36% from age 65-74 to 75-84, then fall 14% to 85+, nursing home days rise by factor of 6.4x from 65-74 to 85+</td>
<td></td>
</tr>
<tr>
<td>McGrail et al (2000)</td>
<td>1986, 1993</td>
<td>65, 75-76, 85-87, 90-93</td>
<td>Canadian acute care, nursing home, home care, and primary care</td>
<td>n</td>
<td>Last year vs. more than one year</td>
<td>Age 65 to 90-93, medical falls 32% in 1986 and 36% in 1993, Social/nursing rises by a factor of 6.9x in 1986 and 5.2x in 1993</td>
<td></td>
</tr>
<tr>
<td>Yang, Norton, and Stearns (2003)</td>
<td>1992-1998</td>
<td>65 and higher</td>
<td>Medicare, Medicaid, hospital, nursing homes, and out-of-pocket costs</td>
<td>n</td>
<td>1 year or less to death versus 1 year or more to death</td>
<td>Total costs in last year of life stable, hospital costs fall 50% from 65-69 to 90-94, nursing home costs rise by factor of 5x</td>
<td></td>
</tr>
<tr>
<td>Busse, Krauth, Schwartz (2002)</td>
<td>1989-1995</td>
<td>20-85+ in five-year bands</td>
<td>German hospital days and costs</td>
<td>n</td>
<td>Each of last three years vs. more than 3 years</td>
<td>Average hospital days fall for 85+ vs. 65-74 by 36% in last year, 50%-60% in 2nd and 3rd last years</td>
<td></td>
</tr>
</tbody>
</table>
### Table 2.1 (continued): Summary of Cost-of-Dying Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Age - Time-to-Death Combined Effect</th>
<th>Time Trend in Age and Time-to-Death Effects</th>
<th>Other Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roos, Montgomery and Roos (1987)</td>
<td>The effect of time-to-death diminishes for both nursing home and hospital days. At ages 65-74, all eight years before death significantly different from year nine or more. For 85+ only last year different for hospital and last four years for nursing home</td>
<td>Not available</td>
<td>In first sample, using 20th quarter before death as comparison, significant difference remains only to quarter 7. Coefficients can be negative closer to quarter 20 (e.g. quarter 19 expected expenditures less than quarter 20)</td>
</tr>
<tr>
<td>Zweifel, Felder and Meiers (1999)</td>
<td>Quarters 1-6 significantly different from 8 in first time period. In second time period only quarters 1-3 (all ages) and quarter 1 (65+) significantly different. In second time period, effect of time-to-death appears reduced at older versus younger ages</td>
<td>Between first and second time period, effect of time-to-death appears reduced for all ages and older ages</td>
<td></td>
</tr>
<tr>
<td>Seshamani and Gray (2004b)</td>
<td>Significant for years 1 to 13. Time-to-death / expenditure curve gets flatter with older ages (i.e. time-to-death is less significant with age)</td>
<td>Time-to-death / expenditure curve gets flatter with more recent cohorts (i.e. time-to-death is recently less significant)</td>
<td></td>
</tr>
<tr>
<td>Seshamani and Gray (2004a)</td>
<td>Quarters 1-3, 5 and 8 significantly different from 20. Quarter 1 has negative coefficient (due to curtailed length-of-stay). In last quarter of life, costs peak at ages 80-85, decline thereafter</td>
<td>Not available</td>
<td>Different effects of age than Zweifel, Felder, and Meiers. Age effect is parabolic, rising to age 85 and falling thereafter</td>
</tr>
</tbody>
</table>
### Table 2.1 (continued): Summary of Cost-of-Dying Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Survivor-Age Trend</th>
<th>Decedent / Survivor Ratio</th>
<th>Other Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Madsen, Serup-Hansen and Kristiansen (2002)</td>
<td>Hospital costs rise by 66% from age 65 to 95+, Primary care costs rise by 12% from age 65 to 85 then fall by 29% from 85 to 95+</td>
<td>Hospital from 10 (65) to 1.8 (95), Primary from 1.2 (65) to 0.6 (95)</td>
<td>Not comparing individuals in one time period rather comparing last 2 years to earlier history among same cohort, mix changes to nursing homes</td>
</tr>
<tr>
<td>Spillman and Lubitz (2000)</td>
<td>No trend</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hoover et al (2002)</td>
<td>Total costs rise 144% from ages 65-74 to 85+, Medicare costs rise 56%, non-Medicare costs rise by factor of 3.6x</td>
<td>Total cost from 2.7 (age 85+) to 6.5 (ages 65-74)</td>
<td>Medicare ratio from 3.6 (age 85+) to 8.7 (age 65-74) and non-Medicare from 2.1 to 3.7 for same ages.</td>
</tr>
<tr>
<td>Roos, Montgomery and Roos (1987)</td>
<td>Hospital days rise 133% from age 65-74 to 85+, nursing home days rise by factor of 11.8x over same ages</td>
<td>Based on four-year average, hospital from 6.5 to 3.5, nursing home from 4 to 2.5</td>
<td>Hospital utilization is affected by pending death as much as eight years in advance. This effect declines with age. Primary care and nursing home utilization are not significantly affected by age at death or time to death</td>
</tr>
<tr>
<td>McGrail et al (2000)</td>
<td>Age 65 to 90-93, medical rises 150% in 1986 and 144% in 1993, Social/nursing rises by a factor of 30x in 1986 and 42.5x in 1993</td>
<td>1993 Medical from 18.1 (65) to 4.8 (90-93), Social/nursing from 13.5 (65) to 2.0 (90-93)</td>
<td>Total costs for decedents rise 40%-50% in between 65 and 90-93 while for survivors rise 6x-9x</td>
</tr>
<tr>
<td>Yang, Norton, and Stearns (2003)</td>
<td>Total costs rise by a factor of 4x from age 65-69 to 90-94, hospital costs rise slightly, nursing home costs rise more than 20x</td>
<td>From 6 at age 65 to 1.5 at age 95</td>
<td>Medicare and hospital costs fall sharply with age for decedents and rise gradually for survivors. Medicaid and nursing home costs rise sharply with age for decedents and survivors</td>
</tr>
<tr>
<td>Busse, Krauth, Schwartz (2002)</td>
<td>Average hospital days rise by 80% for age 85+ vs. 65-74 not in last three years of life</td>
<td></td>
<td>The fall in average hospital days for decedents is nearly equally attributed to lower probability of entering hospital and lower average lengths of stay</td>
</tr>
</tbody>
</table>
The combination of slow or no growth in total decedent costs and rapid growth in survivor costs with age leads to an increasingly small difference between decedents and survivors at older ages. The ratio of decedent to survivor costs for all services falls from 6 times or higher at age 65 to lower than 3 times at ages older than 85 (Hoover et al. 2002, McGrail et al. 2000, Yang, Stearns and Norton 2003). A smaller difference between decedent and survivor costs at older ages is perhaps not surprising. Since the remaining life expectancy of survivors is shorter at older ages, the distinction between decedents and survivors is less clear.

2.3.3 Time Trends in Decedent and Survivor Costs

The evidence thus far compiled from the cost-of-dying literature identifies a number of conflicting forces that could bear on health care systems as the population ages. On one hand, decedents in any age group cost more than survivors, suggesting that lower mortality rates would reduce expenditures. Countering this, as more individuals survive to older ages, the difference between decedent and survivor costs falls, so that further mortality decreases at these ages carry much less of a cost benefit. As average age at death rises with declining mortality, a greater percentage of the population may experience a longer period of morbidity so that, at the population level, expansion of morbidity may appear to hold.

Yet the compression versus expansion of morbidity debate introduced in Section 2.2 is not so much about how end-of-life morbidity changes with age as about how end-of-life morbidity at any age changes over time. One key issue, as the proponents of the compression of morbidity theory might argue, is whether the high cost of elderly survivors is likely to change over time. The typical 90-year-old of the future may be different in terms of health status, lifestyle, and preferences than the 90-year-old of today, and may as a consequence use the health care system in different ways. Insight into
potential future changes can only be gained by examining current changes as they occur and using these as a basis for projecting future developments.

Few cost-of-dying studies directly estimate time trends in either the ratios or in survivor and decedent costs separately. General trends can be inferred by comparing studies from different time periods, but care must be taken to ensure that the data and methods that support the studies are consistent and comparable.

Spillman and Lubitz (2000) and Lubitz, Beebe and Baker (1995) employ the same methodology, the same (Medicare) data set, thus enabling calculation of changes in Medicare costs from age 65 until two years before death and Medicare costs over the last two years of life for different ages to obtain an indication of trend. Table 2.2 shows the results of this calculation for ages 70 and 90. Both end-of-life care and regular care grew at faster rates for younger versus older ages, and survivor costs for all ages grew much faster than decedent costs.

Table 2.2: Changes in Medicare Expenditures, 1989-1996

<table>
<thead>
<tr>
<th>Age at Death</th>
<th>Medicare expenditures last 2 years of life</th>
<th>Medicare expenditures prior to last 2 years of life</th>
<th>Lifetime Medicare expenditures</th>
</tr>
</thead>
<tbody>
<tr>
<td>70</td>
<td>$22,590</td>
<td>$39,000</td>
<td>$12,921</td>
</tr>
<tr>
<td>90</td>
<td>$15,237</td>
<td>$25,000</td>
<td>$47,778</td>
</tr>
<tr>
<td>Inflation-adjusted</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>$34,337</td>
<td>$39,000</td>
<td>$19,640</td>
</tr>
<tr>
<td>90</td>
<td>$23,160</td>
<td>$25,000</td>
<td>$72,623</td>
</tr>
<tr>
<td>Growth, 1989-1996</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>14%</td>
<td>70%</td>
<td>34%</td>
</tr>
<tr>
<td>90</td>
<td>8%</td>
<td>45%</td>
<td>36%</td>
</tr>
</tbody>
</table>

* 1989 expenditures are in 1990 dollars while 1996 expenditures are in 1996 dollars. CPI inflation over this period grew 20%, while medical care CPI grew 52%. Inflation-adjusted results are in 1996 dollars, adjusted for medical CPI. Growth rates reflect inflation adjustment.

† Expenditures prior to the last 2 years of life begin at age 65 and therefore represent a different number of years for different age groups.

In contrast to the 1989-1996 comparison, a direct time trend analysis of Medicare expenditures provided by Lubitz and Riley (1993) for the period 1976-1988 finds that inflation-adjusted decedent and survivor costs grew at close to the same rate for all ages, with survivor costs growing slightly faster than decedent costs for ages 65-74 and decedent costs growing faster at ages beyond 75. Interestingly, growth rates for both decedent and survivor cost increased with age: costs for ages 65 to 69 were approximately 32% higher in 1988 than 1976, while costs for ages 85+ grew 44%. Overall, for all ages over 65, growth in survivor costs was 43% versus 40% growth in decedent costs.

These differences in trends in Medicare costs indicate how health care provision and consumption may have changed in past decades. After a period where the highest growth in Medicare costs occurred at the oldest ages, the more recent data suggest higher growth in expenditures for younger age cohorts and for surviving populations. The timing of the change coincides fairly closely with the period in which morbidity prevalence rates among the elderly began to decline and health-adjusted life expectancy began to grow relative to total life expectancy (see Section 2.2). The relationship between these coincidental trends is complex. More aggressive treatment for survivor conditions may be part of a broader focus on health among the new elderly cohorts that has contributed to their declining morbidity. Additionally, higher growth in costs for survivors could be caused by a higher success rate of treatment so that mortality rates fall and costs that would previously have been attributed to decedents now accrue to survivors. Relatively less growth in decedent expenditures and among the oldest cohorts could be due as much to changes in the health system as to individual health status. Despite mixed evidence on the cost-reducing potential of changes to end-of-life care such as hospice care, do not resuscitate orders, and other advanced directives (Scitovsky 1994) these developments may have had some effect.
McGrail et al. (2000) provide some additional context to the American Medicare trends by examining hospital and social/nursing costs among decedents and survivors in British Columbia, Canada for the years 1986 and 1993. In contrast to the Medicare data during the same time period, total inflation-adjusted per capita costs actually declined between the beginning and the end of the period for all ages. During the period, provincial budgets in Canada were under some pressure leading to constrained health care spending. Nevertheless, the relative patterns among decedents and survivors and among different ages confirm those from the Medicare studies considered above. Decedent medical costs – mainly hospital and physician visits – declined more than survivor costs, and experienced their largest decline for the oldest age group, 90-93. Nursing costs behaved differently from medical costs in that decedent costs rose over the period while survivor costs fell. Both the largest rises in decedent nursing costs and the largest drops in survivor nursing costs were experienced by the youngest age groups, so that the difference between the two widened significantly for the younger old and was nearly unchanged for the oldest old.

The contrast between developments in medical and social/nursing costs in British Columbia in combination with the Medicare trends from the US tells a story that fits relatively well with an improvement in elderly morbidity and changes in intensity and mix of health care service provision. Medical costs are evidently growing more quickly among survivors than among decedents; and among decedents they are growing more quickly in younger than older populations. At the same time, social/nursing costs are growing faster among decedents, particularly the younger decedents. The combination of reduced social care costs for survivors and increases for decedents among the younger age groups supports the assertion that in recent years, cohorts of seniors (survivors) are increasingly independent. With younger survivors accounting for the smallest decrease in medical costs at the same time as younger decedents are receiving the largest increase in social/nursing services, it appears – albeit from a relatively limited sample – that health care systems are improving their ability to identify and care for patients with the best prospects of recovery while providing social care for those that cannot be cured. For
older cohorts, aggressive medical care is being scaled back while the cost of social care remains elevated for decedents and survivors alike.

### 2.4 Time-to-Death Models of Health Care Expenditures

One step beyond comparing decedent and survivor populations within age cohorts is to calculate expenditures for known decedents in regular time intervals counting backwards from the date of death (e.g. Roos, Montgomery and Roos 1987; Miller 2001). Using these data, costs can then be modeled as a function of time-to-death, providing a comprehensive estimate of the effect of pending death on expenditure trajectories. In comparison to relative cost-of-dying studies, such models avoid issues that might be raised by dividing populations into decedents and survivors based on what is essentially an arbitrary, if convenient, threshold of time left alive. There is no theoretical reason why the point at which individuals enter their last 12 months should mark a natural health transition, such as that represented by the transition to the shaded portion of the bars in Figure 2.2.

Indeed, the exploratory work of Roos, Montgomery, and Roos (1987) indicates that the transition may occur much earlier than one year before death. The authors model hospital and nursing home days as a function of age, sex, and time-to-death, with time-to-death being represented by a series of dummy variables (taking the value 1 or 0) for each of the last eight years of life. This method compares utilization in these last eight years to that incurred by all individuals known to be more than nine years from death.

The results are stratified by age. For individuals less than 75 years old, utilization in each of the last eight years of life differs significantly from that in all years greater than nine for both hospitals and nursing homes, implying that the group who eventually died was experiencing higher average morbidity rates for an extended period of time prior to death.
For ages 75-84, the difference remains significant in all years for nursing homes, but for hospitals the difference is only significant through the sixth year before death. At ages 85 and older, however, the effect of time-to-death on hospital utilization is only significant (at levels of 5% or lower) in the last year of life while it remains significant in the last four years for nursing home days.

As in the cost-of-dying analyses, the time-to-death model employed by Roos, Montgomery and Roos (1987) finds a diminishing difference between decedents and survivors from younger to older ages. But where cost-of-dying expresses this difference in the terms of a declining ratio between costs for those in the last year of life versus all others, the time-to-death model expresses it by a decreasing length of time at which the difference is significant when the analysis is essentially repeated further and further from the event of death. By focusing the analysis on the length of time before death during which decedents and survivors of the same age can be distinguished from one another, the time-to-death empirical approach relates more directly to the question of end-of-life morbidity and health-adjusted life expectancy described in Section 2.2 and depicted in Figure 2.2. To be sure, health care expenditures may only be an indirect indication of health status. But the point in time before death at which decedent and survivor use of the health care system begins to separate provides a useful empirical estimate for the point where, on average, healthy life ends and end-of-life morbidity begins. Roos, Montgomery and Roos’s paper provides the foundation for an emerging literature of time-to-death expenditure modeling, which we review in the remainder of this section.

2.4.1 Estimating the Duration of End-of-Life Morbidity

As was the case in the cost-of-dying literature, in time-to-death models much depends on the way time-to-death is incorporated into the model and how the surviving population is characterized. As can be seen from the survey in Table 2.3, the majority of the time-to-death models include only known decedents in their sample (Zweifel, Felder and Meiers
1999; Seshamani and Gray 2002, 2004a, 2004b). Where only decedents are included, the comparison is typically established between a baseline of observations furthest from death and every subsequent observation as death approaches. The baseline for comparison in the literature reviewed here ranges from the 16th-to-last year of life (Seshamani and Gray 2004b) to the 8th-to-last quarter (Zweifel, Felder and Meiers 1999; Seshamani and Gray 2004a; Stearns and Norton 2004). Results show that expenditures begin to increase over a very long time period as death is approached, even from a baseline as far back as 16 years for hospital expenditures, where the difference becomes significant at year 13 before death (Seshamani and Gray 2004b).

Studies that include individuals with no known date of death in the baseline group for comparison are relatively few and use varying methodologies, so it is difficult to identify any consistent conclusions from their results. In their study of Medicare expenditures, Stearns and Norton (2004) use all individuals known to be nine or more quarters from death as their baseline cohort, and find that expenditures in each of the last eight quarters of life differ significantly from the average of this baseline. The effect of time-to-death appears even stronger than when only decedents are included, an unsurprising result since low-utilization survivors are now captured in the comparison.

Werblow, Felder, and Zweifel (2007) and Breyer and Felder (2006) also find a strong effect for time-to-death in their Swiss sickness fund data, using a slightly different technique for incorporating survivors and for time-to-death modeling in general. Instead of representing each year or quarter with a dummy variable, time-to-death is represented as a linear variable taking the value 1 in the last year or quarter of life, 2 in the second-last year or quarter, and so on. For the surviving cohort the time-to-death variable is maximized at the minimum known time of life. For example, any individual known to live more than five years is assigned a time-to-death of 60 months even if their actual time-to-death is much higher (Werblow, Felder and Zweifel 2007). Unfortunately, from the perspective of this review, representing time-to-death as a linear variable eliminates
the ability to identify a notional transition point – i.e. the beginning of the shaded bars in Figure 2.2 – that is made possible with dummy variables for each individual time period.

### 2.4.2 Time-to-Death and Age

Findings from time-to-death models generally confirm the cost-of-dying result that pending death increases expenditures, but that the magnitude of the difference tends to diminish at older ages. Seshamani and Gray (2002, 2004a, 2004b) find that hospital costs from Oxford, UK, in the last years peak at ages 80-85, declining thereafter. On the survivor side, Breyer and Felder (2006) calculate survivor costs that rise steadily with age using Swiss sickness fund data. The result of comparing age-expenditure curves for decedents and survivors is a time-to-death effect that declines with age, especially in the oldest age groups. Stearns and Norton (2004) use US Medicare data to directly measure the effect of the interaction between age and time-to-death. They find that the positive effect on expenditures of being in any of the last eight quarters preceding death is significantly diminished with age. A similar negative effect of age / time-to-death interaction is estimated in the Swiss sickness fund model of Werblow, Felder and Zweifel (2007).

The effect of age on health care expenditures after controlling for time-to-death is of particular interest to researchers and is germane to the policy questions that concern the future health care demands of an aging population. In particular, researchers have been asking the question of whether the positive relationship between age and health expenditure is simply an artifact of higher mortality rates at older ages. Grossman’s (1972) highly influential model of health care as an investment in human capital indicated that, for a given health status, a decreasing value of healthy time and decreasing expected length of life could reduce the equilibrium level of desired health as age rises. If this is so, any model that includes both time-to-death and age should estimate a negligible, or even negative, effect for age.
Table 2.3: Summary of Time-to-Death Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Year(s) of Data</th>
<th>Age Group(s) Studied</th>
<th>Sector(s) of Health Care System Included</th>
<th>Baseline for Comparison</th>
<th>Effect of Time-to-Death</th>
<th>Effect of Age, Controlled for Time-to-Death</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roos, Montgomery and Roos (1987)</td>
<td>1973-1982</td>
<td>45-64, 65-74, 75-84, 85</td>
<td>Canadian acute care, nursing home, and primary care</td>
<td>9 or more years before death versus each of the last 8 years of life</td>
<td>More significant for nursing home days than for hospital days, especially at older ages</td>
<td>Age controlled for time-to-death still has a positive and significant effect with the exception of hospital days for ages 85+. The effect of age diminishes for both hospitals and nursing homes with older strata</td>
</tr>
<tr>
<td>Zweifel, Felder and Meiers (1999)</td>
<td>1981-1992, 1991-1994</td>
<td>All ages, 65+, deceased only</td>
<td>Swiss sick fund, broad multi-sector</td>
<td>8th quarter before death</td>
<td>Quarters 1-6 significantly different from 8 in first time period. In second time period only quarters 1-3 (all ages) and quarter 1 (65+) significantly different</td>
<td>Negative effect, statistically insignificant, for ages 65+. Significant effect for all age sample (positive 1981-1992, negative 1991-1994). Coefficient for Age$^2$ is reverse sign in all cases</td>
</tr>
<tr>
<td>Seshamani and Gray (2004b)</td>
<td>1963-1999</td>
<td>Dying at ages 65+ in 1970 and after</td>
<td>UK data from a single hospital</td>
<td>16th year before death</td>
<td>Significant for years 1 to 13</td>
<td>Age is positive and significant. Age$^2$ negative but not significant</td>
</tr>
<tr>
<td>Seshamani and Gray (2004a)</td>
<td>1963-1999</td>
<td>Dying at ages 65+ in 1970 and after</td>
<td>UK data from a single hospital</td>
<td>20th quarter before death</td>
<td>Quarters 1-3, 5 and 8 significantly different from 20. Quarter 1 has negative coefficient (due to curtailed length-of-stay)</td>
<td>On expenditures, statistically insignificant both for Age and Age$^2$. On probability of utilization, age is significant and positive</td>
</tr>
</tbody>
</table>
Table 2.3 (continued): Summary of Time-to-Death Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Year(s) of Data</th>
<th>Age Group(s) Studied</th>
<th>Sector(s) of Health Care System Included</th>
<th>Baseline for Comparison</th>
<th>Effect of Time-to-Death</th>
<th>Effect of Age, Controlled for Time-to-Death</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stearns and Norton (2004)</td>
<td>1992-1998</td>
<td>66-99, survivors and decedents</td>
<td>Medicare</td>
<td>Not specified, assumed to be all persons 9 or more quarters from death</td>
<td>Significant in each quarter of the last two years of life</td>
<td>Remains almost as strong as uncontrolled effect of age. In both cases the coefficient for ages 66-70 through 90-95 are positive and significant relative to higher ages. Age 70-75 is the highest expenditure age range</td>
</tr>
<tr>
<td>Breyer and Felder (2006)</td>
<td>1999 All ages</td>
<td>Swiss sick fund, broad multi-sector</td>
<td>Entire population surviving 43 months of more beyond 1999</td>
<td>Stable (visible on graph) effect for time-to-death in each of the four years before death</td>
<td>Effect of Age is negative, effect of Age$^2$ positive, significance not given</td>
<td></td>
</tr>
<tr>
<td>Werblow, Felder and Zweifel (2005)</td>
<td>1999-2004</td>
<td>Swiss sick fund, broad multi-sector</td>
<td>Compared to all individuals 5 or more years from death</td>
<td>Time-to-death is a linear variable in this model. It is found to be significant for total costs, and to have greatest effect on hospital costs</td>
<td>Effect of Age and Age$^2$ are of opposite sign but signs change depending on the service measured. Broad result is that age has minor effect on expenditures, peaking at around 80 for the elderly, but age is more significant and positive for social and physician care</td>
<td></td>
</tr>
</tbody>
</table>
Table 2.3 (continued): Summary of Time-to-Death Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Age - Time-to-Death Combined Effect</th>
<th>Time Trend in Age and Time-to-Death Effects</th>
<th>Other Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roos, Montgomery and Roos (1987)</td>
<td>The effect of time-to-death diminishes for both nursing home and hospital days. At ages 65-74, all eight years before death significantly different from year nine or more. For 85+ only last year different for hospital and last four years for nursing home</td>
<td>Not available</td>
<td>In first sample, using 20th quarter before death as comparison, significant difference remains only to quarter 7. Coefficients can be negative closer to quarter 20 (e.g. quarter 19 expected expenditures less than quarter 20)</td>
</tr>
<tr>
<td>Zweifel, Felder and Meiers (1999)</td>
<td>Quarters 1-6 significantly different from 8 in first time period. In second time period only quarters 1-3 (all ages) and quarter 1 (65+) significantly different. In second time period, effect of time-to-death appears reduced at older versus younger ages</td>
<td>Between first and second time period, effect of time-to-death appears reduced for all ages and older ages</td>
<td></td>
</tr>
<tr>
<td>Seshamani and Gray (2004b)</td>
<td>Significant for years 1 to 13. Time-to-death / expenditure curve gets flatter with older ages (i.e. time-to-death is less significant with age)</td>
<td>Time-to-death / expenditure curve gets flatter with more recent cohorts (i.e. time-to-death is recently less significant)</td>
<td></td>
</tr>
<tr>
<td>Seshamani and Gray (2004a)</td>
<td>Quarters 1-3, 5 and 8 significantly different from 20. Quarter 1 has negative coefficient (due to curtailed length-of-stay). In last quarter of life, costs peak at ages 80-85, decline thereafter</td>
<td>Not available</td>
<td>Different effects of age than Zweifel, Felder, and Meiers. Age effect is parabolic, rising to age 85 and falling thereafter</td>
</tr>
</tbody>
</table>
Table 2.3 (continued): Summary of Time-to-Death Studies

<table>
<thead>
<tr>
<th>Study</th>
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<th>Other Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stevens and Norton (2004)</td>
<td>Significant in each quarter of the last two years of life. Age has a negative influence on the effect of time-to-death for all quarters before death. This effect is not so much on likelihood of utilization as on intensity of utilization</td>
<td>Not available</td>
<td>The effect of age is on likelihood of use. Expenditures given use are not sensitive to age. Model results used in projections predict Medicare expenses in 2020 9% lower than models not using time-to-death</td>
</tr>
<tr>
<td>Seshamani and Gray (2002)</td>
<td>Time-to-death has a fairly consistent (rising) effect in the last four years of life on expenditures, but survivor expenses rise steadily with age, so relative comparison falls</td>
<td>Not available</td>
<td>Data from (2004b) are used to project UK hospital expenditures 2002-2026. Projections using time-to-death are 12% lower than baseline. Expenditures due to last year of life as share of total projected to fall for every age group</td>
</tr>
<tr>
<td>Breyer and Felder (2006)</td>
<td>The coefficient of the interaction of the binary dummy variable for death and age is consistently negative and significant, so that older age reduces the effect of death (except for nursing homes). Interaction with time-to-death is not available.</td>
<td>Not available</td>
<td>Projections for 2050 assuming rise in life expectancy are compared using (1) time-to-death estimates; (2) age only survivor status-naive; (3) time-to-death with medical technology growth of 1%. The technology effect in (3) dramatically outweighs the difference between (1) and (2)</td>
</tr>
<tr>
<td>Werblow, Felder and Zweifel (2005)</td>
<td>Time-to-death outweighs the effects of age for hospital costs, but age is the more important effect for long-term care and home care costs</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The time-to-death literature is mixed on the question of the effect of age after controlling for time-to-death. In one of the first models of this type, Zweifel, Felder, and Meiers (1999) used Swiss sickness fund data from the years 1981-1994 and found that the effect of age was negative and statistically insignificant for the cohort of all individuals 65 and over. This result is the catalyst for their oft-cited assertion that age is a ‘red herring’ and is not in fact an important determinant of expenditures beyond the effect of increasing mortality. However, the result of age-neutral expenditures when controlled for time-to-death does not hold in other similar studies. The estimated effect of age is positive and significant in time-to-death models of Oxford hospital expenditures (Seshamani and Gray 2004a, 2004b), Medicare expenditures (Stearns and Norton 2004), and for long-term care and physician expenditures from the same Swiss sickness fund originally studied by Zweifel, Felder, and Meiers (1999; data from a later time period) (Werblow, Felder, and Zweifel 2007; Breyer and Felder 2006). The authors of the latter study do confirm the ‘red herring’ result for individuals that do not use long-term care services, effectively amending their thesis to a ‘school of red herrings’ consisting of selected sectors of the health care system.

It is not entirely surprising that the evidence on age as a ‘red herring’ is mixed. Our review of the cost-of-dying literature in Section 2.3 identifies several age trends that should be captured in the single coefficient of age in the time-to-death models. On one hand decedent costs rise with age for some services and fall with age for others, and in some cases rise to a certain age and then fall thereafter. On the other hand survivor costs generally rise with age for all services. Typically we might expect that, with survivors consisting of the majority of any population and costs rising with age, age would still have a positive effect on expenditures even after controlling for proximity to death. The ‘red herring’ studies of Zweifel, Felder, and Meiers (1999) and Werblow, Felder, and Zweifel (2007) show that age-neutrality of expenditures after controlling for death exists
in populations within five years of death. However, it is possible that the inclusion of longer-surviving populations in the analyses could alter this result.

2.4.3 Time Trends and Future Predictions

The greater detail of the statistical models in the time-to-death literature affords an opportunity for more specificity in identifying both time trends in the relationship between expenditures and death and in adjusting forecasts of future health expenditures. For data sets covering a number of years, calendar time itself can be included as a variable in the model specification, as is done in Zweifel, Felder, and Meiers (1999) and in the Seshamani and Gray (2004a; 2004b) studies. Coefficients of the calendar year dummy variables steadily rise with time, capturing the general rising trend in per capita health care expenditures that has been the rule in the developed world.

Were calendar time variables interacted with time-to-death variables in the models, the coefficients of these interaction terms would represent statistical estimates of the time trend in the effect of time-to-death. Unfortunately, the models reviewed here have not taken this step. But two of the studies do provide some evidence on time trends in other ways. Zweifel, Felder, and Meiers (1999) break their data into two separate time periods, 1981-1992 and 1991-1994. Using the 8th quarter before death as a benchmark, they find that expenditures in the last six quarters are significantly different in the first sample, while only the last three quarters (all ages) or last quarter (65+) are significantly different in the second, indicating that the duration of end-of-life morbidity – the shaded bars of Figure 2.2 – may be shrinking. It is important to note, however, that this shorter duration could be due as much to rises in costs in the 8th quarter before death as to declines in the quarters that follow, and that the analysis is limited to just the last two years of life, so that firm conclusions on compression versus expansion of morbidity cannot be drawn. Using a longer period for their analysis, Seshamani and Gray (2004b) plot time-to-death / expenditure curves for the last ten years of life for cohorts dying in 1970, 1980, and 1990,
showing that the slope of the curve has progressively flattened over time. The results of these two studies expand on the findings from the cost-of-dying literature that health care expenditures during time periods close to death are growing at slower rates than those further from death. While the evidence to date is fairly limited, the potential for time-to-death studies to provide more detailed confirmation of these trends, and to expand on them by examining how they change with age, presents an opportunity for future research.

The application of results to modify forecasts of future health care expenditures is also in its early stages. Typically, two different methods of assigning future expenditures are applied to one or more demographic projection scenarios. The first method assumes constant age-specific spending rates while the second incorporates the effects of time-to-death. By adjusting for the effects of time-to-death, the second method effectively takes into account the possible health expenditure effects of a change to future mortality. In the case of a demographic scenario where mortality rates do not change, little difference would be expected between the two methods.

The results of these projections are fairly consistent. As a rule, greater projected mortality reductions and longer projection periods lead to larger differences between projection methods. Stearns and Norton (2004) apply their Medicare time-to-death model to expenditure forecasts for cohorts aged 66-70 in 1998 and 2020, projecting lower expenditures than a strictly age-based model by 9% and 15%, respectively. Miller (2001) also uses a Medicare model to test the effect of time-to-death on different mortality scenarios through the year 2070. Under the most moderate mortality reductions (life expectancy in 2070 equal to 82.0), the reduction in forecast expenditures is 15%, while under the most aggressive scenario (life expectancy of 93.5) the reduction grows to 57%. The difference between the time-to-death and age-based models using Seshamani and Gray’s (2002) Oxford hospital data for projections to 2026 is estimated at 12%. 
Similar exercises using broader data sets – including social care such as nursing homes and home care – from continental Europe estimate lower differences between projection methods. Madsen, Serup-Hansen and Kristiansen (2002) reduce projections of Danish health care costs in 2020 by 3.4% using time-to-death methods, while Breyer and Felder obtain a reduction of 3.6% using Swiss sickness fund data and moderate mortality improvement through the year 2050. Since social care costs depend relatively more on age and associated frailty and less on time-to-death than medical services such as hospital treatment, the effect of including social care in projections of health care expenditures in an environment of falling mortality is to increase the positive influence of growing elderly cohorts and to decrease the importance of expense reductions due to fewer deaths.

Breyer and Felder add two interesting dimensions to their projection method. First, they introduce changes to end-of-life morbidity by shifting the age-expenditure curve by the amount of expected increase in life expectancy. This adjustment reflects the postponement of morbidity scenario 2b from Figure 2, and has the effect of reducing future expenditure projections by a further 4.4%, for a total reduction of 8.0% when the effect of time-to-death is also included. If the compression of morbidity scenario in 2c were to occur the reduction would be greater still.

A reduction of eight percent in expenditure forecasts, while relatively small, may still be important given the size of the health care sector in developed countries. But the second added dimension to the Breyer and Felder model helps put the reduction in context and points to other possibly more important sources of health care cost increases. The authors introduce an age-independent growth factor of 1% in per capita expenditures, attributed to technological change in medicine and based on a calculation for such change in the years 1970-1995. Stretched out through the year 2050, this 1% external growth adds 77% to the projected expenditures for that year, dwarfing the impact of different mortality and time-to-death scenarios. If the future is anything like the past in terms of technology and other drivers of health care cost inflation, attributions of rising health care
expenditures to population aging – even as the percentage of the population over 65 rises significantly – may be missing the true culprits.

2.5 Conclusions

The literature reviewed in this chapter creates a reasonably detailed picture of the role of age, morbidity, and death in health care expenditures. The picture is not a uniform one; there is considerable variation across categories of expenditures, as well as across age groups, and the trends are not always stable across jurisdictions or time periods. Compression of morbidity appears have taken place in recent years for any given age, but the duration and severity of morbidity increases at older ages, so an aging population may experience more morbidity at the aggregate level. Lifetime usage of hospital care grows relatively slowly with age at death to age 90 and not at all thereafter, while lifetime usage of nursing home and home care services experiences accelerated growth to age 90 and beyond.

The results point to the likely source of future age-driven pressures on expenditures. Social care services to maintain health and lifestyle are likely to grow much faster as a consequence of population aging than medical treatments provided by hospitals and doctors. Prescription drugs, which are used for both curative and maintenance purposes could fall somewhere in the middle. Yet in recent years, prescription drugs have been one of the fastest growing areas of the health care system, with costs growing for survivors and decedents alike. This discrepancy highlights the point made through the forecasts of Breyer and Felder (also see e.g. Mayhew 2000), that there are other inflationary forces at work, particularly technology, which certainly applies to the case of pharmaceuticals. Even as population aging accelerates it may not be decisive in determining how health care expenditures develop.
The existence of factors potentially more important than age in contributing to future health spending growth should not discourage further exploration of the relationship between, aging, mortality, and health care expenditures. Incorporating both age and proximity-to-death in expenditure models represents an important advance over simple age-based models, especially for the elderly where mortality rates are high. Taking forecasts of mortality improvement into account in predicted per capita expenditures as well as in population counts reduces forecast total expenditures. While the reduction in total future expenditures may be fairly small, the mix of services that account for these expenditures could change significantly, with important implications for policy and system management.

If the expenditure reductions due to falling death rates and lower costs of dying appear relatively minor, the end-of-life morbidity literature offers an alternative potential contributor to future cost reductions. Compression of morbidity at the end of life could further ease the pressure of aging on health care services by making individuals of a given age and proximity to death healthier and more independent than in the past. However, while the morbidity prevalence data broadly support compression of morbidity, health expenditures have not experienced a corresponding relative decline in the populations where this is taking place. In fact evidence points in the opposite direction, where the costs further from death have been growing at a faster rate and the time-to-death/expenditure curve has flattened. Among possible explanations for this apparent discrepancy are that declines in morbidity have been obtained with the use of more services. More evidence is needed for time trends in both morbidity and health expenditures relative to proximity to death to confirm these or other explanations.

The discrepancy between lower morbidity and higher expenditures also highlights the role of cohort effects. Comparing the expenditure / time-to-death profiles of different ages at any point in time compares cohorts that may be socio-economically very different and may use the health care system in very different ways. If the experience of the first
60 years of the baby boom generation are any indication, the cohort effect could be most dramatic with respect to the baby boom, which is wealthier, better educated, and more inclined to demand preventive and personalized health care services. While the baby boom is not yet part of the elderly population, recent growth in per capita health expenditures – in percentage terms has been higher for its age group, 45-64, than for the current elderly (CMS 2006). As cohorts currently experiencing higher expenditure growth age, overall costs may begin to accelerate even if mortality and morbidity continue to drop.

The potential policy responses to these complex dynamics are many. Here we highlight four. First, a continued shift in health care utilization from end-of-life care to prevention, chronic care, and symptom management has significant implications for resource and infrastructure planning for future system needs. A further migration away from hospital care is likely, while new resources may need to be committed to prescription drugs and home care, among other goods and services. Second, from the perspective of publicly funded expenditures, it will become increasingly important to ensure that value is received for preventive care such as diagnostics and precautionary procedures and services. Are the costs of these services justified by gains in future life expectancy, enhancements in quality of life, or anticipated reductions to future system costs? Third, costs within publicly-funded sectors (hospitals, doctors) appear to be growing less than costs financed through a public-private mix, evoking issues about who will be paying for what, whether cost escalation is due in part to relatively less cost control in these mixed sectors, and whether issues will emerge related to access to needed services. And finally, insofar as aging has provided a simple explanation for health care expenditure growth and diverted attention from the larger contributors, a better understanding of the role of aging should help focus the debate on inflationary pressures that could be addressed.

3.1 Introduction

The aging population – commonly expressed as a growing percentage over the age of 65 – is often identified as one of the primary drivers of health expenditure growth (Seshamani and Gray 2002; Meara, White and Cutler 2004; White 2007). Forecasters combine the observation of higher per capita spending at older ages with the larger proportion of the population in these age groups to demonstrate how aging may lead to higher expenditures (Dang 2001; EU 2003; Bains and Oxley 2004). However, age-specific per capita expenditures are not constant over time. In the United States, while inflation-adjusted per capita health spending grew at an annual rate of 0.7% for all ages between 1987 and 1999, growth for the 65+ population was half that rate or lower, and among those 85 and older per capita spending declined 0.2% per year (BLS 2006; CMS 2006). Lower growth rates among older age cohorts mitigated the effect of general population aging.

One possible reason for the low expenditure growth at older ages could be reduced mortality. Between 1985 and 2000 U.S. mortality rates fell by 15.5% for the cohort aged 65-74 and by 4.5% for those 75 and older (CDC 2006). With mortality rates falling, the share of Medicare expenditures attributed to individuals that died in a given year has fallen. Lubitz and Riley (Lubitz and Riley 1993) attributed 31% of 1980 Medicare expenditures to decedents, while Hoover (Hoover et al. 2002) found this figure had dropped to 26% during the period 1992-1996.
With the aging trend in developed economies set to accelerate in the coming decades (OECD 2006), there is growing value in refining our understanding of health expenditures among the elderly, and how these might respond to different scenarios for changes in mortality and life expectancy. One approach to achieving this objective is to separate cohorts according to their proximity to death. Using individual retrospective data, where the date of death (or continued survival status) is known, each age group can be classified according to the minimum number of years remaining in their lives and the expenditures for each class can be measured separately and compared.

The most common applications of this type of method in the literature compare the expenditures and/or utilization of individuals who die in a given year (‘decedents’) to those of the same age who continue to live beyond that year (‘survivors’). These ‘cost-of-dying’ studies can provide valuable insight into the way in which health care resources are allocated. For example, studies have shown that the average amount of spending on decedents declines with age at death for hospitals and the U.S. Medicare program (Gornick, McMillan and Lubitz 1993; Lubitz and Riley 1993; Lubitz, Beebe and Baker 1995; McGrail et al. 2000; Levinsky et al. 2001; Miller 2001; Busse, Krauth and Schwartz 2002; Hoover et al. 2002; Madsen, Serup-Hansen and Kristiansen 2002; Polder, Barendregt and van Oers 2006) while it increases with age at death for the U.S. Medicaid program, nursing homes, and home-based care (McGrail et al. 2000; Spillman and Lubitz 2000; Hoover et al. 2002; Yang, Norton and Stearns 2003; Polder, Barendregt and van Oers 2006). In contrast, for survivors, the average cost of all services rise with age, and dramatically so for nursing homes and home care (McGrail et al. 2000; Hoover et al. 2002; Yang, Norton and Stearns 2003; Polder, Barendregt and van Oers 2006).

These results suggest that, to use the dichotomy employed by Polder, Barendregt and Van Oers (2006), treatment of health crises associated with death shifts from medical “cure” to social “care” services for older ages, while the provision of social care to survivors grows with age. Each of these trends suggests that older populations and longer life
expectancy could increase pressure on social care resources. However, it is not clear from the literature how these observations have changed over time. The past several decades have witnessed a shift in many jurisdictions from facility-based to community-based care; increases in pharmaceutical utilization and outpatient procedures (Strunk, Ginsburg and Gabel 2002); significant decreases in inpatient hospital admissions and lengths-of-stay (Sochalski, Aiken and Fagin 1997; Busse, Krauth and Schwartz 2002; Strunk, Ginsburg and Gabel 2002); and declines in age-specific mortality and morbidity (Freedman, Martin and Schoeni 2002; Fries 2003; Mathers et al. 2004). Measuring how decedent and survivor expenditures have responded to these trends would help to inform expectations for future expenditures given assumed continuation of or changes to the underlying population health and health care policy environment.

There are relatively few cost-of-dying studies that include comparisons of their results over calendar time. Lubitz and Riley (1993) found that US Medicare expenses grew more rapidly for ages 75 and older as compared to ages 65-74 between 1976 and 1988. In both age groups there was little difference between the expenditure growth rates for decedents and survivors. The studies of Spillman and Lubitz (2000) and Lubitz, Beebe and Baker (1995) use similar data in different time periods and can be combined to derive comparative results for the period 1989 to 1996. In contrast to the Lubitz and Riley findings for 1976-1988 the comparison of 1989 and 1996 Medicare data shows significantly higher growth in survivors’ versus decedents’ costs, and higher growth at younger versus older ages.

McGrail et al (2000) provide a comparison of a more comprehensive set of decedent and survivor health expenditures for the years 1986 and 1993 in British Columbia. They also find that the costs of medical care (roughly comparable to the US Medicare program) grew faster for survivors and younger ages than for decedents and older ages, respectively. However, costs of social care services such as home care and nursing home care behaved differently: decedents’ costs grew faster than survivors’ did.
These initial results raise two important issues concerning forecast of future health expenditure growth. First, differing rates of cost growth among decedents and survivors will change the way projections of future mortality rates influence expenditure forecasts. If life expectancy continues to grow (i.e. mortality falls), the number of people dying will not grow as fast as the number of people aged 65 and over, at least in the near term. Furthermore, a greater proportion of deaths will take place at older ages, where the cost of dying is lower. To the extent that dying individuals account for a disproportionate share of overall expenditures, growing life expectancy would be expected to mitigate expenditure growth due to aging.

Models that take into account the cost of dying and assume mortality declines have predicted expenditures between 3% and 57% lower than simpler models that assume constant age-specific costs, with the range depending on the services included in expenditure estimates and the amount of mortality improvement assumed. (Miller 2001; Madsen, Serup-Hansen and Kristiansen 2002; Seshamani and Gray 2002; Breyer and Felder 2006) If, however, differing rates of cost growth among decedents and survivors cause the gap between decedent and survivor costs to narrow or widen, the results of these models would change. To improve accuracy, any observable historical trend in the relationship between decedent and survivor costs should be taken into account in demographic-based expenditure forecasts.

Our study seeks to shed light on the question of time trends in the cost of dying among the elderly. We expand on the existing literature by using a longer – and more recent – time period and by tracking results year by year instead of only comparing the end points. The study covers a broad spectrum of health care services, using data from British Columbia Linked Health Database (BCLHD), the same source used in McGrail et al. (2000).
In Section 3.2 we provide the policy backdrop for Canadian health care, and the province of British Columbia specifically. Section 3.3 introduces the data source, while Section 3.4 describes the data in more detail, as well as the assumptions and manipulations undertaken to prepare the data for our analysis. Section 3.5 provides the results, while the final sections address the limitations and the implications of our study.

3.2 Policy Context

The study period – as described in greater detail in the Section 3.4 – covers the years 1991 through 2001. The 1990s saw significant changes in both health care spending and health care policy in most Canadian provinces, and British Columbia was not an exception. After more than a decade (1980 to 1991) of inflation-adjusted growth at approximately 3%, per capita health care spending in Canada in 1991 was second only to Switzerland and the United States (Schieber, Poullier and Greenwald 1994; CIHI 2006). Yet by this time Canada was confronting both an economic recession and growing voter and lender pressure to rein in unwieldy government deficits. Real growth in health care spending slowed significantly in 1992, and was negative for four consecutive years beginning in 1993 (Romanow 2002; CIHI 2006).

In 1993, Canada elected a new Liberal government with a mandate to bring the federal deficit under control. This was done largely through cuts in federal transfers to the provinces. Federal transfer programs were targeted at a basket of social services delivered by the provinces and supported by the federal government, the largest of which were health care and education. After growing at an annual rate of 2.8% between 1981/82 and 1991/92, inflation-adjusted transfers grew by only 0.7% per year in the following four years, and then fell at an annual rate of 8.2% in the next two years (Romanow 2002). With an improvement in the federal fiscal condition, the end of the decade saw a return to rapid growth in real transfers, which expanded at a 5.6% annual rate from their low point in 1997/98 to 2001/2002 (Poschmann 1999; Romanow 2002).
While post-secondary education spending bore a significant portion of the decline in federal transfers, health care spending, which is the largest provincial budget item, was restrained in all Canadian provinces during the early and mid-1990s. British Columbia was no exception, as can be seen in Figure 3.1 (CIHI 2005). Inflation-adjusted total public health spending growth, depicted by the bold line, declined from 1992 to its lowest point in 1996, the year in which federal transfers dropped by 10%. Growth remained low until 1999 when new federal funding was announced.

Figure 3.1 also demonstrates substantial variation both within and between growth rates of different areas of the health care system. This reflects a combination of general trends – such as increasing use of prescription drugs – and more specific changes in the British Columbia policy environment. The 1990s saw significant health policy activity in B.C.. In 1991, a report to the government was delivered by the Royal Commission on Health Care and Costs. In response to this, the New Democratic Party announced a policy change in 1993 which provided for the establishment of regional health authorities with substantial decision-making power and accountability to the public through election (BC Health 1993).
It was expected that the new power vested in the regional authorities could balance what was thought to be excessive power in existing health care institutions such as hospitals and the medical associations (Davidson 1999), and allocate more resources to preferred programs such as health prevention and home care. The pressure on hospital spending growth in the early 1990s can be seen in Figure 3.1, with hospitals consistently lagging other sectors.

The goals of the policy change were substantially watered down in 1995, as a waitlist crisis emerged for various surgical procedures, and the policy focus was forced to shift from improving outcomes to ensuring access (Ramsay 1998; Davidson 1999). When the Regional Health Authorities (RHAs) were finally commissioned in 1997, the
environment was quite different from the one envisioned in the 1993 policy. Board members were appointed instead of elected and the bulk of new spending was committed to hospitals and specialist physicians instead of prevention and community care. Waitlist pressures for surgical procedures were reduced by approximately half between 1995 and 2001 (Ramsay 1998; Levy et al. 2005; BC Health 2007).

With spending being directed to hospitals and physicians, other services such as community care bore the brunt of any budget squeeze. In 1999, the BC Ministry of Health initiated a policy in which access to community care was restricted to those with the greatest need. While those who met the access criteria were to receive higher levels of service, the overall impact of the changes was intended to control continuing care spending (CHSPR 2007a; McGrail 2007).

Residential long-term care also experienced limited growth during the study period. After increasing by 18% in the 1980s to over 24,000 beds, the capacity of the publicly-funded long-term care system remained static during the 1990s (McGregor et al. 2006). Rapid growth in the elderly population meant that the ratio of long-term beds per elderly individual fell during the decade, a trend common to most long-term care systems in North America and other Western economies (Miller 1993). The trend reflected a desire to deinstitutionalize eldercare, moving the location from the nursing home to the community (Coyte and McKeever 2001).

3.3 Data Introduction

The British Columbia Linked Health Database (BCLHD) contains vital statistics as well as individual-level utilization records for hospitals, physicians’ services, prescription medicines, and home- and facility-based continuing care. We use these data to estimate
the costs of services utilized for each individual in each year, and relate these costs to an individual’s survivor status and known date of death (if any).

In British Columbia, as in all of Canada, the majority (approximately 70%) of health care expenditures are financed by the government (CIHI 2005). Ninety-four percent of hospital and 99% of physician expenditures are publicly financed. While prescription drugs are not universally covered, coverage is provided to the poor and the elderly (over 65), similar to the Medicaid program in the United States. Although the Canadian Institute for Health Information (CIHI) does not report on expenditures in a category directly analogous to BC’s continuing care, public coverage for the three categories in which continuing care would mostly fall was 87% for ‘other institutions’ and 85% for ‘other health spending’, and 9% for ‘other professionals’.

Overall, public coverage of health spending in BC was 73% in 2002. Since the BCLHD covers all public utilization records for all individuals in the province, the data source provides a highly comprehensive view of the true utilization patterns that are prevalent in the population, and avoids the selection problem that may be present in more limited datasets from other jurisdictions.

The BCLHD was established in 1988 by a cluster of researchers at the University of British Columbia (UBC), the BC Ministry of Health, and the BC Cancer Agency with the goal of linking individuals’ interactions with the health care system over time. The database integrates and links health service records, population health data, and census statistics from 1985 onwards through use of a unique, but encrypted, Study ID (CHSPR 2007b).

Research use of the BCLHD commenced in 1996 after an agreement between the BC Ministry of Health and the BC Privacy Commissioner that governed use of the data.
Access to the database is granted by the Ministry of Health. Researchers complete a Data Access Request form (DAR), in which they specify the data sources (e.g. hospital separations, medical billings, census, vital statistics, etc.) they are interested in; the elements within each data source they want included; and the definition of the cohort for which they are requesting the data. The Ministry of Health grants approval after consultation with the custodians for each data source requested in the DAR.

The DAR for this study was originally submitted in September 2004. Data was requested from the following five sources:

1. Medical Services Plan Registration and Premium Billing (Contains all individuals registered and eligible for provincial health coverage. Used as a census to determine the population size and for birth and death dates of individuals)
2. Medical Services Plan Payments (Contains all physician billings reimbursed by the province)
3. PharmaCare (Contains all pharmaceutical prescriptions partially or fully reimbursed by the province. The PharmaCare plan covers all BC residents 65 years of age and over)
4. Hospital Separations (From the Discharge Abstract Database, contains records for every inpatient admission as well as for day surgeries)
5. Continuing Care (Contains records of government-funded residential care, adult day care, home support, and home visits by nurses and other professionals)

The cohort for which we requested the data was defined as all individuals aged 65 or over in each year. Individuals appear in our dataset the year they turn 65 and drop out from the dataset due to death or departure from the province. We chose 65 as our cut-off since PharmaCare coverage is not provided to the under-65 population on a universal basis, so that government data on drug costs for this cohort would not be comprehensive. Furthermore, since deaths for ages 65 and older account for more than 70% of all deaths
and since death rates are much higher at older ages (CDC 2006; Statistics Canada 2007), from the perspective of health care budget impacts cost-of-dying analysis is most important for the elderly.

The database is maintained by UBC’s Centre for Health Services and Policy Research (CHSPR). Once approval is granted by the BC Ministry of Health, CHSPR programmers then prepare the data for release according to the request.

Due to a backlog of requests, approval for access took slightly more than a year and the data were received in November 2005. After a familiarization process with the data supplied, it was determined that more data were needed from the hospital and Continuing Care files so an amendment to the request was submitted. The amended data were received in July 2006.

The data were requested for the full duration of the time period covered: i.e. from 1985 to the most recent year. At the time the data were prepared the most recent year for which data were available was 2003. Some files were based on the provincial fiscal year, ending March 31st. As a result, the latest calendar year for which data from all files were available for the full year is 2002. Due to the way in which years are adjusted for decedents to align year-end with the date of death (described later in this section), it was necessary to stop the analysis at 2001.

Two considerations led to the decision to begin the study in the 1991 calendar year, as opposed to in 1985. First, Continuing Care data collection was standardized only in 1990. Records were available for earlier years, but their reliability is not guaranteed by the custodians. Continuing Care was provided by CHSPR in two separate files: one for 1985-1989 and a second for 1990-present. The data were different in the two files, and
the duration of service episodes cannot be estimated for 1985-1989 because end dates are not available.

The second reason to begin the study in 1991 was due to the hospital costing methodology. As is later described in greater detail, hospital costs are estimated by multiplying the Resource Intensity Weight (RIW) of each record by a cost per weighted case obtained from the Ministry of Health. RIWs are based on factors such as Case Mix Group (CMG) for inpatient admissions or the Day Procedure Group (DPG) for outpatients (similar to American DRGs); primary and secondary diagnoses; and length-of-stay. The calculation methodology for RIWs, in addition to the CMG and DPG classifications, were developed by the Canadian Institute of Health Information (CIHI) (CIHI 2002, 2007). CMGs and RIWs are available only from the 1990/1991 fiscal year, so that the first complete calendar year with RIWs available is 1991. To estimate costs for hospital days in earlier years would require either replicating the CIHI method with different data or using a standard day rate instead. Given that the Continuing Care data were also effectively unusable prior to 1990 it was decided to begin our data analysis from 1991.

In the following section we describe the methods used to calculate utilization and costs for each of the individual services and then the method by which these costs were combined and assigned to different ages and times-to-death, in preparation for the cost-of-dying analysis.
3.4 Data Details and Manipulation

3.4.1 Medical Billings and Pharmaceutical Prescriptions

Medical billings and pharmaceutical prescriptions data were, in comparison to the hospital and continuing care data, relatively straightforward to handle. Since each file contained the dollar value of the service or prescription, there was no challenge in converting utilization to costs. From each file we simply used the Unique Study ID of individuals, and the date and cost of the service. In the case of pharmaceutical prescriptions, we used the total amount paid – the sum of the ingredient cost and the professional dispensing fee – as the cost.

3.4.2 Hospital Separations

The hospital separations database contains a great deal of data regarding the diagnosis, services and outcomes of each hospital visit. We requested and received data concerning: the admission and discharge date; discharge reason and destination; primary and secondary diagnoses; most responsible diagnosis; the case mix group (CMG) into which the patient was classified; the resource intensity weight (RIW) for that patient’s stay; the admission category (urgent or elective); the level of care (acute, day surgery, rehab, extended, etc.); the code for the specific hospital where the care took place; and several other fields.

In order to calculate the costs of each hospital episode we first determined the length of stay, equal to the separation date minus the admission date plus one. We could then apply a per diem rate based on the billing rate for external claims or some other estimation (e.g. see Hollander 2001) or, more specifically, we could use the RIWs and CMGs to differentiate among cases according to their severity. Choosing the latter
method for its improved specificity, we determined the RIW for each stay and multiplied that RIW by the cost per weighted (CWC) case for that year. Special considerations needed to be taken into account for both the RIW and CWC.

### 3.4.2.1 Resource Intensity Weights (RIW)

RIWs are calculated by the Canadian Institute for Health Information (CIHI) using Canadian data to model how case costs and expected length of stay vary according to CMG, complexity, and age (CIHI 2007). Estimates are made for both acute care inpatients and ambulatory care. Across Canada, the average RIW is set to 1.0. Average RIW in British Columbia has been somewhat higher than the 1.0 Canadian average, and for seniors the average is significantly higher than one (Hollander 2001).

Expected length of stay (ELOS) is calculated using regression analyses, and adjusted for three different age categories (0-17, 18-69, 70+). The per diem resource intensity of a particular case can be estimated by dividing the estimated RIW by the actual length of stay. The average RIW per day is equal to the average RIW divided by average length of stay. Hollander found that the higher average RIW for seniors is due almost entirely to longer lengths of stay, so that RIW per day for seniors is not significantly different from the general population.

In our data the average RIW per day across all episodes in the study period was 0.2101. It is important to note that RIWs are based on average observed experiences in Canada and are not specific to any individual province, let alone specific hospitals or individuals. In addition, by calculating a value for RIW per day, we are smoothing the resource consumption of individual episodes. Actual resource consumption is likely to be more volatile and more concentrated at the beginning of the stay when operations are more likely.
Two different calculation methods are available for the RIW during the study period, which CHSPR has labeled as RIW 2001 and RIW 2003. RIW 2003 is based on the International Classification of Diseases (ICD) 10, which was first used in BC in fiscal year 2001/2002. CIHI recommends continuing to use RIW 2001 (based on ICD9 codes) until the reliability of RIW 2003 can be confirmed through the analysis of several years of data (CIHI 2004). Furthermore, RIW 2003 is not available for years earlier than 2001/2002. As a result, we use RIW 2001, but note that there may be some discontinuity between 2000/2001 and 2001/2002 since RIW 2001, switches from being applied to ICD9 data to being applied to ICD10 data.

A second question concerns those episodes for which no RIW is available. As can be seen in Table 3.1, Acute Care and Day Surgery make up over 95% of all separations and all have RIWs assigned. Rehabilitation also has assigned RIWs for nearly 100% of its episodes. The challenge is for the 3.6% of episodes that do not fall into these categories. While these episodes only account for 3.6% of the total, since they are often a long-stay type of chronic or long-term care, the length of the episodes is much longer than the remaining 96.4% and could represent a significant cost. In fact, the 3.6% of episodes that had no RIW attached had an average length of stay of 242 days and represented 55.0% of all hospital days. While we were able to eliminate 85% of these days due to double-counting with continuing care days (see Section 3.4.5), even after this elimination, hospital days with no RIW attached represented 15.5% of total days.

Although no Extended Care episodes during the study period had an RIW available, there were 89 episodes with separation dates between January 1st 2002 and March 31st 2003 in our data that did have RIWs assigned. The average RIW per day for these episodes was 0.1096, just slightly more than half of the average RIW per day of 0.2101 for all episodes during the study period. Given the cost-per-weighted case estimates described in the Section 3.4.2.2, an RIW of 0.1096 translates to per diem costs ranging from $263 to $314.
in 1991 dollars. In comparison, Hollander (2001) used inter-provincial billing rates to estimate a per diem for all hospital stays of $400-$500 in 1991 dollars. The lower rate seems appropriate for the non-acute nature of extended hospital stays.

Table 3.1: Hospital Separations by Level of Care and RIW Status, 1991-2001

<table>
<thead>
<tr>
<th>Level of Care</th>
<th>Total Episodes</th>
<th>Total Days</th>
<th>Days per Episode</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (Acute Care)</td>
<td>1,504,685</td>
<td>16,265,773</td>
<td>10.81</td>
</tr>
<tr>
<td>D (DPU/GEAR - geriatric assessment unit, discontinued after 2000/01)</td>
<td>0</td>
<td>1,010,018</td>
<td>59.99</td>
</tr>
<tr>
<td>E (Extended care units)</td>
<td>0</td>
<td>55,152</td>
<td>348.44</td>
</tr>
<tr>
<td>I (Intermediate care)</td>
<td>0</td>
<td>1,462</td>
<td>281.50</td>
</tr>
<tr>
<td>L (Long-term care holding)</td>
<td>1</td>
<td>49</td>
<td>42.78</td>
</tr>
<tr>
<td>R (Rehabilitation)</td>
<td>6,001</td>
<td>282,027</td>
<td>47.00</td>
</tr>
<tr>
<td>S (Day Surgery)</td>
<td>857,485</td>
<td>857,730</td>
<td>1.00</td>
</tr>
</tbody>
</table>

With this information in hand, the options considered for assigning costs to long-stay levels of care were four: 1) assign a per diem rate similar to that used in Hollander (2001) to all D, E, I and L episodes; 2) assign the average RIW per day (case RIW divided by case length of stay) for the 89 Extended Care episodes to all D, E, I, and L episodes; 3) assign the average RIW per day for the 89 Extended Care episodes only to the remaining 57,047 Extended Care episodes with no RIW; 4) keep only A, R, and S level-of-care episodes.

Given the scale and scope of the data and the analysis; the numerous assumptions made; and the relative, as opposed to absolute, nature of the intended results, we opted to assign the lower RIW rate based on the 89 Extended Care episodes to the long-stay levels of care episodes. As a result we chose option 2), and applied the RIW per day of 0.1096 to all D, E, I and L episodes.

As mentioned earlier, analysis of Continuing Care data indicated that further adjustment was necessary in the long-stay levels of care hospital episodes. We determined that some care episodes were counted in both the hospital and Continuing Care databases. Where
this was the case, we eliminated these episodes from the hospital data and counted them as Continuing Care only. This is described in greater detail in Section 3.4.5.

3.4.2.2 Costs per Weighted Case (CWC)

To attach a cost to each estimate, the calculated RIW needs to be multiplied by the cost per RIW, also referred to as the cost per weighted case (CWC). CWCs for each year are estimated by dividing the sum of all eligible hospital costs by the total of all RIWs incurred during that year.

We obtained CWC estimates for the years 1991-1993 and 1996-2004 from the Health Information Support unit of the BC Ministry of Health (Lee 2004). While these were available for each individual hospital, since the hospital codes in our data were encrypted we were unable to link individual hospitals to their site-specific CWC. As a result we applied a uniform provincial CWC to all hospital separations for each year. To bridge the gap for the missing CWCs in 1994 and 1995, we linked the 1993 and 1996 estimates (which were quite close, at $2936 and $2920, respectively) by a straight line. The estimated CWCs for 1991 through 2003 are presented in Table 3.2, with the two approximated years in bold. The data and method used for inflation adjustment is described in a later section.

The Health Information Support unit stressed several limitations to consider in interpreting the CWC data. First, CWC was originally developed to compare hospitals for efficiency. It was not the intent to use this measure to develop individual case costs. Second, when using a provincial CWC, it should be noted that not all hospitals reported either or both of net inpatient costs and total weighted cases, so the provincial figure is not comprehensive. Some individual cases will take place in hospitals that did not contribute to the provincial CWC figure. Finally, the methodology for calculating CWCs
changed in both 1993 and 1998. Before 1998, BC used an internally developed method for assessing these costs, while after 1998 a standardized method provided by CIHI was applied. The change in methodology in 1993 was a shift in BC’s internal methodology. While all methodologies applied the same general approach of summing and comparing inputs (dollar costs) and outputs (RIWs), the differences in methods concerned the level of detail; the order of steps in the calculation process; available data for calculation; proxies used; and the allocation of regional costs (Lee 2004).

Table 3.2: British Columbia Cost per Weighted Case by Year 1991-2003

<table>
<thead>
<tr>
<th>Year</th>
<th>CWC</th>
<th>Inflation Adjusted (2002 dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991</td>
<td>$2675</td>
<td>$3444</td>
</tr>
<tr>
<td>1992</td>
<td>$2963</td>
<td>$3704</td>
</tr>
<tr>
<td>1993</td>
<td>$2936</td>
<td>$3556</td>
</tr>
<tr>
<td>1994</td>
<td>$2930</td>
<td>$3475</td>
</tr>
<tr>
<td>1995</td>
<td>$2925</td>
<td>$3440</td>
</tr>
<tr>
<td>1996</td>
<td>$2920</td>
<td>$3399</td>
</tr>
<tr>
<td>1997</td>
<td>$2940</td>
<td>$3378</td>
</tr>
<tr>
<td>1998</td>
<td>$3246</td>
<td>$3626</td>
</tr>
<tr>
<td>1999</td>
<td>$3761</td>
<td>$4109</td>
</tr>
<tr>
<td>2000</td>
<td>$3736</td>
<td>$3971</td>
</tr>
<tr>
<td>2001</td>
<td>$4429</td>
<td>$4564</td>
</tr>
<tr>
<td>2002</td>
<td>$4946</td>
<td>$4946</td>
</tr>
<tr>
<td>2003</td>
<td>$5406</td>
<td>$5300</td>
</tr>
</tbody>
</table>

Bold values are unavailable and estimated by interpolation

*Source:* (Lee 2004)

The change to a CIHI methodology in 1998 coincides with a shift from a relatively flat trend in inflation-adjusted CWCs to a fairly strong increasing trend. While it is certainly possible that the change in methodology contributed to the shift towards increasing costs, it is likely not the most responsible factor. The falling CWCs observed in the early-to-mid-1990s may reflect the policy environment at the time (see Section 3.2). The CWCs
received from the Ministry of Health are reasonably close to data on public hospital spending. Figure 3.2 compares the trend in CWC from 1991 to the trend in total public spending on hospitals over the same period, as provided by CIHI (CIHI 2005). The CWC is more volatile, and there is a departure between 1993 and 1997, where CWC is falling while public hospital spending is rising. However, over the entire study period, the trends are quite similar. The impact of volatile CWC inputs on our study is discussed further in our limitations section.

**Figure 3.2: Comparison of Cost per Weighted Case (CWC) and Total Hospital Spending, Normalized (1991=100), 1991-2002, Inflation-Adjusted**

![Comparison of Cost per Weighted Case (CWC) and Total Hospital Spending](image)

*Sources: (CIHI 2005; Stats Canada 2007b; Lee 2004)*

### 3.4.3 Continuing Care

Continuing Care data were provided in five separate files: a Master Record, with client information including a client number specific to Continuing Care, marital status and death date; a History Record, with history start and end dates; an Assessment Record,
with the date of assessment and the recommended type and level of care approved by the assessor; Care Advice for LTC, containing a record of service episodes for residential care, adult day care, and home support services; and finally, Care Advice for Direct Care Services, containing a record of service visits by care professionals such as nurses, occupational therapists, and physiotherapists.

We use three of the five files in our analysis. The master record is used for the death date, to cross check with the death dates from the Registry file. The procedure by which death dates from the Registry and LTC files were reconciled is described in the next section.

The Care Advice for LTC file is used to calculate the number of days on service for residential care, adult day care, and home support services. And Care Advice for Direct Care is used to calculate the number of professional visits received in a period of time.

The Direct Care file provides a Service Start Date and a Last Visit Date for each record, along with a count of visits that took place during this period. The duration of records can sometimes cover multiple years. Of the 731,403 total Direct Care records 41,504, or 5.7% covered durations longer than 365 days. Furthermore many more records of length less than 365 days still overlap more than one calendar period for the analysis. For such records, visits were assigned to different years using the assumption of a uniform time distribution of visits.

We do not use the assessment record file because the pricing source we used for Continuing Care services (Hollander 2001) builds in the cost of assessors and case managers to the per visit and per diem rates.
3.4.3.1 Costing for Continuing Care

Our first hope for costing Continuing Care services was to obtain direct Ministry of Health estimates similar to those we received for the hospital cost per weighted case. Unfortunately, after lengthy conversations with Ministry personnel we were told that there was too much variability in estimates and the information was too sensitive to release.

Failing access to the government source, we use detailed calculations made by Marcus J. Hollander in connection with the National Evaluation of the Cost-Effectiveness of Home Care (2001). Hollander uses the same BCLHD data to calculate total costs for residential and community clients in BC for the years 1991/92 and 1996/97. Hollander worked for the BC Ministry of Health during the 1990s and applied unit costs to obtain per diem rates for facility care, by level of care, and for adult day care and homemaking services. Costs for direct care visits were calculated using an assumed professional salary of $40,000 (in 1991/92), plus 20% for benefits, a further 20% for administrative overhead, and a final 10% to account for the costs of assessment and case management. These costs per professional were divided by an assumed visit rate of five per day to obtain a cost per visit of $55 in 1991/92 and $66 in 1996/97.

Service costs for years other than 1991/92 and 1996/97 were estimated by interpolating using a straight line between Hollander’s estimates for 1991/92 and 1996/97 and by extrapolating the 1996/97 forward through 2001 at the rate of health care services inflation (see next section).
3.4.4 Inflation

All service costs have been adjusted for medical inflation rates from British Columbia, as calculated by Statistics Canada (Statistics Canada 2007). Statistics Canada provides five sub-indexes to the health care industry group: health care goods; medicinal and pharmaceutical products; prescribed medicines; non-prescribed medicines; and health care services. We chose to use the prescribed medicines deflator for pharmaceutical costs, while using the health care services deflator for medical services, long-term care services, and direct continuing care visits. For hospital costs, which include elements of both services and goods, we chose to use the overall health care industry deflator. The difference in rates of inflation between the different deflators is relatively small. Between 1991 and 2001, the change in the deflator for the health care industry as a whole was 24.9%, while the prescribed medicines deflator rose 30.4% and the health care services deflator increased 27.1%.

All service costs are reported in 2002 values. We believe that taking inflation out of cost trends helps better identify the change in real spending relationships. Nevertheless, the effect on the relative comparison between decedents and survivors and among different ages of including or excluding inflation should be relatively minor.

3.4.5 Adjusting for Overlap between Hospital and Continuing Care Stays

When combining costs for all services, we noticed a significant number of individuals with long stays – often greater than one year – on record in both the hospital and continuing residential care files. Our conversations with Continuing Care data specialists at the BC Ministry of Health confirmed that until relatively recently Extended Care episodes in hospitals were reported in both the Continuing Care data system and in the Hospital Discharge Abstract Database (DAD) (Gillan 2006).
To account for this duplication we compared residential days and hospital Extended Care (level ‘E’) days for all individuals with positive level ‘E’ hospital days at any time. We decided that, for cases of overlap, we would choose the long-term care records in place of the hospital records. This decision was made because of the relative imprecision in the hospital costing of applying the average RIW per day from 89 episodes to the many thousands of actual episodes that exist. Since the care type is contained in the Continuing Care database, we thought it more appropriate to apply Continuing Care costing methods where overlap exists.

We applied two tests to determine where to eliminate the hospital extended stay records: if the sum of hospital and continuing residential care days in a given year was greater than 366; or if the number of continuing care days in a given year was within three days less or greater than the number of hospital days in a given year.

There were 40,354 unique individuals that had some level ‘E’ hospital days on record (the number is less than the total ‘E’ level episodes reported in Table 3.1 due to occurrences of multiple ‘E’ level episodes for one individual). Of these, 28,173 (69.8%) had all level ‘E’ hospital days eliminated after our corrective procedure. Table 3.3 shows that over 90% of all level ‘E’ hospital days were eliminated by this procedure through 1999, with the remainder likely representing hospital-attached extended care beds that were not part of the continuing care system. After 1999, the rate of reduction of hospital level ‘E’ days began to drop, reflecting a gradual elimination of the double counting in record-keeping systems.
Table 3.3: Results of Reconciling Continuing Residential Care and Level ‘E’ Hospital Days

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital days</td>
<td>1,702,577</td>
<td>2,040,404</td>
<td>2,220,221</td>
<td>2,333,964</td>
<td>2,327,251</td>
<td>2,282,790</td>
<td>2,129,276</td>
<td>1,660,274</td>
<td>1,464,252</td>
<td>766,639</td>
<td>45,005</td>
<td>22,641</td>
</tr>
<tr>
<td>Hospital days - corrected</td>
<td>117,713</td>
<td>113,034</td>
<td>100,626</td>
<td>96,350</td>
<td>101,757</td>
<td>110,067</td>
<td>118,071</td>
<td>125,867</td>
<td>135,956</td>
<td>98,342</td>
<td>28,528</td>
<td>21,070</td>
</tr>
<tr>
<td>% Hospital days reduced</td>
<td>93.1%</td>
<td>94.5%</td>
<td>95.5%</td>
<td>95.9%</td>
<td>95.6%</td>
<td>95.2%</td>
<td>94.5%</td>
<td>93.3%</td>
<td>90.7%</td>
<td>87.5%</td>
<td>36.6%</td>
<td>6.9%</td>
</tr>
</tbody>
</table>
3.4.6 Reconciling Date of Death from Registry and Continuing Care Files

The Master Record from the Continuing Care files provides a death date field. This enabled a cross-check with the deaths file from the Registry files. Registry files contained 266,030 deaths that occurred on January 1st, 1991 or later. Multiple deaths were recorded for 66 Study IDs. These Study IDs were excluded from the study, so after the removal of 132 death records associated with these Study IDs, there were 265,898 unique deaths from the Registry file.

In addition to the 265,898 unique deaths from the Registry file, there were a further 10,498 death dates in the Continuing Care Master Record for Study IDs that had no death dates in the Registry file. It is possible that, because Continuing Care data was amended and received seven months after the Registry data, it may contain more recent deaths that had not been recorded in the Registry file. However many of the death dates from Continuing Care that were not in the Registry data are for earlier years suggesting some errors or omissions in one or both of the data sources.

To ensure that the death data used in our study was as accurate as possible, we aggregated all deaths from the Registry and Continuing Care sources and cross-checked them against service utilization. This was done by getting the latest date of service from each of hospital, medical, pharmaceutical, Continuing Care LTC, and Continuing Care direct care and comparing them to the death dates from each source.

We found that the vast majority of death dates from both sources were consistent with the maximum utilization dates from all services and were therefore usable. There were 3,476 cases in which the dates of death from Continuing Care and Registry differed. Of these 2,224 (64%) were different by one month only (to protect privacy, death dates were
month and year only, so comparisons were exact only to the month level). Typically the Continuing Care death date was later than the Registry death date. This is likely due to the fact that the Registry source is a more official record whereas the Continuing Care tracking of death dates is for internal purposes. Continuing Care may simply record the death date as the date of data entry, when the service record is terminated. When we compared the 3,476 cases with death dates from both sources, we found that the Registry source agreed with the maximum utilization dates for all services (i.e. no service utilization took place in the months following the month of death), and we therefore chose to use the Registry death for all of these cases.

For the remainder of death dates – from either of Registry or Continuing Care source but not from both – we performed similar checks against maximum service utilization dates to ensure reliability of the data. Table 3.4 breaks down the number of Study IDs with maximum utilization dates greater than Registry death date over four minimum thresholds. Table 3.5 performs a similar exercise for Continuing Care deaths.

There is clearly evidence of some delay in record keeping and accounting for deaths in all services except for hospital records. The fact that there are no hospital episodes occurring after the date of death from either the Registry or Continuing Care source is encouraging because hospital records are likely more carefully tracked due to their greater expense. The largest discrepancy seems to be with direct care visits from the Continuing Care files, when compared to the Registry date of death. It is quite likely here that the Last Visit Date is simply the date at which client eligibility for visits was terminated and that actual visits terminated with the date of death.

We chose to be as inclusive as possible with cases where maximum utilization dates were greater than death dates. Since the majority of the errors (for Registry Dates) were within three months we did not want to exclude these IDs. Records where utilization occurred more than one year after date of death were eliminated from the study. This resulted in
eliminating 2,868 of the Registry death dates (1.1%) and 252 of the Continuing Care death dates (2.4%). Totals do not add to the sum of the last rows of Table 3.3 and Table 3.4 due to some Study IDs having more than one service maximum utilization date over one year later than date of death.

Table 3.4: Number of Study IDs with maximum utilization dates greater than Registry death date, by service and minimum time difference (total n = 265,898)

<table>
<thead>
<tr>
<th>Utilization Later than Death by at least:</th>
<th>Hospital Separation</th>
<th>Medical Billings</th>
<th>Pharma Prescription</th>
<th>Long-Term Care</th>
<th>Direct Care Visits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>0</td>
<td>2307</td>
<td>1160</td>
<td>2959</td>
<td>19264</td>
</tr>
<tr>
<td>2 months</td>
<td>0</td>
<td>1455</td>
<td>445</td>
<td>2300</td>
<td>6232</td>
</tr>
<tr>
<td>3 months</td>
<td>0</td>
<td>1233</td>
<td>340</td>
<td>2061</td>
<td>4081</td>
</tr>
<tr>
<td>1 year</td>
<td>0</td>
<td>636</td>
<td>141</td>
<td>1086</td>
<td>1184</td>
</tr>
</tbody>
</table>

Table 3.5: Number of Study IDs with maximum utilization dates greater than Continuing Care death date, by service and minimum time difference (total n = 10,498)

<table>
<thead>
<tr>
<th>Utilization Later than Death by at least:</th>
<th>Hospital Separation</th>
<th>Medical Billings</th>
<th>Pharma Prescription</th>
<th>Long-Term Care</th>
<th>Direct Care Visits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 month</td>
<td>0</td>
<td>130</td>
<td>82</td>
<td>61</td>
<td>53</td>
</tr>
<tr>
<td>2 months</td>
<td>0</td>
<td>130</td>
<td>82</td>
<td>61</td>
<td>52</td>
</tr>
<tr>
<td>3 months</td>
<td>0</td>
<td>130</td>
<td>82</td>
<td>61</td>
<td>51</td>
</tr>
<tr>
<td>1 year</td>
<td>0</td>
<td>116</td>
<td>80</td>
<td>59</td>
<td>50</td>
</tr>
</tbody>
</table>

The final data set after combining Registry and Continuing Care deaths and eliminating multiple deaths and IDs where service utilization was one year or more after death contained 875,430 unique individuals, of which 273,276 (31.2%) had a date of death (study death rates, as reported in more detail in Appendix A, agree closely with Statistics Canada life tables). Of these death dates 10,246 (3.7%) were obtained from the Continuing Care file.
3.4.7 Assigning Utilization Events to Years, Ages, and Times-to-Death

With the data set clean and death dates determined for all individuals, utilization had to be allocated to a given year, age, and time-to-death (if a death date exists). For all individuals who did not have a date of death, utilization was simply allocated on the basis of calendar year. All medical services and pharmaceutical prescriptions billed in that year were included as well as all days spent in hospital or on long-term care services and all direct care visits.

For individuals with a date of death, in order to align time-to-death calculations, the year-end date needed to be reset from December 31st to the date of death. To ensure that the average year for decedents was equal to the December 31st year for survivors, individuals whose month of death was June or earlier were allocated to the previous year. For example, the year 1999 would run from November 1st, 1998 to October 31st, 1999 for an individual who died in October of 2001, while for an individual who died in February of 2002, the year 1999 would run from March 1st, 1999 to February 29th, 2000. In this way, 1999 year-end dates for decedents run from July 31st to June 30th and average to the regular calendar year used for survivors.

A consequence of having only the month of death as opposed to the exact day of death is a loss of precision in the last year. In order to ensure that we capture all utilization up to the date of death we use the last day of the month of death as the year-end date. While this method allows all services at the end of life to be captured (in addition to some of the delayed records described in the previous section) it does result in some understatement of costs in the last year of life. This is due to the fact that the average final year for decedents includes 15 days (half a month) after death at the end of the year so that the actual utilization year is in fact only 350, as opposed to 365, days. While taking this underestimate into account, we are comfortable with it because it allows us to capture the
heaviest utilization at the end of the period as death approaches and loses only 3.2% of
the year at the beginning where utilization is likely the lowest. Furthermore, while costs
in the last year of life may be slightly understated, the time trends and relative
comparisons across age groups should be unaffected as long as the method of
measurement is consistent.

As noted earlier, our method of adjusting decedent years to end at the date of death
means that we must cut our sample one year short at the end of the study period.
According to the method, the year 2002 can end anywhere from July 31, 2002 to June 30,
2003 for decedents. Since our data do not extend beyond 2002 (or beyond March 31,
2003 at the latest), for decedents with month of death between Jan 1 and June 30, 2003
these individuals would have their utilization – and costs – understated.

Once utilization is assigned to calendar years, we then need to calculate the time-to-death
for decedents and the minimum known period of survival for survivors. Time-to-Death
for decedents is straightforward. For decedents dying between July 1st, 1999 and June
30th 2000, for example, their last year would be 1999 and their time-to-death in that year
would be equal to one. Similarly 1998 would be assigned a time-to-death of two, 1997
three, and so on.

For survivors, we use the Medical Services Plan Registry as our master list. The great
majority of survivors were registered and remained in the province through the end of
2001. For these individuals, their minimum survival time would be two years in 2001 (as
opposed to one year time-to-death for those who died in that year), three years in 2000,
and so on. For individuals who disappear from the registry but do not have a death on
record (likely mostly due to migration out of the province) the minimum survival time is
set to one in their last year of registration, two in their second-to-last year of registration
and so on. As a result, when comparisons are drawn between individuals in their last
year of life and survivors who live beyond the current year, survivors who were not
registered in the following year are not included in the comparison group. The drop-out rate due to reasons other than death was approximately one half of one percent per year.

The registry is quite comprehensive. To determine the coverage level, we compare to the 65-and-over population of British Columbia as provided by BC Stats (2007). Table 3.6 shows that the number of people included in the registry was slightly more than the total population estimate in every year of the study period. The reason for the higher value is because the cohort provided by BCLHD contains all individuals who turn 65 at any time during the year, whereas population estimates would probably count some of these individuals as 64 at the time. If we include only half of the 65-year-old cohort from the BCLHD sample, coverage is below, but very close to 100%. It is slightly lower in the first years of the study period, but over 99% from 1994.

Table 3.6: Comparison of number of 65-plus individuals in BCLHD MSP Registry and the 65-plus population estimates from BC Stats – with full 65 cohort and with half 65 cohort

<table>
<thead>
<tr>
<th>Year</th>
<th>Population 65+</th>
<th>BCLHD All</th>
<th>Coverage</th>
<th>BCLHD half 65 cohort</th>
<th>Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991</td>
<td>428,680</td>
<td>432,291</td>
<td>100.8%</td>
<td>418,229</td>
<td>97.6%</td>
</tr>
<tr>
<td>1992</td>
<td>440,371</td>
<td>445,749</td>
<td>101.2%</td>
<td>431,599</td>
<td>98.0%</td>
</tr>
<tr>
<td>1993</td>
<td>450,796</td>
<td>458,821</td>
<td>101.8%</td>
<td>444,047</td>
<td>98.5%</td>
</tr>
<tr>
<td>1994</td>
<td>462,936</td>
<td>473,503</td>
<td>102.3%</td>
<td>458,546</td>
<td>99.1%</td>
</tr>
<tr>
<td>1995</td>
<td>475,315</td>
<td>487,646</td>
<td>102.6%</td>
<td>472,056</td>
<td>99.3%</td>
</tr>
<tr>
<td>1996</td>
<td>486,504</td>
<td>500,927</td>
<td>103.0%</td>
<td>485,396</td>
<td>99.8%</td>
</tr>
<tr>
<td>1997</td>
<td>498,530</td>
<td>513,246</td>
<td>103.0%</td>
<td>497,690</td>
<td>99.8%</td>
</tr>
<tr>
<td>1998</td>
<td>509,444</td>
<td>523,506</td>
<td>102.8%</td>
<td>508,214</td>
<td>99.8%</td>
</tr>
<tr>
<td>1999</td>
<td>518,992</td>
<td>532,823</td>
<td>102.7%</td>
<td>517,505</td>
<td>99.7%</td>
</tr>
<tr>
<td>2000</td>
<td>528,578</td>
<td>541,032</td>
<td>102.4%</td>
<td>525,327</td>
<td>99.4%</td>
</tr>
<tr>
<td>2001</td>
<td>539,635</td>
<td>551,236</td>
<td>102.1%</td>
<td>535,307</td>
<td>99.2%</td>
</tr>
<tr>
<td>2002</td>
<td>550,412</td>
<td>562,468</td>
<td>102.2%</td>
<td>546,395</td>
<td>99.3%</td>
</tr>
</tbody>
</table>

The near complete coverage of the MSP Registry provides confidence that the data is not missing a large cohort of individuals that have no interaction with the health care system.
By using the registry as the basis for compiling data, we are able to analyze nearly the entire elderly population of BC, regardless of whether they used health care services or not. This helps address concerns about whether zero-utilization individuals are captured in the analysis that have been raised in time-to-death regression models (Salas and Raftery 2001; Seshamani and Gray 2004).

Once every individual has been assigned a time-to-death or minimum survival time, we then use SAS to aggregate the 875,430 records into classes with the same birth year, death status (decedent or survivor), and minimum time (survival or time-to-death). For each class we sum the number of individuals in the class and the total expenditure in each year (1991 through 2001) for each of the four services (long-term care and direct continuing care are combined) and for the four combined. This produces 8,464 classes that can then be analyzed in Microsoft Excel.

3.5 Results

The population is separated into four age groups for analysis: 66-70, 71-80, 81-90, and 91+. We leave age 65 out of the analysis to avoid any issues with inclusion or exclusion from the sample. In particular, while all individuals turning 65 in a given year may be included in the data set, they would be eligible for drug coverage for only that portion of the year that falls after their 65th birthday. The number of individuals in each age group in the registry is presented in Table 3.7.
Table 3.7: Number of individuals in BCLHD sample – by age group and by year

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>66-70</td>
<td>136,030</td>
<td>137,643</td>
<td>138,753</td>
<td>141,242</td>
<td>142,901</td>
<td>145,703</td>
<td>148,210</td>
<td>150,064</td>
<td>150,275</td>
<td>150,202</td>
<td>150,497</td>
</tr>
<tr>
<td>71-80</td>
<td>187,442</td>
<td>192,269</td>
<td>202,828</td>
<td>209,315</td>
<td>214,769</td>
<td>220,361</td>
<td>226,008</td>
<td>231,455</td>
<td>236,529</td>
<td>240,315</td>
<td>242,839</td>
</tr>
<tr>
<td>81-90</td>
<td>69,092</td>
<td>72,514</td>
<td>76,267</td>
<td>81,171</td>
<td>86,499</td>
<td>90,890</td>
<td>94,546</td>
<td>97,269</td>
<td>100,344</td>
<td>103,537</td>
<td>109,192</td>
</tr>
<tr>
<td>91+</td>
<td>10,703</td>
<td>11,023</td>
<td>11,424</td>
<td>11,861</td>
<td>12,297</td>
<td>12,911</td>
<td>13,370</td>
<td>14,134</td>
<td>15,039</td>
<td>15,567</td>
<td>16,850</td>
</tr>
</tbody>
</table>
3.5.1 Decedent Costs

Figure 3.3 provides the results for average total inflation-adjusted costs in the last year of life for total expenditures for those who died in each study year. Inflation-adjusted costs were fairly stable over the period, with a slight dip in the mid 1990s followed by a rise later in the decade. Over the full period, decedent costs rose between 5%-10% for all age groups with the exception of the 91+ group, where decedent costs were flat. Decedent costs are higher for older ages, but are elevated for all age groups.

Figure 3.3: Last Year of Life Average Costs by Age Group, All Services 1991-2001:

With hospitals as a focus for cost-cutting, the dip in decedent hospital costs during the mid-1990s was deeper than for total expenditures, at 15%-25% versus 5%-10%. But similar to total expenditures, by 2001 decedent hospital costs were slightly higher than they were at the beginning of the period in 1991.
Prescription drug costs demonstrated a similar pattern of acceleration after the mid-1990s, but with generally higher growth than other services. Real decedent drug costs grew between 1% and 8% from 1991 to 1996, and between 21% and 41% in the subsequent years. Physician costs were relatively flat through 1996 (or down in the case of the 91+ age group) and, similar to overall decedent costs, up less than 10% by the end of the study period.

Decedent costs for continuing care behaved differently than the other services (see Figure 3.4). Growth was faster in the first half of the study period than in the second. The policy emphasis on community care contributed to growth of 6%-11% in real costs between 1991 and 1996. But from 1996 to 2001 real decedent costs for continuing care fell for all age groups, and were lower than 1991 levels for ages 66-70 and 91+.

Figure 3.4: Last Year of Life Average Costs by Age Group, Continuing Care 1991-2001:

The relationship between age and decedent costs was also quite different for continuing care compared to the other three service categories. For each of hospital, prescription,
and physician costs, decedent costs were highest for the youngest age group and lowest for the oldest. Only for continuing care was this relationship reversed, with the oldest age group incurring the highest average decedent costs. The difference was significant, with decedents aged 91+ incurring an average cost more than five times that of decedents aged 66-70. In comparison, the range for hospital costs is much narrower, with decedents aged 66-70 incurring less than twice the average costs of the oldest age group.

Since continuing care is a large cost category (the largest for decedents aged 81-90 and 91+) and since the difference between ages was larger for continuing care than for hospitals, the age relationship for all costs combined is similar – but not as strong – as that for continuing care: decedent costs rise with age.

Changes over the full study period (depicted in Figure 3.5) were fairly similar for different age groups within each service, but a couple of observations stand out. First, for continuing care and physician costs, growth in decedent costs was flat to negative for the youngest and oldest age groups and up approximately 10% for the two age groups in the middle. Second, the oldest cohort, aged 91+ had the lowest growth in all services except prescription drugs, where its growth was by far the highest, up nearly 50%, albeit off a fairly small base.
3.5.2 Survivor Costs

Several of the observations for decedent costs hold true for those with more than one year to live. Hospital, prescription drug, and physician costs all show weaker growth in the first half versus the second half of the study period (as do total expenditures), while the relationship is reversed for continuing care. Costs rise with age for all services combined and for continuing care. The 91+ cohort has the lowest growth in costs between 1991 and 2001 for hospital and physician services while it had the highest growth for continuing care services.

There were, however, more differences than similarities between decedent and survivor costs in our study period. Most importantly, where inflation-adjusted decedent costs for most services ended the period at higher levels than where they began, such survivor
costs fell over the study period for all age groups for total expenditures (see Figure 3.6), as well as for hospital and continuing care services individually. The drop for continuing care in the second half of the study period was particularly dramatic, with average costs falling between 15% and 25% from 1996-2001 (see Figure 3.7).

**Figure 3.6: More than One Year to Live Average Costs by Age Group, All Services 1991-2001**

Figures 3.8 and 3.9 clearly demonstrate the effect of the policy decision to restrict access to Continuing Care services to all but the most needy. While the probability of utilization of continuing care fell dramatically (restricted access), the cost given positive utilization rose (higher average service levels for higher average needs). The effect of the policy change was least dramatic on the most elderly, who use the most services on average. The probability of utilization dropped 20% for ages 91+ versus 35%-40% for other age groups.
Figure 3.7: More than One Year to Live Average Costs by Age Group, Continuing Care 1991-2001

Figure 3.8: More than One Year to Live Probability of Positive Utilization by Age Group, Continuing Care 1991-2001, Normalized (1991=100)
The fall in probability of continuing care utilization is likely not exclusively due to policy change. The probability of hospital utilization also fell during the study period (see Figure 3.10). It is possible that improved health among survivor populations could account for some of the observed drop in utilization rates. Figure 3.10 also may indicate that the increased resources dedicated to surgical procedures stabilized utilization rates for all but the oldest age group, where utilization continued to fall through 2001. Older individuals are likely accorded a lower priority for elective procedures such as knee and hip replacements and cataract surgery that were the focus of the wait time crisis.
The increase in survivor hospital costs in the latter half of the study period was due to increases in costs given positive utilization, as can be seen in Figure 3.11. After falling by 20%-30% through 1996, costs given positive utilization recovered to their 1991 levels for ages 66-70 and 71-80, and to a lesser extent for the older age groups. While costs given positive utilization are highest for the oldest age group, the gap narrowed significantly, particularly during the first several years of the study period when there was an effort to eliminate long stays in hospitals that were more appropriate for lower-cost residential care settings.

Physician and prescription drug costs for survivors behaved in a very similar fashion to costs for decedents. Physician survivor costs were up 10% or less for all age groups except 91+, which was down slightly, while prescription drug costs were up significantly
– by over 30% for all age groups (see Figure 3.12 for percentage changes for all age groups and service categories over the full study period).

Figure 3.11: More than One Year to Live Average Costs Given Positive Utilization by Age Group, Hospital Services 1991-2001
3.5.3 Decedent/Survivor Ratio

Table 3.8 summarizes decedent and survivor costs in the first and last year of the study period as well as both the ratios of those costs and the change in the ratio. The combination of relatively flat decedent costs and falling survivor costs resulted in a rising decedent/survivor ratio. Those aged 81-90 experienced the highest percentage rise in the ratio, by 23% from 3.1 to 3.8.

All services demonstrated a pattern of lower ratios at older ages. Ratios were highest for hospital services and lowest for prescription drugs. Ratios changed by less than 10% for drugs and physicians, but increased substantially for hospitals and continuing care. The largest percentage increase was experienced by the oldest age groups for hospital services.
(ages 91+ up 43% from 2.4 to 3.5) and by the youngest age groups for continuing care (ages 66-70 up 44% from 7.5 to 10.8 and ages 71-80 up 49% from 4.4 to 6.6).

Table 3.8: Decedent and Survivor Average Costs and Ratios, 1991 and 2001

<table>
<thead>
<tr>
<th>Service Type</th>
<th>1991 Decedents</th>
<th>1991 Survivors</th>
<th>2001 Decedents</th>
<th>2001 Survivors</th>
<th>Change in Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ages 66-70</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital</td>
<td>$17,104</td>
<td>$1,928</td>
<td>$17,932</td>
<td>$1,831</td>
<td>10.4%</td>
</tr>
<tr>
<td>Doctor</td>
<td>$2,463</td>
<td>$908</td>
<td>$2,577</td>
<td>$981</td>
<td>-3.2%</td>
</tr>
<tr>
<td>Drugs</td>
<td>$863</td>
<td>$525</td>
<td>$1,056</td>
<td>$703</td>
<td>-8.5%</td>
</tr>
<tr>
<td>Continuing Care</td>
<td>$12,977</td>
<td>$2,548</td>
<td>$14,583</td>
<td>$2,264</td>
<td>26.5%</td>
</tr>
<tr>
<td>Ages 71-80</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital</td>
<td>$19,122</td>
<td>$1,382</td>
<td>$20,679</td>
<td>$1,122</td>
<td>13.7%</td>
</tr>
<tr>
<td>Doctor</td>
<td>$3,246</td>
<td>$809</td>
<td>$3,472</td>
<td>$832</td>
<td>4.0%</td>
</tr>
<tr>
<td>Drugs</td>
<td>$1,183</td>
<td>$476</td>
<td>$1,484</td>
<td>$621</td>
<td>-3.8%</td>
</tr>
<tr>
<td>Continuing Care</td>
<td>$4,804</td>
<td>$948</td>
<td>$4,718</td>
<td>$438</td>
<td>44.0%</td>
</tr>
<tr>
<td>Ages 81-90</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital</td>
<td>$18,122</td>
<td>$1,391</td>
<td>$20,679</td>
<td>$1,122</td>
<td>11.6%</td>
</tr>
<tr>
<td>Doctor</td>
<td>$2,867</td>
<td>$948</td>
<td>$3,161</td>
<td>$1,039</td>
<td>0.6%</td>
</tr>
<tr>
<td>Drugs</td>
<td>$1,012</td>
<td>$550</td>
<td>$1,225</td>
<td>$748</td>
<td>9.6%</td>
</tr>
<tr>
<td>Continuing Care</td>
<td>$8,180</td>
<td>$1,839</td>
<td>$8,931</td>
<td>$1,346</td>
<td>49.1%</td>
</tr>
<tr>
<td>Ages 91+</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital</td>
<td>$16,739</td>
<td>$7,705</td>
<td>$17,793</td>
<td>$7,573</td>
<td>7.7%</td>
</tr>
<tr>
<td>Doctor</td>
<td>$2,092</td>
<td>$1,008</td>
<td>$2,276</td>
<td>$1,085</td>
<td>1.2%</td>
</tr>
<tr>
<td>Drugs</td>
<td>$728</td>
<td>$550</td>
<td>$957</td>
<td>$733</td>
<td>-1.5%</td>
</tr>
<tr>
<td>Continuing Care</td>
<td>$16,240</td>
<td>$6,693</td>
<td>$17,375</td>
<td>$5,385</td>
<td>33.0%</td>
</tr>
</tbody>
</table>

3.5.4 Cost Share by Service: 1991 versus 2001

Table 3.9 summarizes the changes that took place between 1991 and 2001 in the relative share of costs accounted for by each service for each age group. Changes were fairly minor in the allocation of decedent costs, and more substantial in the allocation of survivor costs. Decedent costs showed a shift in emphasis from continuing care to hospital services for the youngest and oldest age groups, while the allocation to prescription drugs increased for all age groups. Allocation of survivor costs shifted from hospital services and continuing care to physician billings and prescription drugs for all ages except 91+. The 91+ cohort saw the largest increase in allocation of survivor costs in continuing care. The share of spending allocated to decedents is discussed in Appendix A.
Table 3.9: Contribution of Each Service to Total Health Care Costs, 1991 and 2001

<table>
<thead>
<tr>
<th>Services</th>
<th>Hospital Services</th>
<th>Continuing Care</th>
<th>Physician Billings</th>
<th>Pharmaceutical Prescription</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decedents</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>66-70</td>
<td>67.5%</td>
<td>68.1%</td>
<td>0.6%</td>
<td>16.9%</td>
</tr>
<tr>
<td>71-80</td>
<td>61.3%</td>
<td>61.2%</td>
<td>-0.2%</td>
<td>26.2%</td>
</tr>
<tr>
<td>81-90</td>
<td>46.0%</td>
<td>45.4%</td>
<td>-0.6%</td>
<td>46.0%</td>
</tr>
<tr>
<td>91+</td>
<td>27.6%</td>
<td>28.2%</td>
<td>0.7%</td>
<td>67.8%</td>
</tr>
<tr>
<td>All Ages</td>
<td>51.2%</td>
<td>49.6%</td>
<td>-1.6%</td>
<td>38.8%</td>
</tr>
<tr>
<td>Survivors</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>66-70</td>
<td>38.0%</td>
<td>37.2%</td>
<td>-0.8%</td>
<td>20.7%</td>
</tr>
<tr>
<td>71-80</td>
<td>36.4%</td>
<td>35.5%</td>
<td>0.1%</td>
<td>35.0%</td>
</tr>
<tr>
<td>81-90</td>
<td>28.0%</td>
<td>27.7%</td>
<td>-0.3%</td>
<td>58.4%</td>
</tr>
<tr>
<td>91+</td>
<td>19.9%</td>
<td>16.5%</td>
<td>-3.4%</td>
<td>74.4%</td>
</tr>
<tr>
<td>All Ages</td>
<td>32.6%</td>
<td>31.7%</td>
<td>-0.9%</td>
<td>43.1%</td>
</tr>
</tbody>
</table>

3.5.5 Decomposition of expenditure growth

Table 3.10 decomposes the growth in health expenditures over the study period and compares such growth rates to those for the US Medicare program for the period 1987-1999. The BC attribution adds a greater level of detail to that for the US by accounting for the effect of per capita survivor and decedent expenditures individually, as well as the effect of lower death rates. For both the US and the BC study population, medical inflation and population growth were the main factors that accounted for overall expenditure growth. In BC, the effect of the higher cost of dying somewhat offset lower survivor costs. Looked at another way, the combination of lower death rates and lower per capita survivor costs counteracted the effect of the shift in age distribution (i.e. the aging of the 65+ cohort).


<table>
<thead>
<tr>
<th>Component</th>
<th>US Medicare</th>
<th>BC Health</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Rate of medical inflation</td>
<td>5.78%</td>
<td>2.24%</td>
</tr>
<tr>
<td>2. Rate of population growth</td>
<td>1.33%</td>
<td>2.33%</td>
</tr>
<tr>
<td>3. Age-weighted growth in per capita HCE, adjusted for medical inflation</td>
<td>0.24%</td>
<td>0.13%</td>
</tr>
<tr>
<td>3a. Effect of change in last-year-of-life costs</td>
<td>0.24%</td>
<td>0.13%</td>
</tr>
<tr>
<td>3b. Effect of change in survivor costs</td>
<td>-0.18%</td>
<td>-0.76%</td>
</tr>
<tr>
<td>4. Effect of shift in age distribution</td>
<td>0.33%</td>
<td>0.83%</td>
</tr>
<tr>
<td>5. Change in total costs due to change in death rates</td>
<td>-0.13%</td>
<td>-0.13%</td>
</tr>
<tr>
<td>Annual growth rate, HCE*</td>
<td>7.76%</td>
<td>4.57%</td>
</tr>
</tbody>
</table>

*Medicare age distribution is in 10-year cohorts (65-74, 75-84, 85+), while BC age distribution is in 1-year cohorts
**Components may not sum to exact total due to rounding and intersection effects
3.6 Discussion

The overall decedent and survivor cost time trends differ from previous evidence in the literature. For hospital costs, continuing care costs, and all costs combined, decedent costs were generally stable, dipping in the mid 1990s and recovering to 1991 levels by the end of the period; for survivors, costs of the same services declined at rates between 5% and 30%. The highest declines in survivor costs were experienced in the 91+ age group for hospital services (down 29%) and in the 66-70 age group for continuing care services (down 32%). These declines were offset to some extent by increases in pharmaceutical prescription costs and physician billings.

Findings from earlier time periods describe the opposite relationship between decedent and survivor medical costs (Medicare in the US or hospital costs in Canada and Britain): survivor costs grew faster than decedent costs (Lubitz and Riley 1993; Lubitz, Beebe and Baker 1995; McGrail et al. 2000; Spillman and Lubitz 2000; Seshamani and Gray 2004). Our results for continuing care costs do agree with those of McGrail et al., who use the same BCLHD data and find slightly rising decedent costs and falling survivor costs between 1986 and 1993.

As a result of the differences between our study and earlier US Medicare studies, where decedents were found to account for a declining portion of overall Medicare spending between the years 1980 and 1996 (see introduction, Section 3.1), decedents in BC actually accounted for a growing share of publicly-financed health care costs, even as the proportion of the elderly dying in a given year fell slightly. The interpretation of this apparently important shift depends, naturally, on its possible causes.

The reduced expenditure on survivor populations could be due to a combination of health and policy factors. Certainly, the policy changes enacted in British Columbia during the 1990s – to shorten hospital stays and to restrict continuing care access to the most needy
– appear to have had an effect on those two service areas, reducing the amount of care provided to survivor populations. In the case of continuing care specifically, the Canada Health Act (CHA), which legislates medical services that must be covered by the provinces, does not mandate coverage of home care or other community services. It is therefore likely that a large part of reductions in government funding would take place in the area of community care. Furthermore, governments may find it least disruptive from a system planning perspective to cut back in community care since there is a large informal supply that can act as a substitute. It is possible that at least a portion of the decline in community care costs for survivors was due not to overall lower utilization, but to a larger proportion of utilization taking place in the informal or private market. Coyte (2000) found that the private share of non-CHA services in Canada rose from 52% to 57% between 1975 and 1999, while the private share of CHA services was much smaller, but also grew marginally from 5% to 6%.

Besides possible public-private substitution, it is also possible that reduced spending on survivors could reflect an improvement in health status. (In Appendix B we consider and rule out evidence for an independent cohort effect.) While data are not available for BC specifically, numerous studies from the industrialized world have found broad decreases in age-specific morbidity among the elderly (Robine and Ritchie 1991; Jacobzone 2000; Robine and Michel 2004; Spillman 2004). To the extent that improved health is due to lifestyle and not to more health care, lower morbidity would be associated with lower utilization of intensive services such as hospitals and continuing care. In this context, relatively higher utilization of less intensive services more oriented towards prevention and maintenance – such as physician visits and pharmaceutical prescriptions – is not surprising.

Regardless of the cause, the trend towards stronger growth in decedent versus survivor costs could have the effect of additional reductions in forecasts of future expenditure growth if it continues in combination with mortality declines. Miller (2001) found that
forecast Medicare expenditures for the year 2070 could be reduced by as much as 57% if the relative cost of dying is taken into account and mortality is assumed to continue to fall. While the 57% reduction depended on their assumption that life expectancy would grow to 93.5 years by that time, even a much more moderate assumption of life expectancy growth to 82 years reduced forecast costs by 15%.

Comparing our results to Miller’s, we find a wider difference between decedents and survivors. Miller calculated that decedent Medicare expenditures for all individuals over 65 years old in 1989/1990 were nearly seven times as high as average expenditures incurred 10 or more years earlier (adjusted for inflation). Comparing our results for individuals dying in 2001 to those 10 or more years from death in 1991, we obtain a ratio greater than twelve. Furthermore, the ratio between decedent and survivor costs widened over the study period, driven by decreases in survivor expenditures. This trend is strongest in the older age ranges where an increasingly large share of total deaths is expected to take place.

As Miller demonstrated with his different mortality scenarios, the effect of cost of dying on future expenditure forecasts depends critically on the direction of future mortality. If mortality reductions continue, as is assumed by Miller and projected by the Congressional Budget Office in their Medicare forecasts (CBO 2004), the proportion of individuals at any given age in their last year of life will fall, leading to a decline in overall average spending levels at each age, and for the population as a whole. If the difference between decedents and survivors is widening, as our evidence suggests, the decline in forecast expenditures could be greater still. If, on the other hand, longevity approaches a limit, as forecast by Fries and Olshansky (Fries 1980; Olshansky, Carnes and Cassel 1990), or longevity is reduced due to more sedentary lifestyles, higher obesity, and the concomitant comorbidities (Olshansky et al. 2005), the reverse could be true. Regardless of their true direction, an increase in the spending share attributed to decedents places increased importance on future mortality rates.
Future mortality changes will also influence the relative growth experienced by different sectors of the health care system. Lower mortality rates would shift costs from hospitals to all other services since hospitals account for a higher proportion of decedent versus survivor expenditures at all ages. This gap is narrowing, however, so the effect of future mortality changes could be reduced. The trend toward reduced survivor expenditures on continuing care suggests the possibility for some relief to this sector, which has experienced significant pressures with regard to labour shortages in recent years (Anonymous 2002). As mentioned earlier, it is also a potential indication that survivor health is generally improving, since continuing care usage is often driven by long-term functional disabilities. This fits with recent evidence of reduced disability among the elderly and the compression of morbidity theory proposed by Fries (1980).

The divergence between decedent and survivor cost trends during the study period raises policy questions relating to the allocation of health care resources. As described in the background to British Columbia health policy, the New Directions policy was aimed at shifting the emphasis of care to the community and increasing prevention and maintenance services while decreasing the intensity of emergency care. While the increase in the share of survivor expenditures devoted to drugs and physicians is in agreement with these objectives, the increase in the share of hospital and continuing care expenditures allocated to decedents – even as the death rate fell – may be less so. For example, if Do Not Resuscitate Orders or Advanced Directives were implemented in the study period to reduce intensive and invasive care for terminal patients, they do not appear to have had a significant effect on decedent costs. Garber, McCurdy and MacClellan (1998) noted a similar trend in US Medicare expenditures between 1988 and 1995, where, in spite of increased use of hospice and home health care by dying beneficiaries, overall usage of hospital services and the intensity of end-of-life treatment did not decline. Increasing intensity of services for the dying could raise concerns with respect to health care system efficiency as health care accounts for an increasing share of the economy.
3.7 Limitations

The limitations to this study concern primarily pricing assumptions, omission of health care services not covered by the government, and the nature of demand in an environment of government-controlled supply. For hospital and continuing care costs, we needed to make assumptions about the pricing of a wide variety of services delivered by hundreds of providers across the province over a period of eleven years. The generalization involved would not capture the difference in expense between teaching and non-teaching hospitals, for example. The provincial cost-per-weighted case methodology changed midway through the study period, and the results changed from a relatively stable cost to one that was rapidly increasing. This could have an effect on our calculations of the share of decedent and survivor expenditures going to hospital services, but the effect on the relative comparison between decedents and survivors for hospitals or total expenditures would be negligible. Our continuing care cost estimates were based on two point estimates for 1991/92 and 1995/96, respectively, with no more recent information available. Generally, we believe that the broad nature of the study makes the necessary cost assumptions tolerable, and that they would not have a significant effect on provincial averages or comparisons.

While the Canadian health care system is among the most universal and comprehensive, there are still some services and costs that are not covered by the public insurer and thus would not be captured in our data. In particular, there is a significant market for private services in continuing care, such as home nursing services and retirement homes that offer care services (Coyte and McKeever 2001; CIHI 2005). Some types of physiotherapy or occupational therapy may not be covered; dentistry and over-the-counter medicines are not captured in the public data either. Bearing these limitations in mind, we feel that our data covers the vast majority of health care expenditures for the
elderly and compares favourably in terms of comprehensiveness to data used in other cost-of-dying studies.

Interpretation of the results and discerning supply versus demand effects is a more important limitation. For example, reduced spending on continuing care among survivors could be due to improved health among these populations, as we speculate above, or it could simply be due to limited supply of these services, as was likely the case in continuing care after the policy changes in the mid-1990s. Societal preferences for allocation of care may influence changes in consumption more than underlying changes in health (Ubel 1999). Labour shortages and a constrained supply of facility beds would likely mean that services get allocated to those with greatest need – i.e. decedents – first and survivors’ consumption might decline regardless of whether actual need for these services in fact declined (Chernichovsky and Markowitz 2004). While it is likely not possible to attribute changes exclusively to one of supply or demand effects, we believe the results are nevertheless informative and represent the result of a combination of both. The amount of health care services consumed depend both on the population’s need for those services as well as the economy’s ability to supply them. Regardless of the relative importance of each factor, the trends observed in this study, if continued, will have material consequences on the future allocation of resources in the health care sector and the economy at large.

3.8 Conclusion

Our study examines the relationship between decedent and survivor expenditures in British Columbia and the time trends in each for both individual sectors of the health care system and the system as a whole. The result of falling survivor costs, particularly for hospital and continuing care expenditures is a potentially important one for future health care system development and resource planning. Further research is needed to determine the extent to which falling survivor utilization reflects improved health and lower need on
one hand, or reduced access given supply constraints and rationing on the other. The implications of these two possible causes differ considerably.

An increasing decedent/survivor ratio suggests that a forecast of future health expenditures using our cost-of-dying data and assuming increased life expectancy could significantly reduce expected costs in comparison with simple age-based models. Aging may not be the significant threat to health care budgets that is commonly assumed, and researchers and policy makers should take care that a focus on the effects of aging does not distract from other causes of health care cost inflation such as technology, labour market, and income effects.
4 Statistical Modeling of Time to Death, Age, and Health Expenditures

4.1 Introduction

As described in our literature review (Payne et al. 2007), the literature covering the relationship between health expenditures, aging, and time-to-death includes both descriptive and statistical data analyses. While the descriptive analyses are typically sufficient as a basis for estimation of the relative cost of dying and for forecasting future expenditures, they cannot provide estimates of the direct relationships between variables, causal or otherwise. Statistical analysis is needed to isolate these relationships from multivariable models, and to estimate their significance.

Our research interest in these statistical models is twofold. First, we want to add a Canadian perspective to confirm or augment the conclusions reached by Zweifel and colleagues using Swiss data that, when the effect on expenditures of dying is taken into account, aging is a ‘red herring’ in that on its own it does not have an appreciable effect on health expenditures. In other words, aging appears to have an effect on expenditures only through increasing mortality rates. This was the finding of Zweifel, Felder and Meier (1999, hereafter referred to as ZFM) in their first study of a Swiss Sick Fund between 1984 and 1992, and was in part confirmed by Werblow, Felder and Zweifel (2007, hereafter referred to as WFZ) when they broke total expenditures into categories such as acute and long-term care.

Our cost of dying descriptive analysis indicated that the Canadian data may support different conclusions (Payne, Chapter 3; et al. 2009). Survivor expenditures rise with age for all health care services through age 80 and continue to rise into older ages for the
most expensive services, hospital and continuing care. Continuing care costs represent
the majority of total costs after age 80 in our data (Payne et al. 2009), and their very
strong rate of increase with age leads to a similar increase in total survivor expenditures.
Since survivors are all at least one year away from death, something other than mortality
may be influencing the relationship between age and health expenditures and it may be
possible that age is not a red herring, at least not for continuing care services in Canada.
To confirm this conjecture, however, or at least to add confidence to the claim, requires
more detailed statistical modeling and consideration of a longer period before death than
just the last year of life.

Our second research interest is to investigate whether the relationship between
expenditures, age, and time-to-death, is changing over time. Many of the forecasts based
on cost-of-dying or time-to-death research have assumed that these relationships remain
static over time (e.g. Miller 2001 and Madsen, Serup-Hansen, and Kristiansen 2002).
However, as different cohorts enter high-mortality age groups and as health systems
evolve, it is reasonable to expect that there may be some change in the way in which
health care spending reflects aging and mortality. Relatively little work has been done to
estimate such temporal change, likely in large part due to the substantial data
requirements. Seshamani and Gray (2004a), in their studies of the hospital data from
Oxfordshire England, found a decrease in the effect of time-to-death between cohorts
dying in 1970 and 1990. ZFM’s original ‘red herring’ study (1999), which used two
sequential datasets, also showed a potential reduction in the effect of time-to-death,
represented by decreasing significance of the time-to-death dummy variables from the
earlier to the later study period. Other studies, however, offer opposite conclusions
(Payne et al. 2007). Felder, Meier, and Schmitt (2000, hereafter referred to as FMS), and
WFZ (2007), who study the effect of age controlled for time-to-death using the same
Swiss data sources as in ZFM, did not include a temporal element.
In this chapter we will focus on the first research interest: estimating the effect of age on health care expenditures, controlling for time-to-death. We will also add an element of temporal analysis by separating the data into two periods and looking for changes over that time, both in the controlled effect of age and in the effect of time to death, analogous to the work reported by Seshamani and Gray (2004a). Similar to WFZ, the analysis will be organized around different sub-categories of overall health care utilization. In our case, we look at four expenditure components: hospital services; continuing care (including home care and long-term residential care); physician billings; and prescription drug costs.

4.2 Theoretical Context

The cost-of-dying and time-to-death literature is more concerned with methodology and measurement than with theory, but there are some theoretical considerations that apply. These chiefly concern the roles that age plays in affecting the demand for health and/or health care. In particular, when considering the impact of age on its own, it is important to separate the mortality-related effects of age on health care utilization from the other factors that drive demand that might be mediated by age.

The concept of age as a ‘red herring’ was alluded to as early as Grossman’s seminal work characterizing health as an investment good (1972). Grossman’s model incorporates a depreciation function in the health stock that increases with age and, all things equal, leads to an increased demand for health care in older individuals. However, higher rates of depreciation also increase the cost of health capital, leading to a substitution away from health capital to other capital goods. As a result, the equilibrium desired health stock is lower through the aging process and investment in health does not grow at the same rate as depreciation.
The Grossman model supposes two offsetting dynamics driving how age influences health care utilization, both driven by the increasing depreciation function: as individuals age, on one hand there is a decline in health status and the need to replenish health capital, while on the other increasing cost of capital leads to a substitution to non-health investment goods. While the first dynamic increases demand for health care services, the second reduces it. A more recent model from the time-to-death literature sets up a similar framework of offsetting age-driven dynamics (FMS). Instead of optimizing a desired stock of health, as in Grossman, the authors imagine individuals faced with a mortality hazard function, and set up a maximization problem to determine individuals’ willingness to pay to reduce this mortality risk.

The variable to be maximized in FMS’s framework is the utility of future lifetime consumption, subject to a mortality hazard function and a wealth constraint. In this case the mortality hazard function is assumed to be of a Gompertz form, so that the probability of dying increases at some exponential rate with time (and age):

\[ q(t) = a \cdot e^{bt}, \quad (a, b \geq 0) \]

As an individual ages, the expected remaining lifespan decreases, and so too does the expected value of future consumption. So long as income is not expected to rise (a reasonable assumption for the elderly), individuals will be willing to pay less for a reduction in mortality risk as they get older and have less consumption utility to gain. On the other hand, assuming no bequests, higher mortality risk shortens the expected life horizon over which the remaining consumer surplus will be allocated, leading to higher optimal rates of consumption. Since higher mortality risk leads to higher rates of consumption discounted over a shorter period of time, it increases the expected utility of the optimal consumption path and willingness to pay to reduce this risk is accordingly higher. Restated, the model hypothesizes that increasing age for a given mortality hazard function – i.e. a movement along the morality/age curve – reduces willingness to pay for
health (thus reducing demand) while a shift higher in the mortality risk function for a given age has the opposite effect.

The offsetting dynamics of age in Grossman and in FMS are different in their formulation, yet similar in the conclusions they generate. Where Grossman posits increasing health deterioration and prohibitive cost of health investment with age, FMS posit increasing risk of death and reduced expected consumer surplus. Each model creates a technical representation to describe the possibility that, while health problems grow with age, the value of future life and the demand to address those problems declines.

Placing a value on human life, and making distinctions in that value based on one’s age, as is implicit in both theories discussed above, is, of course, politically and ethically fraught (see e.g. Harris 1994; Cutlas 2008), and may not fully or accurately reflect the real-world decisions made by individuals and those who administer their care. Turning away from economic optimization problems, the Andersen behavioral model used to model health service utilization may help provide some additional context. As first described (Aday and Andersen 1974, and later in Andersen 1995), the model suggests that an individual’s use of health services depends on three groups of factors: predisposing characteristics such as age, gender, how an individual manages problems, and beliefs about health and health care (religious or otherwise); enabling characteristics including access to and knowledge of the health care system, family and community support, and the necessary financial means for care; and, finally, health characteristics, or the assessed true ‘need’ for care, from both the individual’s and the caregiver’s perspective.

In this construct, which is necessarily general and all-encompassing, we can see a number of areas in which age may come into play in determining health care service utilization, and relate these to the more specific economic models of Grossman and FMS. First,
actual health status, reflected in Grossman’s depreciation and FMS’s mortality risk function, is best captured in the behavioral model with need. Interestingly, Aday and Andersen distinguish between self-assessed need and the assessment (or ‘evaluation’) of the caregiver, highlighting the difficulty of objectively defining health status and need beyond the absolute of mortality. Nevertheless, although it may be difficult to measure objectively, health status is intuitively an important driver of health care utilization.

The Andersen framework also provides insight into the non-health-related factors through which aging might influence health care demand. Coping with the process of aging and dying is a very personal matter, and individuals’ beliefs and desires about the last years of their life might change according to their age. Older individuals may be more mentally prepared for death and less willing to undergo the indignities and inconveniences of examinations and treatments and may therefore be less predisposed to seek health care even in the face of mounting health problems. Access, too, may be reduced with age, due to reduced mobility and smaller community networks. The behavioural model can provide real-world descriptions of why utilization of health care services given constant health status may be lower for older individuals.

Andersen’s model can also suggest how and why the relationship between age, health status, and health care utilization might differ between different health care services. For example, reduced mobility and smaller networks may lead to lower likelihood of visiting the doctor or filling a prescription at the drug store, but on the other hand it may also contribute to a higher likelihood of receiving home care or being institutionalized. Similarly, older individuals unwilling to undergo the indignities of treatment may also choose not to visit their doctor or even to receive home care, but in an eventual crisis that leads to hospitalization or institutionalization they may no longer have a choice.

We use the notion of different levels of patient discretion for different services to generate hypotheses in the following section. Although discretion may be difficult to
define and measure concisely, there is some precedent discussion of the concept in the literature. Mitchell and Krout (1998) categorize health services according to the extent to which they can be considered ‘discretionary’, with hospital services being the least discretionary, and homemaking or meal services most discretionary. When the behavioural model was applied to each group of services independently, it was found that predisposing and enabling factors were more important predictors for the most discretionary services. Wolinsky et al. (1983) found that the predictive power of the behavioural model was stronger when applied to community-based, as opposed to formal, health care. In a subsequent study, the behavioural model was found to explain more of the variation in physician services than hospital services (Wolinsky and Coe, 1984). At the same time, health status factors were more important predictors of hospital than physician services. These studies provide some empirical support for the theory that behavioural factors such as reduced access and lower predisposition to seek care with age would have a greater effect on health service categories whose utilization is relatively more the choice of the patient.

It is not only individual behaviours and characteristics that determine the quantity of health care utilization. In most jurisdictions supply is to some extent rationed and some decisions relating to utilization of health care rest in the hands of administrators from public or private insurers or of the care providers themselves. In the Canadian system, individuals can choose when to visit their primary care physician. For other services, the primary care provider must agree to make a referral for the care and the providers who receive the referral may choose whether or not to see the patient. Prescription drugs must be prescribed by a physician. Hospitals can choose, with some limitations, whether or not to admit and when to discharge. Continuing care case managers can ration home care and government-funded long-term care beds. (In fact, in British Columbia during our study period a policy decision was made to provide more intensive care to the higher-need individuals and to ration care to lower-need applicants.)
The choices made by administrators and providers, though not explicitly stated, are also in many cases influenced by age (Hurst et al. 2006; Loewry 2005). Even where not based on age alone, rationing decisions may be made based on factors that are correlated with age, such as disease severity or providers’ judgment of the patient’s quality of life (Hurst et al. 2006). Age can influence the utilization of care not only through individual behaviours and health status but through how it changes the assessments of those responsible for allocating care.

4.3 Hypotheses

We do not have a priori reasons for forming hypotheses regarding total expenditures and age. Instead, we generate hypotheses about the four different service categories in our study which, if they hold true, and given the relative size of each service category, can provide an indication of how they might impact the total. Our category-level hypotheses are based on three sets of assumptions: different levels of discretion for different services; age-related changes in supply and demand-side preferences for place of death and location of care; and declining health status in the survivor cohort with age.

Our first set of assumptions concerns the level of patient discretion in the decision to utilize care for different service categories. We assume that hospital and continuing care services involve relatively low levels of patient discretion while discretion is higher for doctor services and prescription drugs. Although each of hospital and continuing care includes elements that may be more discretionary (e.g. elective surgery and homemaking or meal services), they are dominated by large spending for non-discretionary situations such as emergency acute events for hospitals and long-term residential care for continuing care. On the other hand, both doctor billings and pharmaceutical prescriptions are triggered by the voluntary event of visiting a doctor and further, for prescription drugs, of filling the prescription and taking the drug(s) according to instructions.
As a consequence of our assumptions regarding the level of discretion involved in different service categories, we expect to see different patterns in the doctor and drug categories versus hospitals and continuing care. In particular, the effect where the predisposition to seek care is reduced with age should be more visible in the more discretionary categories. This would manifest in age/health expenditure curves with lower slopes for doctors and drugs than for hospitals and continuing care.

Our second set of assumptions is with respect to changing preferences with age for the location of care and the types of treatment given to dying individuals. Individuals dying in the younger age range of our study population (65 to 75 or 80) are more likely to die from an acute event (accident, cardiac arrest, or aggressive cancer) while deaths in the older ranges are more likely to be from chronic causes or simply due to ‘old age’ or other unspecified causes (Lunney, Lynn and Hogan 2002; Alperovitch et al. 2009). On the supply side, policy makers are wary of using expensive hospital beds to house long-term chronic cases, and complicating factors such as co-morbidities may make invasive treatment of individual diseases less likely (e.g. Samet et al. 1986). Furthermore, demand side preferences for home-based care and less invasive treatments rise with age (Coyte, Laporte, and Stewart, 2001). One potential result of such policies and preferences is a substitution effect where continuing care increasingly substitutes for utilization of hospital services for older patients. This would be the case particularly for individuals near death, but we also expect to see some evidence for this substitution among our survivor cohort.

Our final assumption driving our hypotheses is that the health of the survivor cohort in our study declines with age. We define the survivor cohort as those known to live at least three years beyond the year in which expenditures are being measured. Unlike the case of decedents, where remaining life expectancy is the same by definition – one to three years, depending on the value of time to death – regardless of age, our survivor cohort
will have a life expectancy that declines with age. As a result, the shape of the age/health expenditure curve for survivors will be guided by two dynamics that influence health care utilization in generally opposite directions: the changing propensity to seek and provide care and the greater need for care due to deteriorating health status. In the case of decedents, with health status being equal, it is only the former dynamic that drives our hypotheses.

The foregoing discussion leads us to the following broad hypotheses that compare the age profile of health expenditures for different service categories and different survivor statuses:

1. The slope of the age/expenditure curve will be lower for doctors and drugs than for hospitals and continuing care for both decedents and survivors
2. The slope of the age/expenditure curve will be lower for hospitals than for continuing care for both decedents and survivors
3. The slope of the age/expenditure curve will be lower for decedents than for survivors across all service categories

Since continuing care and hospitals are much larger spending categories than doctors and drugs, we expect the age/expenditure curve for total expenditures will more closely resemble the curves for those services, with relatively higher slope.
4.4 Methods

We use data from the British Columbia Linked Health Data (BCLHD) database covering the years 1991-2002. The steps in data and preparation are previously described in detail in the Data section of the cost-of-dying portion of this thesis (Sections 3.3 and 3.4, and in Payne et al. 2009). We have created three time-to-death dummy variables and nine interaction terms where each of age, age-squared, and sex are interacted with each of the three time-to-death dummy variables. The complete list of variables in the model is as follows:

Panel (cross section and time series) variables:

- **Study_ID**: Unique identifier for individual
- **Reg_Yr**: Calendar year to which expenditure is assigned

Dependent variables:

- **total**: Total expenditures
- **hospital**: Hospital expenditures
- **ltc**: Continuing care expenditures
- **doctor**: Doctor billings
- **ph**: Prescription drug expenditures

Independent variables (18):

- **SE_Dec**: Socio Economic Decile of the individual’s census subdivision
- **Docs_per10k**: Number of practicing doctors (general and specialist) in individual’s health region, per 10,000 inhabitants
- **M**: Dummy variable taking value one if individual is male
- **Age**: Individual’s age, in years
- **Age2_100**: Individual’s age, squared, and divided by 100
- **Asex**: Equal to **Age * M**
- **TTD1**: Dummy variable equal to one if individual in last year of life
- **AgeTTD1**: Equal to **Age * TTD1**
- **Age2TTD1**: Equal to **Age2_100 * TTD1**
- **MTTD1**: Equal to **M * TTD1**
**TTD2**

Dummy variable equal to one if individual in second-last year of life

**AgeTTD2**

Equal to \( Age \times TTD2 \)

**Age2TTD2**

Equal to \( Age2_{100} \times TTD2 \)

**MTTD2**

Equal to \( M \times TTD2 \)

**TTD3**

Dummy variable equal to one if individual in third-last year of life

**AgeTTD3**

Equal to \( Age \times TTD3 \)

**Age2TTD3**

Equal to \( Age2_{100} \times TTD3 \)

**MTTD3**

Equal to \( M \times TTD3 \)

The first two independent variables listed above are intended to represent the enabling factors in Andersen’s behavioral model. The doctors per capita variable represents access to the health care system, while the socioeconomic decile is intended to capture factors such as education and income. The doctors per capita variable is from 2002 and is time invariant, while socioeconomic decile can change with change of home address. While these variables are broad and are measured at the regional, as opposed to individual, level, they can still shed light on the role of Andersen’s enabling factors, and in particular how that role might change between different health care service categories. Furthermore, neighbourhood socioeconomic decile may more closely reflect family wealth than does annual income, which can be highly variable. Buckley et al. (2004) suggest that household resources (i.e. wealth), as opposed to annual income, are likely the more important determinant of health status, an argument that can be extended to health care utilization as well. Andersen’s predisposing factors are represented in our model by gender and age, while health characteristics are represented by the time-to-death dummies.

We include a quadratic term for age to allow for estimation of potential second derivative effects and inflection points where the effects of age on health expenditures turn from positive to negative. Under the FSM model, if expected income is rising with age, the willingness to pay for an improvement in health with age may increase. Although this may be less of an issue with our study population of seniors where incomes are generally...
fixed or falling, it is possible that for some ages near 65 expected incomes may still be rising for some individuals. Similarly, the reduced predisposition to seek care in the Andersen framework may not be linear in age, and may not even be visible until a certain age that could quite possibly be older than 65. Quadratic specifications of age allow the estimated effect to change over the range of ages in our study.

Age in interaction terms with time to death is also specified to the quadratic level. Our literature review showed that the relative cost of dying decreases significantly with age, and similar age-driven changes have been found in time-to-death models of expenditures (Payne et al. 2009; Seshamani and Gray 2004a). It is not clear from the literature whether age may have non-linear interactive effects with time to death, but our quadratic specification allows for this possibility. Finally, the sex/time-to-death interaction terms are included to capture possible differences in the effect of time to death between men and women. These might arise due to differences in informal care arrangements, spousal survival rates, or causes of death.

We have separated the data into two time periods to allow for the investigation of changes over time. We are limited to analyzing expenditures for the years 1999 and earlier due to our specification of time-to-death up to three years. Since we know deaths only to 2002, for expenditures in the year 2000 we cannot populate the $TTD_3$ variable, for 2001 expenditures we cannot populate $TTD_2$ or $TTD_3$, and so on. With the remaining nine years of expenditure available, we chose the time periods to be as large as possible without overlap. The result was two four-year periods beginning five years apart: 1991-1994 and 1996-1999.
4.4.1 Model specification

Our model is a two-part panel data analysis, following the method used in the Oxford hospital data studies of Seshamani and Gray (2002; 2004a; 2004b). The first part is a probit analysis in which the probability of positive utilization is estimated according to the following regression:

\[
Pr (HCEij > 0 \mid X = x_{ij}) = \Phi (x_{ij}'B_p + \varepsilon)
\]

where \(\Phi\) is the cumulative normal distribution function, \(X\) is the vector of independent variables (with \(x_{ij}\) representing the observed values of \(X\) for individual \(i\) in year \(j\)), and \(B_p\) is the vector of coefficients estimated using a probit model.

The second part estimates the amount of spending conditional on positive utilization, with \(B_r\) representing the coefficients of the simple regression:

\[
E (HCEij \mid HCEij > 0, X = x_{ij}) = x_{ij}'B_r + \varepsilon
\]

We have chosen to use the simple two-part estimation in place of the Heckman model used by ZFM, following on the reasoning established by Salas and Raftery (2001) and Dow and Norton (2003). The Heckman model is intended to handle the possibility of selection bias in models of potential outcomes where many outcomes are unobserved. Dow and Norton (2003) cite as an example of a model of potential incomes that of potential wages, where individuals not working would have zero observed wages but their potential wages would be non-zero. Modeling only the observed positive wages could create selection bias since the non-working population will likely have different potential wages than those working. Since our model is concerned with actual health
expenditures, including observed zeros, the Heckman model is not needed to correct for selection bias and the two-part model is appropriate.

Beyond the question of zero-value observations, it seems reasonable to expect that the error terms for the probit and conditional regression equations are not significantly correlated. While omitted variables that could have a similar effect on both the probability of positive utilization and conditional expected spending might be found among health status measures such as diagnoses and acute events, variables such as these were not available for testing. It is also our belief that the prevalence of such health conditions is to some extent reflected in a more general sense through the time-to-death dummy variables, which serve as a proxy for health status in this study.

Due to very high probabilities (greater than 95%), the probit segment of the two-part model would not converge for doctor billings. For this service category we used a single-step, simple panel data regression on expected expenditures. For prescription drugs, hospital services, and continuing care, where probabilities of positive utilization were much lower (particularly so with the latter two services), we used the two-part model as specified above.

The challenges of aggregating results derived from different modeling techniques for different service categories led to the decision to model total expenditures in a separate model instead of summing the results of the four categories. The difference between a separate model and summing the four categories was less than 3% for decedent predicted expenditures and as high as 23% for survivors where the base expenditure amounts are lower. In the case of survivor expenditures where the difference is higher, separate modeling is always preferred to summing in that predicted values are closer to the actual known averages.
We used a one-way random effects specification of the panel data model, for reasons similar to those outlined by Seshamani and Gray (2004b). Namely, individuals with all-positive or all-zero observations would be dropped from the model under a fixed effects specification. While the Hausman test comparing fixed and random effects indicates a systematic difference in coefficient estimates, the differences in individual coefficient estimates are generally small. Furthermore, the predicted values from the random effects model are much closer to the observed data than those from fixed effects estimation. The one-way random effects panel data model takes account of unique individual-specific effects.

4.4.2 The question of transforming the dependent variable

The raw data, as is common in health expenditure datasets (Manning, Basu and Mullahy 2005), is skewed and normality hypotheses are rejected (see Table 4.1 for descriptive characteristics of each variable in log and raw form). The log transformation substantially reduces, and in some cases eliminates, skewness. Kurtosis is also reduced but remains above zero, indicating that even after transformation the tails of the distribution are fatter than under the assumption of normality. Other common transformations, such as the negative binomial, box-cox, or square route, were similarly unable to correct for positive kurtosis.

The log transformation, commonly used in health econometrics, and used in all but one of the studies of health expenditures and time to death, was evaluated for its potential to improve the normality of the dependent variable, and therefore the accuracy of the model. While normality assumptions are more valid under the transformation, there are problems relating to retransformation and the outcome of post-estimation calculations. In particular, heteroskedasticity in the data and the non-linear nature of the logarithmic transformation can lead to systemic underestimation of predicted values (i.e. $XB$ for given values of $X$).
The problem of retransformations is well known in health econometrics (Manning, Basu, and Mullahy 2005; Manning and Mullahy 2001) but generally not addressed in the literature concerning time-to-death models of health expenditures. WFZ, however, do address the problem in their 2007 study. Their approach is to model the data untransformed so as to avoid the retransformation problem. They model both simple OLS and GLM, eventually choosing OLS after comparing mean square errors of both models. In our data, OLS, in avoiding the issue of non-linear logarithmic retransformation, also delivers predicted values that are much closer to the true population averages (see Appendix C for graphic examples and further discussion). After
Table 4.1: Distribution descriptives of 1996-1999 Data Set, by Dependent Variable, Comparing Logged versus Raw Values

<table>
<thead>
<tr>
<th></th>
<th>tot</th>
<th></th>
<th>hosp</th>
<th></th>
<th>ltc</th>
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<tr>
<td></td>
<td>log</td>
<td>raw</td>
<td>log / raw</td>
<td>log</td>
<td>raw</td>
<td>log / raw</td>
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<tr>
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<td>$1,121</td>
<td>$6,456</td>
<td>17.4%</td>
<td>$8</td>
<td>$2,102</td>
<td>0.4%</td>
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<tr>
<td>Positive-only mean (retransformed for log)</td>
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<td>$6,796</td>
<td>23.9%</td>
<td>$3,217</td>
<td>$8,156</td>
<td>39.4%</td>
</tr>
<tr>
<td>Rate of positive observations</td>
<td>97.0%</td>
<td>97.0%</td>
<td>25.8%</td>
<td>25.8%</td>
<td>16.2%</td>
<td>16.2%</td>
</tr>
<tr>
<td>Whole sample skewness</td>
<td>-1.07017</td>
<td>4.519952</td>
<td>1.233564</td>
<td>9.774643</td>
<td>2.003965</td>
<td>3.804561</td>
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<tr>
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<td>4.411931</td>
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<td>5.352347</td>
<td>-1.0386</td>
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<tr>
<td>Whole sample kurtosis</td>
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<td>37.1118</td>
<td>2.708235</td>
<td>151.3807</td>
<td>5.219863</td>
<td>16.94092</td>
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<table>
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<tr>
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<th>ph</th>
<th></th>
<th>med</th>
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</thead>
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<td></td>
<td>log</td>
<td>raw</td>
<td>log / raw</td>
<td>log</td>
</tr>
<tr>
<td>Whole sample mean (retransformed for log)</td>
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<td>$557</td>
<td>16.2%</td>
<td>$417</td>
</tr>
<tr>
<td>Positive-only mean (retransformed for log)</td>
<td>$261</td>
<td>$687</td>
<td>38.0%</td>
<td>$601</td>
</tr>
<tr>
<td>Rate of positive observations</td>
<td>81.0%</td>
<td>81.0%</td>
<td>96.3%</td>
<td>96.3%</td>
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<td>Whole sample skewness</td>
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<td>-1.90451</td>
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<tr>
<td>Positive-only skewness</td>
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<td>Positive-only kurtosis</td>
<td>3.162533</td>
<td>267.7225</td>
<td>3.335118</td>
<td>33.1503</td>
</tr>
</tbody>
</table>
significant consideration of questions of transformation, in particular the natural logarithm, we chose, similar to WFZ, to use basic OLS for its greater predictive powers.

4.4.3 Seemingly Unrelated Regression (SUR)

The possibility of using Seemingly Unrelated Regression (SUR) estimation techniques was also considered. As noted in the hypotheses section (4.3), we expect that expenditures for some categories of services will change depending on utilization of other categories. This type of codetermination would indicate that SUR estimation could add to the efficiency of the model. In our two-stage model, SUR would only apply to the first stage, where probability of positive utilization is estimated. The second stage, where conditional expenditures are modeled, uses a different data set for each expenditure category, so a general system of equations would not apply in this instance.

We were unable to find within STATA or SAS the capacity to run a SUR system of equations in the form of a panel data regression. Our exploration of SUR probit modeling of single-year cross sectional expenditures (using PROC QLIM in SAS) revealed that there were some apparent gains in efficiency and consistency between the individual years. To capture this gain, and consistent with WFZ, we chose to model the probit stage of our models jointly using SUR. We used STATA to run bivariate probit models as a SUR system. Continuing care and hospital probabilities were modeled together, following on our supposition that these services can act as substitutes for one another. Pharmaceutical probabilities were derived in combination with hospital probabilities, since hospital inpatient drug costs are mostly covered by the hospital. Medical and total spending were not modeled in the SUR system, since these were only one-stage models without a probit component.
4.4.4 Measuring the derivative with respect to age

Since we are interested in the overall effect of age on health expenditures, after controlling for time-to-death, and in particular the slope of the age/expenditure curve, we examine the partial derivative, with respect to age, of the model equations. This concept was first introduced in ZFM, in which they used a Heckman model where age entered into the equation in three variables: age, age-squared, and an age-sex interaction term. The authors examined the hypothesis that the coefficients for each of these three variables was zero, and found some support for this hypothesis in individuals aged 65 and over, similar to the age group in our study.

In our study, discerning the modeled effect of age is more complex due to three reasons: 1) age is interwoven much more deeply in the model specification, involved in nine explanatory variables; 2) the predicted values are the product of a two-stage model, requiring more complex differentiation; 3) the very large size of the dataset is likely to make coefficient estimates significant even if the overall effect on predicted values is not. As a result, instead of ZFM’s simple hypothesis that all age coefficients are zero, we go through the process of evaluating the derivative of the model equations with respect to age. The partial derivative of the expected value, using the chain rule, can be expressed as

\[
\frac{\delta EY}{\delta A} = \frac{\delta}{\delta A} \left[ \Phi (X'\beta_p) \ast (X'\beta_r) \right]
\]

\[
= \frac{\delta \Phi (X'\beta_p)}{\delta (X'\beta_p)} \ast \frac{\delta (X'\beta_p)}{\delta A} \ast (X'\beta_r)
\]

\[
= \text{pdf} (X'\beta_p) \ast \frac{\delta (X'\beta_p)}{\delta A} \ast (X'\beta_r)
\]

\[
+ \Phi (X'\beta_p) \ast \frac{\delta (X'\beta_r)}{\delta A}
\]
where pdf is the probability density function of the standard normal distribution and both \( \frac{\delta (X'B_p)}{\delta A} \) and \( \frac{\delta (X'B_r)}{\delta A} \) consist of the nine explanatory variables involving age differentiated and evaluated for given \( X \) and \( B \).

We estimate 95\% confidence intervals for the age-derivative of the expected value of each of the health care expenditure categories using the \textit{lincom} command in STATA. \textit{Lincom} generates point estimates and confidence intervals for given linear combinations of explanatory variables from estimated regressions equations. We examine the age-derivative for individuals in their last year of life and survivors with more than three years lifetime remaining. The derivative is evaluated at eight ages between 66 and 99. We focus primarily on the results from the later, 1996-1999 dataset, and subsequently use the 1991-1994 dataset to compare the two time periods.

### 4.5 Results

The 1991-1994 dataset contains 1,755,060 observations of annual expenditures for 505,813 individuals, for an average of 3.5 years per individual. The 1996-1999 dataset contains 2,037,093 observations for 595,255 individuals, averaging 3.4 years per individual. While death rates remained stable (Payne et al. 2009) between the two periods, the number of individuals entering the cohort at the age of 65 increased, therefore increasing the number of incomplete panels and slightly reducing the average years per individual.

The results of the OLS regressions and bivariate probits for the 1996-1999 dataset are presented in Tables 4.2 and 4.3, respectively. Not surprisingly for such a large dataset, most coefficient estimates are statistically significant, as shown by their Z-scores. In some cases (e.g. hospital and medical OLS regressions and hospital and continuing care
<table>
<thead>
<tr>
<th>Variable</th>
<th>Total</th>
<th>Med</th>
<th>Hosp</th>
<th>LTC</th>
<th>Ph</th>
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<td>Z</td>
<td>Coef</td>
<td>Z</td>
<td>Coef</td>
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<td>0.117545</td>
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</tr>
<tr>
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<td>5014.268</td>
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<td>174.1636</td>
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</tr>
<tr>
<td>asex</td>
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<td>-42.62</td>
<td>6.0207</td>
<td>17.07</td>
<td>-66.2463</td>
</tr>
<tr>
<td>ttd1</td>
<td>-72505.3</td>
<td>-18.33</td>
<td>10766.7</td>
<td>26.56</td>
<td>-30106.5</td>
</tr>
<tr>
<td>agettd1</td>
<td>2586.537</td>
<td>26.3</td>
<td>-152.794</td>
<td>-15.14</td>
<td>1407.538</td>
</tr>
<tr>
<td>age2ttd1</td>
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<td>-27.83</td>
<td>45.63757</td>
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<td>-1058.54</td>
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<tr>
<td>ttd2</td>
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<td>3100.05</td>
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<td>1.1</td>
<td>-264.404</td>
</tr>
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<td>ttd3</td>
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<td>-6.29</td>
<td>1820.997</td>
<td>4.9</td>
<td>9561.525</td>
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<tr>
<td>age2ttd3</td>
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</tr>
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<td>-1408.63</td>
</tr>
<tr>
<td>mtt3</td>
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<tr>
<td>_cons</td>
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<td>54.27</td>
<td>-6123.97</td>
<td>-48.24</td>
<td>17314.21</td>
</tr>
</tbody>
</table>

adj r-squared | 0.2563 | 0.0897 | 0.1072 | 0.1185 | 0.027 |
probits) estimates for TTD=2 and TTD=3, along with their associated interactions with age, are less significant. Since these coefficients are often of opposite signs defining a parabolic influence on the curve (i.e. age interaction positive and age-squared interaction negative, or vice versa), this could indicate a more linear and less exponential relationship at these levels of TTD.

Table 4.3: Estimated Coefficients and Z-Scores for Bivariate Probit Models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Hosp Prob</th>
<th>Ltc Prob</th>
<th>Ph Prob</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Coef</td>
<td>Z</td>
<td>Coef</td>
</tr>
<tr>
<td>se_dec_cl</td>
<td>-0.00295</td>
<td>-9.17</td>
<td>-0.003049</td>
</tr>
<tr>
<td>docs_per10k</td>
<td>-0.00444</td>
<td>-51.83</td>
<td>0.003021</td>
</tr>
<tr>
<td>m</td>
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<td>-4.54</td>
<td>0.815626</td>
</tr>
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<td>age</td>
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<td>-0.04139</td>
</tr>
<tr>
<td>age2_100</td>
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<td>-0.0145</td>
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The coefficients for socioeconomic decile (se_dec_cl) and the number of doctors per capita (docs_per10k) in an individual’s region are statistically significant, with the exception of the OLS for doctor billings. As a gauge of clinical significance, Table 4.4 presents the partial changes when these coefficients are applied to high, medium, and low values of each variable (1996-1999 data). Table 4.4 shows that, after controlling for age,
Table 4.4: Partial Changes in Dependent Variable for Given Levels of Regional Socioeconomic Decile and Doctors per 10,000 Residents, 1996-1999

<table>
<thead>
<tr>
<th>se_dec_cl</th>
<th>Value</th>
<th>All Services</th>
<th>Doctors</th>
<th>Hospital</th>
<th>Cont Care</th>
<th>Drugs</th>
<th>Hosp Prob</th>
<th>C Care Prob</th>
<th>Drug Prob</th>
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<td>-$71</td>
<td>-$117</td>
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<td>0.01</td>
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<td>-$586</td>
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<td>$792</td>
<td>$5</td>
<td>$715</td>
<td>$1,172</td>
<td>$23</td>
<td>0.03</td>
<td>0.30</td>
<td>0.11</td>
</tr>
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<table>
<thead>
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<th>docs_per10k</th>
<th>Value</th>
<th>All Services</th>
<th>Doctors</th>
<th>Hospital</th>
<th>Cont Care</th>
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<th>C Care Prob</th>
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<tr>
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<td>-0.10</td>
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<tr>
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<td>$51</td>
<td>$1</td>
<td>$54</td>
<td>$346</td>
<td>-$18</td>
<td>-0.05</td>
<td>0.03</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Table 4.5: Combined Effects of Sex and TTD = 1, 2, and 3 on Dependent Variables for Ages 66 and 99, 1996-1999

<table>
<thead>
<tr>
<th>Effect</th>
<th>Age 66</th>
<th>Age 99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 66</td>
<td>$511</td>
<td>-$37</td>
</tr>
<tr>
<td>Age 99</td>
<td>-$5,030</td>
<td>$161</td>
</tr>
<tr>
<td>TTD1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 66</td>
<td>$24,528</td>
<td>$2,670</td>
</tr>
<tr>
<td>Age 80</td>
<td>$26,167</td>
<td>$1,464</td>
</tr>
<tr>
<td>Age 99</td>
<td>$17,786</td>
<td>$113</td>
</tr>
<tr>
<td>TTD2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 66</td>
<td>$7,746</td>
<td>$803</td>
</tr>
<tr>
<td>Age 80</td>
<td>$10,614</td>
<td>$389</td>
</tr>
<tr>
<td>Age 99</td>
<td>$10,298</td>
<td>-$133</td>
</tr>
<tr>
<td>TTD3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 66</td>
<td>$4,733</td>
<td>$493</td>
</tr>
<tr>
<td>Age 80</td>
<td>$6,483</td>
<td>$243</td>
</tr>
<tr>
<td>Age 99</td>
<td>$6,696</td>
<td>-$80</td>
</tr>
</tbody>
</table>
sex, and time-to-death, there remains a fairly substantial effect by which individuals living in higher income regions with more practicing doctors are more likely to use health care services in larger amounts. There are a few exceptions to this rule, for example where drug spending is higher in regions with fewer doctors per capita, as is the likelihood of using hospital services, possibly indicating some substitution. However, largely due to the two highest-value services of continuing care and hospitals, higher socioeconomic class and access to more doctors lead to overall spending nearly $1,000 higher than the lower end of these categories. This could be considered a minor validation of the framework of Andersen’s behavioural model concerning access to care.

Although the enabling factors of supply (doctors per capita) and access (socioeconomic decile) have a positive effect on overall spending, the differences in this effect between different health care services categories are at variance with the literature that explores the discretionary nature of services. The largest effects for enabling factors, both in absolute dollar values and in relative percentage terms, are in what we assumed to be the non-discretionary categories of hospitals and continuing care. The effects for drug spending and doctors are minimal by comparison, with the relative effect on doctor spending of both enabling factors less than 1% for all values of age and time to death.

Since the influence of individual factors such as sex or time-to-death is muddied by the interaction terms with age, it helps to apply the coefficients of all terms containing these factors to given ages in order to understand the combined effects. These combined effects are presented in Table 4.5. Looking first at sex, males are associated with generally lower expenditures and lower probability of positive utilization than females. This is particularly true in the probability of using prescription drugs and continuing care, and in the conditional spending on continuing care. The amount by which conditional spending on continuing care is lower increases significantly with age, so that a 99-year-old male user of continuing care is expected to use $7,000 less services versus a female of the same age. For conditional hospital spending, younger males are associated with
higher spending but, as with continuing care, female spending grows much more rapidly
with age, so that by age 99 conditional spending is much lower for males than females.
Doctor billings are the only spending category that increases with age more rapidly for
males than females.

Turning to the time-to-death variables, the positive influence of each of TTD = 1, 2, and
3 in comparison with TTD > 3 can be seen with the combined effect of each variable
being positive in almost all cases. The effect of time-to-death diminishes with age for
nearly all spending categories and probabilities. Conditional continuing care
expenditures are the major exception to this rule, with the influence of TTD = 1, 2, and 3
relative to TTD > 3 being greater at age 99 than 66. This increase in the effect of time-to-
death on continuing care with age is enough to create a similar dynamic for total
expenditures evaluated at TTD = 2 and 3. While the effect of time-to-death on the
probability of positive continuing care usage declines from age 66 to 99, the baseline
probability is much higher at older ages, so the higher conditional expenditures have a
greater influence on the total.

4.5.1 Predicted values

The predicted values for all service categories are presented in Figures 4.1 (for TTD=1)
and 4.2 (for TTD>3). For decedents (TTD=1) total predicted expenditures rise in near
linear fashion with age from over $26,000 at age 66 to over $40,000 at age 99. The
overwhelming influence on total expenditures comes from continuing care and hospital
services. Predicted continuing care expenditures rise with age while predicted hospital
costs fall. As continuing care is the larger cost category, especially for older ages, the net
effect is for steady gains in total spending. For survivors (TTD>3), predicted hospital
Figure 4.1: Predicted Expenditures by Service Category and Age, 1996-1999 Data, Decedents (TTD=1)
Figure 4.2: Predicted Expenditures by Service Category and Age, 1996-1999 Data, Survivors (TTD>3)
spending is much lower, so total expenditures are influenced much more heavily by continuing care expenditures alone. As a result the curve for total expenditures is not linear but exponential, rising with age, similar to the curve for continuing care. Hospital spending for survivors, in addition to being much lower than it is for decedents, rises as opposed to falls with age. The rate of increase is much slower than it is for continuing care. Figures 4.1 and 4.2 show how the effect of age can be dramatically different depending on remaining life expectancy. This will be further demonstrated in our consideration of the age-derivative of the estimation equations in the next section.

Appendix D further analyzes hospital and continuing care predicted expenditures by breaking them down into the probability of positive utilization and expected spending conditional on positive utilization. It also separates males and females and looks for evidence of the hospital-continuing care substitution effect.

Pharmaceutical expenditures and doctor billings are much smaller spending categories than continuing care and hospitals. Predicted expenditures for these categories are shown in Figures 4.3 (for TTD=1) and 4.4 (for TTD>3). Figure 4.3 shows that, like hospital spending, predicted expenditures for both drugs and doctors decline with age for decedents. The declines are in fact slightly steeper than for hospitals, by nearly 70% between ages 66 and 99 versus less than 60% in the hospital category. For survivors, Figure 4.4 shows that drugs and doctor spending again exhibit very similar patterns. While similar to one another, the patterns are quite different than for any other service, rising from age 66 to the early 80s, and falling thereafter. This point where medical and drug spending peaks could be evidence of the reduced propensity to seek discretionary care. Or it could be evidence of a growing substitution effect whereby more drug and doctor costs are covered within hospitals or long-term care homes as the likelihood of using these services increases. However, we find little evidence of such a substitution effect. Figures 4.5 and 4.6 compare predicted drug spending based on the whole sample to that based on a subsample with hospital usage equal to zero, for decedents and survivors, respectively. The shapes of the curves are very similar. Spending is lower for non-hospital users, opposite of what one might expect if a substitution effect were at
Figure 4.3: Predicted Expenditures by Service Category (Medical Billings and Drugs Only) and Age, 1996-1999 Data, Decedents (TTD=1)
Figure 4.4: Predicted Expenditures by Service Category (Medical Billings and Drugs Only) and Age, 1996-1999 Data, Survivors (TTD>3)
work. This may be due to positive hospital utilization indicating lower health status, and therefore higher utilization of drugs and other services.

**Figure 4.5:** Predicted Pharmaceutical Expenditures, Whole Population versus Subsample with Hospital Spending = 0, by Age, 1996-1999 Data, Decedents (TTD=1)

**Figure 4.6:** Predicted Pharmaceutical Expenditures, Whole Population versus Subsample with Hospital Spending = 0, by Age, 1996-1999 Data, Survivors (TTD>3)
4.5.2 Age Derivative of Estimated Equations

Figures 4.7 through 4.10 use the 1996-1999 dataset to plot confidence intervals for the age-derivative of expected expenditures for females for different health service categories and different survivor status, evaluated at eight different ages between 66 and 99.

Figures 4.7 and 4.8 show that the estimated age-derivative of total expenditures is positive for all ages for both decedents and survivors. In both cases the derivative rises with age (second derivative positive), indicating an acceleration of the positive influence of age (controlled for time-to-death) on expenditures. The acceleration is quite gradual for decedents, from a rate of slightly less than $500 per year of age at age 66 to slightly more than $500 per year of age at age 99. In contrast, the age derivative for survivor expenditures grows rapidly from just over $100 at age 66 to approximately $1,300 at age 99. The strongest influence on the age derivative of total expenditures is continuing care spending, which has very high first and second derivatives with respect to age in both decedents and survivors.

Figures 4.9 and 4.10 remove total and continuing care expenditures from Figures 4.7 and 4.8 to provide a better look at the age derivative of the remaining categories. For decedents, medical and drug costs decline with age while hospital costs also decline for ages 75 and older, at an accelerating rate (second derivative negative). For survivors, medical and drug costs both have a negative second derivative, with the first derivative starting positive at younger ages and crossing over to negative in the early 80s. The age derivative for survivors’ hospital spending is positive throughout, growing stronger at younger ages and then fading fairly rapidly at the oldest ages.
Figure 4.7: Age-Derivative of Expected Expenditures, by Age and Service Category, 1996-1999 Data, Decedents (TTD=1)
Figure 4.8: Age-Derivative of Expected Expenditures, by Age and Service Category, 1996-1999 Data, Survivors (TTD=3)
Figure 4.9: Age-Derivative of Expected Expenditures, by Age and Service Category (Hospitals, Drugs, and Doctors Only), 1996-1999 Data, Decedents (TTD=1)
Figure 4.10: Age-Derivative of Expected Expenditures, by Age and Service Category (Hospitals, Drugs, and Doctors Only), 1996-1999 Data, Survivors (TTD>3)
Figures 4.11 and 4.12 compare the confidence intervals for the age-derivative of total expenditures in 1991-1994 (red colour) to 1996-1999 (purple) for decedents and survivors, respectively. The Figures show a significantly higher age-derivative for decedents in the later time period at younger ages (66-80). For survivors, the age-derivative is significantly lower in the later time period for all ages. This corresponds to our descriptive work on the cost of dying (Payne et al. 2009) that showed a slight rise in decedent costs and a fairly large drop in survivor costs over the full 1991-2001 study period. While the effect of age on expenditures is decidedly positive overall, it may have been moderating during the time period under study. Given the large sample size, sensitivity to the choice of significance level was not high. For example, changing the significance level from 5% to 1% resulted in intervals that were 31% wider, with the upper and lower limits widening by slightly more than 2% each. Widening limits by 2% for the 1996-1999 confidence intervals did not cause overlaps with the 1991-1994 intervals if overlaps were not present at the 5% significance level. Changes in the age-derivative of expenditures for the individual categories are described in more detail in Appendix E.

Figure 4.11: 95% Confidence Intervals for Age-Derivative of Expected Total Expenditures, Females. by Age, 1991-94 vs. 1996-1999 Data, Decedents (TTD=1)
4.5.3 Time Changes in the Effect of Time-to-Death

Finally, we examine changes between the two time periods in the relative effects of time to death. Predicted expenditures for TTD = 1, 2 and 3 are compared to those for TTD > 3 and the resulting ratios are charted for ages 66, 80, and 99. The steepness and level of the resulting curves indicate the magnitude of the time-to-death effect. Figures 4.13 through 4.17 present the results for males for total expenditures as well as each of the four component spending categories. The Figures reveal a fairly consistent trend of a growing effect of time to death between the two study periods. For total expenditures (Figure 4.13), this growth is strongest for TTD = 1 (versus 2 or 3) and for age 80 (versus age 66 or 99). The ratio grew by 10%-16% between the 1994 and 1999 datasets for TTD = 1. In contrast, the ratio grew by only 7% for TTD = 3 at age 80, and actually fell by 2% and 5% for ages 99 and 66, respectively.

The stronger growth in the effect of TTD at age 80 is entirely due to continuing care, as can be seen in comparing Figure 4.15, for continuing care to Figures 4.14, 3.16 and 3-17.
for the other services. The ratio comparing all levels of TTD to survivors grew by 30% or more for age 80 versus a range of 0.3% to +4% for ages 66 and 99. The high growth in the TTD ratio is brought on by a large decline in survivor spending (more than 20%) in combination with growth of nearly 10% in decedent costs. For ages 66 and 99, the declines in survivor spending were lower, and decedent costs rose in contrast to the 10% fall at age 80.

**Figure 4.13: Effect of Time-to-Death Versus Survivors (TTD>3) of the Same Age, Total Expenditures, Male, Ages 66, 80, and 99, 1991-94 (dotted lines) vs. 1996-1999 (solid lines) Data**
Figure 4.14: Effect of Time-to-Death Versus Survivors (TTD>3) of the Same Age, Hospital Expenditures, Male, Ages 66, 80, and 99, 1991-94 (dotted lines) vs. 1996-1999 (solid lines) Data

Figure 4.15: Effect of Time-to-Death Versus Survivors (TTD>3) of the Same Age, Continuing Care Expenditures, Male, Ages 66, 80, and 99, 1991-94 (dotted lines) vs. 1996-1999 (solid lines) Data
Figure 4.16: Effect of Time-to-Death Versus Survivors (TTD>3) of the Same Age, Doctor Billings, Male, Ages 66, 80, and 99, 1991-94 (dotted lines) vs. 1996-1999 (solid lines) Data

Figure 4.17: Effect of Time-to-Death Versus Survivors (TTD>3) of the Same Age, Pharmaceutical Expenditures, Male, Ages 66, 80, and 99, 1991-94 (dotted lines) vs. 1996-1999 (solid lines) Data
4.6 Discussion

The results broadly confirm our hypotheses, demonstrating a decline with age in the demand for discretionary health care services that to some extent offsets the demand-increasing effects of declining health status. Confirming Hypothesis 3, declining demand for care with age is most evident in decedents, where health status is more equal across ages, and partial age derivatives are lower than for survivors. Hypothesis 1 is in part confirmed, since the partial age derivative for medical spending and prescription drugs is negative, in contrast to the large positive increases with age for total expenditures and continuing care. On the other hand, hospital expenditures, while rising at age 65 and 70, begin to tail off rapidly at later ages so the decline is in fact larger than that for the doctor and drug categories. It appears that the substitution effects from Hypothesis 2 outweigh the effect of reduced discretion in Hypothesis 1. Overall, while there is evidence of a reduced propensity to seek care and a substitution of expensive hospital services with age, the resulting age-related declines in doctor, drug, and hospital spending is more than offset by the dramatic increases with age in continuing care spending. As cause of death shifts to more chronic conditions or simple frailty (Ostbye et al.1999; Lunney, Lynn and Hogan 2002; Alperovitch et al. 2009), and as informal care resources (particularly spousal care) become less available, the requirement for more intensive social care and maintenance grows even as the demand for discretionary medical treatment declines.

For survivors, the dynamic of declining demand for discretionary categories of care remains evident. The effect is less visible than with decedents, however, since the health status of the survivor cohort declines with age. Hypothesis 1 holds, with the partial age derivative for doctors and drug spending consistently lower than it is for the hospital and continuing care categories. There is also evidence supporting the substitution effect in Hypothesis 2, at least in the older age ranges. While the age derivative for hospital spending is positive for all ages, it declines in value after age 80. In contrast, continuing care spending rises with age at an accelerating rate right through age 99. At old ages,
non-discretionary survivor care increasingly shifts from the hospital to the continuing care system.

There is an alternative explanation to the relatively smaller effect of age on doctors and drugs versus hospitals and continuing care. Andersen’s enabling factors, represented by socioeconomic decile and doctors per capita in our model, also demonstrated small relative effects for doctors and drugs and large effects for hospitals and continuing care. It is possible that, although we assume that spending on drugs and doctors is more discretionary, these categories demonstrate less variation than the larger categories of hospitals and continuing care, and that the relative influence of all factors is therefore smaller (the fact that supply of doctors per capita has the least influence on physician billings suggests that the additional supply may be acting in the employ of institutions such as nursing homes and hospitals and influences supply primarily in these areas). In this interpretation, rather than the negative predisposing influence of age having a larger effect on the discretionary services of doctors and drugs, it may be inferred that the positive effects of age simply have a larger relative effect on the more variable categories of hospitals and continuing care. This interpretation fails however, at least in part, due to the fact that the sign of age’s influence is different for different services. Whereas the influence of enabling factors was consistently positive for all service categories, age had a negative effect on decedent expenditures for hospitals, doctors, and drugs and on survivor expenditures for doctors and drugs in individuals over age 80. Although the alternative explanation calls into question our assumptions about the discretionary nature of the different service categories and the influence of enabling factors thereon, the conclusion that age, controlled for time to death, has a negative influence on doctors and drug spending – and is thus, in that sense, a ‘red herring’ – stands.

Our examination of the changes in the age derivative of expenditures between the 1991-1994 and 1996-1999 shows an accentuation of many of the patterns noted above. The shift from medical care to social care that takes place with age grew stronger over the five
year interval. The second derivative for survivor expenditures grew more negative for hospitals, doctors and drugs and more positive for continuing care. Possible causes of this include improvements in survivor functional health at younger ages, necessitating less continuing care; decreases in the propensity to seek medical care that were relatively larger at older than younger ages; and system rationing that gave preferences to younger over older patients. There is evidence that morbidity and functional disability declined among the elderly in the United States coincident with the study period (Spillman 2004), and that these declines were strongest in percentage terms among the youngest old, the 65-74 age group. Similar trends may have been taking place among the B.C. elderly, as survivor continuing care costs fell the most sharply in the youngest age cohorts in the study (Payne et al. 2009). With respect to policy, the environment during the 1990s in British Columbia, and Canada in general, was one in which growth in publicly provided healthcare was being curtailed, so it is possible that rationing or other policy decisions also had an influence (Romanow 2002; Davidson 1999). Finally, it is also possible that reduced drug and doctor expenditures in survivors beyond age 80 (the inverted U-shape curves in Figure 4.4) reflect a ‘survival of the fittest effect’ where a relatively healthier cohort with less medical care requirements. However, the increases in hospital and continuing care utilization in this group argue against this interpretation.

Comparing our results to those of WFZ, we find some evidence of the ‘school of red herrings’ where age is an insignificant driver of health care expenditures after controlling for time to death and survivor status, but nevertheless find that overall expenditures are strongly increasing with age, both for decedents and especially for survivors. Our results agree broadly in the pattern of expenditures for hospitals, doctors, and drugs, finding declines with age for decedent spending and weak increases or declines at older ages for survivors. There is also agreement in the strong increases with age in the probability of positive continuing care utilization. However, the absolute levels of these probabilities are significantly lower than in our data. For decedents WFZ estimate the probability of positive continuing care utilization ranging from 10% at age 65 to 45% at age 95, while the comparable range for our data is from 50% to 90%. They estimate survivor
continuing care probability for age 95 at less than 20% while we estimate the same probability at greater than 50%. Furthermore, the pattern of conditional spending is also quite different between our study and that of WFZ. WFZ find conditional spending rises slowly with age for decedents and is flat or declining for survivors, in contrast to the strong increase we find in our data.

### 4.7 Limitations

The limitations with respect to data coverage, pricing assumptions, and the role of supply versus demand factors in determining utilization are relevant to our statistical models and are covered in the limitations section of the previous chapter (Section 3.7). Specific to this chapter’s model, additional – and interrelated – limitations concern the departures from normality assumptions in our data; the low explanatory power of the models (as represented by adjusted R-squared values); the lack of individual-level variables beyond basic demographic data; and the potential endogeneity of time-to-death in the health expenditure estimation equation.

The departures from normality assumptions are addressed in our discussions of potential transformations of the dependent variable in Section 4.4.2 and Appendix C. Even though two-part models account for the problem of large numbers of zero observations, the positive observations continue to have high skew and kurtosis, with tails that are both fatter, and in the case of the high end of the distribution, longer than normal. None of the potential transformations we tested rendered the dependent variable close to normal in its characteristics. This is a common problem faced in analyses of health care expenditures; the general response has been to use log transformations, while we chose OLS following the time-to-death models of ZFM (1999), WFZ (2007) and Stearns and Norton (2004) because it returns predicted values more consistent with actual averages. While not transforming the dependent variable may result in greater skew and kurtosis, the
explanatory power of the estimating equations does not appear to be materially worse. For example adjusted R-squared in the conditional spending part of Seshamani and Gray’s (2004b) study of hospital expenditures (using log transformation) was 0.09, while the corresponding value for the OLS estimations in Stearns and Norton, ZFM, and WFZ were 0.09, 0.12, and 0.17, respectively. The higher values in the Swiss studies may be due to the wider range of services captured in their data. While a hospital-only study may miss the substitution effect of an individual using other modalities of care, a more comprehensive dataset would be less prone to this error and therefore have greater explanatory power. This supposition seems to be confirmed in our data, where adjusted R-squared values from our conditional regressions are highest for total expenditures, at 0.26, while the individual service adjusted R-squared values range from 0.03 for drug costs to 0.12 for continuing care.

We do not have individual-level data beyond the basic demographic explanatory variables of age, sex, and time-to-death. The only covariates in model are region-level measures of supply availability and socioeconomic status. Many of the time-to-death studies have included individual level covariates such as participation in supplemental insurance (ZFM; WFZ 2007), marital status (Seshamani and Gray 2004b; Weaver et al. 2008, Pot et al. 2009), social class (Seshamani and Gray 2004b), education level (Pot et al. 2009) or need variables such as hospital diagnosis (Seshamani and Gray 2004b) and levels of functional disability (Weaver et al. 2008; Pot et al. 2009). For the most part these individual-level covariates are statistically significant. Supplemental insurance, unsurprisingly, has a positive influence, as do most need variables. The effect of enabling variables such as education and marital status is more mixed, though being married has a clear negative influence on the likelihood of institutionalization. Although the inclusion of individual-level covariates does not lead to materially higher explanatory power in the studies, expressed in adjusted R-squared values, it could potentially alter the measured effects of the primary explanatory variables, age and time-to-death. For example, it is possible that the inverted U-shaped curves in Figure 4.4 suggesting that age
has a negative effect on survivor expenditures beyond ages in the early 80s could instead be due to an improved health profile that is not captured in the simple observation of at least three years of survival. And certainly part of the positive influence of age on continuing care expenditures could be indirectly due to the higher likelihood of widow/widower status and the concomitant higher probability of institutionalization. Individual-level covariates could also offer potential instrumental variables to deal with potential endogeneity of time-to-death in the equation. It is possible that the use of health care may alter survival probabilities so that time-to-death is in part determined by the dependent variable. However, previous attempts to account for the endogeneity of time-to-death have found a lack of potential correlated variables to serve as valid instruments (Zweifel, Felder, and Werblow 2004; Weaver et al. 2008) and that the findings with respect to age and time-to-death are robust to endogeneity error (Zweifel, Felder, and Werblow 2004). While individual-level covariates could add to the understanding of the relationships studied in this thesis, we believe it unlikely that their omission would detract from the validity of the findings herein. Nevertheless, the question of direction of causality between health expenditures and time-to-death is not definitively answered in the literature or in our study.

4.8 Conclusion

Continuing care spending is the largest category in our data, and its strong increases with age dominate the smaller declines that may be evident in other categories, so that total spending is also found to have a strong positive association with age. In contrast, the lower probabilities of continuing care usage in combination with the weak association of conditional spending with age mean that continuing care has a reduced influence on total spending in WFZ’s study. The Swiss Sick Fund from which WFZ takes the data for their study does not cover ‘non-medical’ continuing care expenses such as homemaking assistance or accommodation in nursing homes. WFZ estimates these non-medical categories to be as much as half of continuing care spending. With probability of
residing in a nursing home rising strongly with age, they are also the categories that are likely to have the strongest association with age, while the medical categories may behave more like the more discretionary doctor services and prescription drugs. While our results largely corroborate those of WFZ, the differences highlight the important role played by non-medical categories of care and how this role grows in importance with age. Age may not be a major driver of medical expenditures after controlling for time to death. However, our study indicates that age is clearly associated with large increases in demand for social care resources and that when social and medical care are combined the overall burden on society’s resources rises with age, irrespective of survivor status.

Our results for hospital spending and time to death are also in broad agreement with the work in Seshamani and Gray’s analyses of hospital data from Oxfordshire, England. We corroborate Seshamani and Gray’s finding that the slope of predicted expenditures as time to death decreases is steepest for the younger ages and flattens with age. However, we find this flattening trend to be much larger in magnitude than Seshamani and Gray. For example, predicted expenditures at TTD = 2 are estimated by Seshamani and Gray to be 23% and 32% of expenditures at TTD = 1 for ages 65 and 95, respectively. In our study, the corresponding figures for hospital expenditures are 24% and nearly 50%. We also find that the time-to-death / expenditure curve for hospital spending steepened between our two study periods, whereas Seshamani and Gray found the curve flattened between 1970 and 1990. It is possible that the differing system and policy environments in Oxfordshire and British Columbia could account for some of these differences. There is also some evidence that elderly morbidity was stagnant or even growing in the 1970s before it began to improve in the last two decades of the century (Crimmins 2004; Crimmins, Hayward, and Saito 1994).

Our findings call into question optimistic assumptions that increasing life expectancy could lower the cost of dying and reduce the burden of an aging population on public resources. While this may be the case for medical spending categories such as hospitals
(Seshamani and Gray 2002; 2004a; 2004b) or for insurance schemes that cover primarily medical services such as Medicare (Miller 2001) or the Swiss Sick Fund studied by Felder, Zweifel and colleagues, quite a different story occurs when the full costs of social and long-term care are taken into account. Indeed, longer life expectancies imply both increasing per capita needs for overall care (medical and social combined) and larger cohorts of elderly expressing these needs. Add to that the financial needs to support long retirements, even if healthy, and the economic pressures of an aging population begin to take clearer shape. While recent reductions in morbidity among the elderly and decreases in survivor continuing care costs in our study suggest possible relief, more evidence will be needed over longer periods of time to confirm these trends. In the meantime it will be important to carefully control costs for medical care, where our evidence suggests aging is not likely to be a large factor, so that public resources are available for social care, where demand is likely to surge.
5 Conclusion

We summarize below the major conclusions of this thesis, and expand upon these in the subsequent paragraphs.

From our literature review:

- Time-to-death models of expenditure can change expenditure forecasts materially in environments of changing mortality rates
- Literature from the last decades of the 20th Century indicate possible compression of morbidity in developed world populations but expenditure data from the same period show survivor costs rising faster than decedent costs
- Time-to-death has a much greater influence for medical categories of care, such as hospitals, than for social categories like long-term residential care

From our empirical work:

- The relative cost of dying increased due to a slight rise in decedent costs and a larger fall in survivor costs
- The time to death / expenditure curve steepened over our study period, in contrast with findings from the literature
- Age, controlled for time to death, still has an overall positive influence on individual expenditures, largely due to costs of social care
- The influence of age on medical care, controlled for time to death, is muted or negative
- Overall, age is not a ‘red herring’ with respect to health expenditures. Even if mortality and morbidity rates continue to fall, aging populations will put increased pressure on long-term residential care and other forms of social care
Time-to-death models improve the sensitivity of expenditure forecasts to mortality changes

Our thesis work confirms that cost of dying and time-to-death modeling is an active area of research among academics and policymakers interested in better understanding the relationship between aging and health expenditures. Research showing weak links between population aging and aggregate health expenditures points to the inadequacy of simple age-based expenditure forecasts and the initial efforts to refine these forecasts by including a time-to-death component have demonstrated material differences. Whether these differences will in fact transpire depends on two important factors: stability in the effect of time to death and changes to mortality and morbidity.

We found relatively little work measuring changes over time in the cost of dying or the effect of time to death. What evidence there was pointed to a decrease in the relative cost of dying and a flattening of the time to death / expenditure curve due to relatively higher growth in survivor versus decedent expenditures. Should survivor health expenditures continue to outpace decedents in the future, the reductions to expenditure forecasts due to reduced mortality would not be less than estimates reported by the studies reviewed herein. Our review also touched on an active debate regarding the potential for future mortality declines. Natural limits to longevity growth figured into Fries’s original compression of morbidity theory, yet mortality has continued to decline. If mortality reductions do indeed come to an end, incorporating the cost of dying into expenditure forecasts will no longer change the results of age-only models, and much more would depend on morbidity developments.

Evidence of compression of morbidity, but no compression of survivor expenditures

We find some evidence that compression of morbidity was taking place among elderly populations in the developed world toward the end of the 20th century. Age-specific mortality rates declined 1% per annum on average in our study population, roughly matching the declines seen in official statistics from other jurisdictions. At the same
time, surveys from across the developed world showed more rapid declines in various measures of morbidity such as rates of functional disability or self-assessed poor health. Although faster decreases in morbidity versus mortality are superficially indicative of compression of morbidity, there is no formal definition of Fries’s concept that can be empirically tested. There is a need for accepted standards for morbidity measurement that can be easily replicated in different settings. It will also be important to increase the measurement of morbidity incidence (as opposed to the more common prevalence measures) so morbidity can be more directly compared with mortality, which by definition is an incidence variable.

Compression of morbidity, to the extent it was taking place, did not lead to lower health care costs in ‘survivor’ populations in the studies we reviewed. Possible reasons for this are timing effects, with the time-to-death models based on older data than the mortality and morbidity surveys; a ‘health care payoff’ effect, where decreases in morbidity were achieved through increased health care spending on prevention and maintenance treatments; or a cohort effect, where lower utilization due to better age-specific morbidity is offset by the passage of higher-consuming cohorts into older age brackets. There is evidence to support the contribution of the first two factors. The finding of relatively lower survivor spending in our relatively recent British Columbia data, though driven at least in part by rationing of continuing care, is at odds with the older studies in our review and more consistent with compression of morbidity. Some studies we reviewed noted that findings of improved morbidity were coincident with increased use of technology and personal aids, indicating that a health care payoff may indeed play a role. And finally, while we do not have direct evidence of a cohort effect, in our study spending growth was generally higher in the younger age ranges where health, as measured by mortality rate, was declining most rapidly. Similarly, in the U.S., elderly disability declines were strongest in the 65-74 age range, yet it was the 85+ age group that had the slowest growth in per capita health costs. Furthermore, the high growth rate in per capita health care expenditures for the baby boom generation, with its notorious consumption
habits, shows how different generations might have different health spending patterns even if health and other factors remain constant.

*The effect of time to death is very different across health care service categories*

The studies covered in our literature review consistently found very different effects of time to death for different health care services. Specifically, the time-to-death expenditure curve was much steeper and the relative cost of dying much higher for hospital, Medicare, and technology-intensive medical services in general, while the reverse was true for more labour-intensive long-term social care such as nursing homes and home care. In addition, whereas decedent costs typically fell with age for medical services, they rose rapidly with age for social care categories. These differences suggest that population aging will likely have very different effects on different categories of health care, and that system-level forecasts should be broken down into component parts for long-term resource planning. Furthermore, care should be taken that conclusions based on individual services in isolation are not extrapolated to the health care system as a whole.

*The relative cost of dying increased in British Columbia in the 1990s*

Our analysis of the cost of dying in the Chapter 3 confirmed the significant differences between medical and social health care categories. The cost-of-dying, expressed as the ratio of decedent to survivor expenditures was consistently higher for hospital services versus continuing care, with the gap widening for older ages. The categories of drugs and doctor billings had even lower decedent/survivor ratios than continuing care. The low ratios suggest a fairly strong component of long-term maintenance and prevention spending for out-of-hospital doctor billings, and especially for prescription drugs. While drugs were the smallest of the four categories, they had the highest expenditure growth for both decedents and survivors, and there was relatively little difference between the two, indicating that lower mortality in the future would be of little relief. Lower mortality is also unlikely to pose any relief to pressures on the largest spending category,
continuing care. Whereas decedent spending falls or stays relatively flat with age for the other three service categories, it grows rapidly with age for continuing care. With survivor expenditures also growing very rapidly with age, lower mortality – which would increase cohort sizes, average population age, and the average age at death – would, all other factors remaining equal, add substantially to the expenditure burden of long-term social care. For hospital services, where decedent expenditures fall with age and the decedent/survivor ratio is the highest of the four categories, lower mortality could help reduce future expenditures.

Our finding that decedent/survivor ratios grew over our study period is an important difference from our review of the literature that pointed in the opposite direction. The declines in survivor costs that drive these growing ratios are in better agreement with the general morbidity declines observed in the developed world over that time period. Should this trend continue, in combination with further morbidity and mortality declines, there could be reason for more optimism with respect to reduced effects of population aging on expenditures. The substantial declines in continuing care costs for survivors are particularly encouraging, but this result carries a very important caveat due to the policy changes that took place during the study period. Further research on temporal change in decedent/survivor ratios and in survivor costs in particular in different jurisdictions and time periods is needed to clarify whether these trends are real and could have sustained effects into the 21st century.

We believe the attribution of health expenditure growth included at the end of the Chapter 3 is novel in the level of detail to which the effects of aging are broken down. It demonstrates how the expenditure pressures of aging (represented by the population growth and shift in age distribution components of the attribution) that are captured in simple age-based forecasts can be at least partially offset by reductions in survivor costs and lower mortality rates. It also draws attention to the relatively small direct effect of population aging, especially in comparison with the general rate of medical inflation,
which has been at elevated levels in the western world for decades. Attributions such as ours could be a valuable tool to improve the understanding of the different ways in which age affects aggregate expenditure and to focus efforts on the largest contributors to expenditure growth.

*The effect of age, controlled for time to death, was much stronger for continuing care than other services*

In Chapter 4 we address the ‘red herring’ argument put forward by Zweifel, Felder and colleagues. Our discussion of the theory offers some insight on how age might influence health care spending at the individual level beyond the obvious fact that health status deteriorates with age. We argue that while the option to undertake preventive, maintenance, or aggressive curative care may be foregone at older ages, social and residential care to help with basic functioning is less discretionary and will likely be driven by other factors in addition to age, such as living arrangements, ethnicity, and economic status. On this basis – and following the findings of Chapters 2 and 3 – we expected to see very different effects of age for different service categories, and to validate the ‘red herring’ thesis only in part if at all.

Our expectations were largely realized in the results of our time-to-death model. We found that age was a strong positive influence on continuing care expenditures for survivors and decedents alike, and that this influence on the largest service category was strong enough to translate to a positive effect on total expenditures as well. For the other three service categories, the effect of age was more mixed, generally negative for decedents and positive for survivors. Because of the large sample size, the model was quite robust and the strict ‘red herring’ test – where zero lies in the confidence interval for the partial derivative with respect to age – was satisfied rarely, typically at inflection points. With that said, the negative effect of age on hospital, doctors, and drug spending for decedents, and for survivors older than age 85 for drugs and doctors is a partial
validation of the ‘red herring’ thesis since age, controlled for time to death, does not have the positive influence on spending that is commonly assumed.

We believe this thesis has contributed to the topics of health care spending, demographics, aging, and time-to-death modeling. We link the modeling and forecasting efforts in cost-of-dying and time-to-death studies with the theories of compression of morbidity and the epidemiological transition, and with economic frameworks for understanding health care markets. We add our own estimates of the effect of time to death to the literature, based on a whole-population data source. These estimates underscore the substantial differences in the role of time to death among different health care categories and highlight continuing care as the category that will likely put the most age-driven pressures on public budgets in the future. Our finding of reduced survivor cost differs from the earlier literature and is more consistent with recent morbidity trends.

The study is limited by generalizability to other jurisdictions and other time periods. There were certainly unique circumstances to the environment in British Columbia in the 1990s. The health care policy environment was one of budget curtailment, an unusual circumstance for a developed-world health system in the last half of the 20th century. Beyond budget restraint, there were also policy changes to shift services from the hospital to continuing care and to increase continuing care services for the most needy while rationing the same services to healthier individuals. A related limitation is the influence of supply-side changes on a model that is dominated by demand factors. Policy and market changes to health care availability can have a significant effect on health care utilization that could distort the estimated effects of age and time-to-death in our model. This is especially true for calculations of temporal change, so it will be important for further research to validate our findings of lower survivor costs and flattening time-to-death/expenditure curves in other jurisdictions and time periods. While we include one explanatory variable related to supply (doctors per capita in an individual’s region) in our model, and it shows some evidence of a supply effect, it is not likely to reflect
discontinuities such as the policy changes noted above. The limitations of
generalizability and supply-side effects are common to virtually all studies in the
literature and can only be overcome with repeated observations from different
environments. With that said, however, there is much commonality between different
developed-world health care systems and societies, with population aging an issue in
every country and governments – directly or indirectly – accounting for a major share of
health expenditures.

Age may be a ‘red herring’ for medical services but not for continuing care

On balance, we conclude that age is not a ‘red herring’ with respect to its likely
influences on future health care expenditures. We do agree that age, after controlling for
time to death, has limited – or even negative – effects on hospital, doctor, and drug
expenditures, and that the effects of population aging have been dwarfed by the
influences of other factors on health expenditure growth. But should mortality and
morbidity declines abate the effects of worsening health at older ages will put increasing
pressures on these expenditure categories, exacerbating the effects of population aging as
the front end of the baby boom passes into official retirement age. And regardless of
mortality and morbidity trends, continuing care, the largest spending category in our
study, shows no evidence of the ‘red herring’ phenomenon. Long-term residential care
and home care promise to be major resource consumers in almost any aging scenario.
Future research could add important detail to our results by further separating the
continuing care category into residential and home-based care, as these are large and
growing categories that may have different relationships with age and time to death.
6 References


Loewy, E. H. 2005. *Age discrimination at its best: should chronological age be a prime factor in medical decision making?* Health Care Analysis 13(2) : 101-17


Appendix A: Death Rates and Proportion of Total Spending on Decedents

The shift in relative spending share for decedents and survivors can be examined from the perspective of the proportion of total costs allocated to decedents, similar to the calculations performed by Lubitz and Riley (1993) and Hoover (2002) for Medicare spending. In the more recent study, Hoover found that decedents accounted for 26% of total spending during the period 1992-1996. During this period, the death rate for individuals over 65 years old was 5.0% (CDC). Analyzing a broader spectrum of costs including home care and drugs in addition to hospitals and physicians, Polder, Barendregt and van Oers (2006) found that decedents accounted for 26% of health costs in the Netherlands in 1999.

Looking at the British Columbia data, we first note that the death rate is nearly 20% lower than that in the US for comparable dates, and fell marginally over the study period, from an average of 4.3% in the first five years to an average of 4.2% in the last five years. Table A.1 shows that the very slight drop in death rates for the entire population masks larger drops for specific ages. The death rate for age groups 66-70, 71-80, and 81-90 fell by over 10% between 1991 and 2001. The death rate for ages 91+, on the other hand, dropped by only 4%. Overall death rates for the 65+ population did not fall as much as for specific ages – by only 2% – because the average age of the 65+ population rose over the period (BC Stats 2007).

Table A.1: Death Rates by Age Group, 1991 to 2001

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<tr>
<td>66-70</td>
<td>1.7%</td>
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<td>1.7%</td>
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<td>71-80</td>
<td>3.5%</td>
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<td>81-90</td>
<td>8.8%</td>
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<td>8.7%</td>
<td>8.8%</td>
<td>8.8%</td>
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<tr>
<td>91+</td>
<td>19.7%</td>
<td>21.0%</td>
<td>20.6%</td>
<td>20.2%</td>
<td>20.4%</td>
<td>20.8%</td>
<td>20.3%</td>
<td>19.6%</td>
<td>20.4%</td>
<td>19.7%</td>
<td>19.2%</td>
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<tr>
<td>All ages &gt; 65</td>
<td>4.2%</td>
<td>4.4%</td>
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Figure A.1 shows the proportion of spending for all services on decedents over the study period for the different age groups. Since decedent costs were stable while survivor costs fell during the study period, the proportion of spending on decedents either fell less than the death rate did, or grew while the death rate fell. For the 66-70 age group, the proportion spent on decedents fell by 3% even as the death rate fell 16%. For 71-80, the proportion of spending on decedents rose 2%, versus a 13% drop in the death rate. For ages 81-90 and 91+, where the death rate fell 11% and 4%, respectively, the proportion of spending on decedents rose by over 8%. For all ages combined, the proportion of spending on decedents rose 8%, even as the death rate fell slightly.

**Figure A.1: Proportion of Costs on Decedents by Age, All Services**

The proportion of spending on decedents by age group agrees fairly closely with the results obtained by Polder, Barendregt and van Oers (2006) for a similar range of costs in the Netherlands in 1999. They found that decedents accounted for between 12% (at age 65) and 57% (age 95+) of total costs. In comparison, results from the BC data range
from 13% for ages 66-70 to 33% for ages 91+. The difference for the older ages is likely due to the limited inclusion of residential care facilities, which account for a very significant proportion of survivor costs for the oldest cohort.

Figure A.2 shows the proportion of spending on decedents for the entire population, broken into the different service types. Hospital and continuing care services are devoted much more to decedents than are medical billings and pharmaceutical prescriptions. The share of prescriptions attributed to decedents is only slightly higher than the death rate. The share of spending attributed to decedents rose from 28% to 30% for hospital services and from 18% to 22% for continuing care, but fell marginally for prescription drugs and medical billings.

Figure A.2: Proportion of Costs on Decedents by Service, All Ages
Appendix B: Cohort Effects

It is difficult to separate cohort effects from time trends, since each cohort-age-calendar year combination is unique. Is the trend towards falling survivor costs at older ages a general age trend or is it due to the passage of a particularly low-utilization group into old age at the time of measurement? With only 11 years of data, we can only look for cohort effects in 11-year ranges, and are unable to capture the full range of effects that might be present over a 35-year age range with cohorts born as early as the 19th century and as late as 1936.

With those caveats in mind, we can describe what a cohort effect might look like pictorially. If costs are plotted for each individual age in increments of one, a cohort effect would be apparent if, for example, an anomalous change from year 1995 to year 1996 at age 66 was repeated from 1996 to 1997 at age 67, from 1997 to 1998, and so on. The trend would be evident in a diagonal line connecting the anomalous points on adjacent age curves.

An example of a cohort effect is depicted in Figure B.1. In this example, average costs are assumed to rise by $50 in each calendar year after 1991 and by $200 for each additional year of age after age 65. In addition to these age and time effects, a cohort effect is introduced where average costs increase by $100 for each year by which the birth year exceeds 1926. The cohort effect is visible in the shift to the right of the diagonal dotted line, which is drawn through the points representing individuals born in 1926. To the right of this line (cohorts born after 1926), the slope of the lines is steeper since the cohort effect is added to the calendar time effect. In addition the distance between the lines is smaller, since the cohort effect is greater for younger ages (later birth years), somewhat mitigating the age effect.
Figure B.1: Cohort Effect Example (Based on Formula Costs = $1,000 + $50 \times (\text{Year} - 1991) + $200 \times (\text{Age} - 66) + \max(0, $100 \times (\text{Birth Year} - 1926))

Figures B.2 and B.3 plot survivor costs for all services for ages 66-74 and ages 87-95, respectively. Similar to Figure B.1, constant birth year cohorts are found in diagonal lines sloping upward and to the right. There is little visible evidence of any diagonal shift that might indicate a cohort effect. In both age ranges, the trends towards higher expenditures at lower ages and lower expenditures in more recent years are much clearer, though there is some volatility at the oldest ages where cohort sizes are smaller.
Figure B.2: Costs by Year for Ages 66-74, Total expenditures, 1991-2002
Figure B.3: Costs by Year for Ages 87-95, Total expenditures, 1991-2001
Appendix C: Problems with Logarithmic Transformations

There are two issues with logarithmic transformation that lead to underestimation of overall class averages (i.e. the average for individuals with similar independent variable characteristics) and inability to predict very high users. The first issue is Jensen’s inequality, which, when applied to statistical estimation, states that, for a convex function (in this case the natural exponent):

\[ \exp(E(\ln Y)) \leq E(\exp(\ln Y)) = E(Y) \]

As applied to our logarithmic transformation, Jensen’s inequality indicates that the retransformation (or exponentiation) of the results of a linear regression on the logarithm of the dependent variable will result in expected values that are generally lower than the actual expected values (or means) of the true population. This can be seen in Figures C.1 and C.2, which compare actual population means to the predicted averages derived from the retransformation of regression results for the natural log of expenditures. The regressions in these comparisons were done using all records in the 1996-1999 dataset. Figure C.1 shows that estimates for final year decedents are fairly consistently underestimating true population averages by roughly 50%. The estimated slope of the line, with respect to age, is fairly consistent with the true slope.

Figure C.2, for survivors of greater than three years, again shows that estimates slopes are consistent with the actual population slopes. The underestimation for total expenditures (Total) and for continuing care (LTC) at young ages is even greater than the 50% seen for decedents. Continuing care expenditures for survivors follow a curve that is highly age-dependent, with very high values (greater than $40,000 for long-term care residents) at old ages being common for a significant portion of the population. At the youngest ages of the study population positive continuing care usage is rare. The predicted curve that
Figure C.1: Comparison of Retransformed Predicted Values from Log Regression (Dotted Lines) to Actual Population Averages (Solid Lines), 1996-1999 Data, by Age, Decedents (TTD=1)
Figure C.2: Comparison of Retransformed Predicted Values from Log Regression (Dotted Lines) to Actual Population Averages (Solid Lines), 1996-1999 Data, by Age, Survivors (TTD>3)
results from inputting this data to our panel model is exponential, with near-zero predicted values and significant underestimation at young ages, and then a rapid acceleration in estimates as ages grow into the 90s. In the case of survivor total expenditures, it appears the degree of underestimation is strongly influenced by its continuing care component. Continuing care is the largest component of survivor expenditures, particularly at older ages. However, since there are more substantial total expenditures at younger ages, the fitted curve is flatter for total than continuing care expenditures. The result is material underestimation (as much as 75%) at the older ages.

The very high expenditures for age-90-and-higher continuing care users point to a second issue causing underestimation. Specifically, even after transformation and separating the model into two stages, the data have ‘fat tails’ relative to the normal distribution – i.e. a high frequency of very low values and very high values. In the case of continuing care, the expenditures of permanent long-term care residents, of which there are many at older ages, are based on per diem rates that are roughly equal across individuals at over $100. So the population consists of three distinct user types: non-users, who can be accounted for in the probit stage of the model; home care users, whose expenditures vary according to service levels; and permanent long-term care residents, whose expenditures are very high and non-variable. This large and uniform high-expenditure cohort is not easily captured in statistical models based on the normal distribution. For other service categories the departure from normality is not as dramatic, but in each case there are significant high-expenditure individuals that are not captured in the model.

As a result of the fat tails of the expenditure distribution, the fitted curve derived from a model based on normality assumptions is flatter than the true curve, and residuals are highly negatively correlated with actual observed values, so that low actual observations are overestimated and high actual observations are underestimated. In the case of a log transformation, this systematic error amplifies the underestimation of the overall mean because the underestimation of high actual values has a greater impact than equal
overestimation of low actual values. For example, the difference between log 11 and log 7 (with a residual of 4) after retransformation is much greater than the difference between log 2 and log 6 (residual -4), specifically 59,000 to 400.

The combination of Jensen’s inequality and the amplification of the estimation errors resulting from above—normal kurtosis leads to OLS delivering predicted values that are much closer to the true population averages than those resulting from log regression and retransformation. Figures D.3 and D.4 are similar to Figures D.1 and D.2, with OLS predicted values in the place of log regression predicted values. The improvement in accuracy evident in these figures is such that we chose to use OLS modeling in our study.
Figure C.3: Comparison of Predicted Values from OLS Regression (Dotted Lines) to Actual Population Averages (Solid Lines), 1996-1999 Data, by Age, Decedents (TTD=1)
Figure C.4: Comparison of Predicted Values from OLS Regression (Dotted Lines) to Actual Population Averages (Solid Lines), 1996-1999 Data, by Age, Survivors (TTD>3)
Appendix D: Expanded Analysis of Hospital and Continuing Care Predicted Values

Figures D.1 through D.4 break down hospital and continuing care, the two largest components of overall spending, into their separate parts: probability of positive utilization and expected spending conditional on positive utilization. They also plot males and females separately for an idea of the different patterns for each sex. In Figures D.1 and D.2, the decline in hospital spending for decedents is shown to be largely due to a decline in the probability of positive utilization, by approximately 50% from age 66 to 99. For those individuals who do use hospital services, expected costs also decline, but at less than half the rate of the probability of positive utilization. For continuing care, both the probability of positive utilization and the expected conditional spending rise strongly with age for decedents. For survivors, hospital spending joins continuing care in showing higher probability of utilization and conditional spending for older ages (see Figures D.3 and D.4). The increase is more dramatic with continuing care in both cases. The probability of positive continuing care use rises exponentially from a very low level (less than 5%) at age 66, while the probability of positive use for hospitals rises through age 85 and then plateaus or falls slightly. Conditional spending on continuing care and hospitals for survivors at age 66 is roughly equal around $5,000. Hospital spending rises gradually to over $10,000 by age 99, while continuing care spending rises exponentially to over $25,000. Comparing the sexes, males have lower conditional spending for hospitals and continuing care, survivors and decedents. They are also less likely to use continuing care services, especially for older survivors, where the difference in probability is over 20 percentage points. Only in probability of positive hospital utilization are men more intensive users of the big spending categories than women.

In Figures D.5 through D.8 we plot hospital probabilities of positive utilization and conditional spending for subsamples with continuing care = 0 and > 0. The hypothesized
Figure D.1: Predicted Probability of Positive Utilization by Service Category and Age, 1996-1999 Data, Decedents (TTD=1)
Figure D.2: Expected Conditional Expenditures Given Positive Utilization by Service Category and Age, 1996-1999 Data, Decedents (TTD=1)
Figure D.3: Predicted Probability of Positive Utilization by Service Category and Age, 1996-1999 Data, Survivors (TTD>3)
Figure D.4: Expected Conditional Expenditures Given Positive Utilization by Service Category and Age, 1996-1999 Data, Decedents (TTD>3)
substitution effect, whereby continuing care substitutes for hospital spending, is most visible in the probability of positive utilization for decedents. The likelihood of positive hospital utilization declines only slightly with age for the subset of the population not using continuing care, while the decline is significantly more dramatic among the population with positive continuing care spending. For ages 90 and higher, decedents not using continuing care have a 15-25 percentage point higher probability of using hospitals than those using the continuing care system (Figure D.5). For survivors (Figure D.7), the substitution effect is not evident. Probability of positive hospital utilization is higher in the continuing care positive population, likely due to the fact that continuing care utilization reflects a difference in health status that is not captured in the survivor status. There is, nevertheless, the same dynamic evident where probability of hospital utilization declines more rapidly in the continuing care population. Turning to conditional spending (Figures D.7 and D.8), again the evidence shows that continuing care usage is more indicative of heavy overall use of the system as opposed to a substitute for hospital spending. For both decedents and survivors, conditional hospital spending is higher in the continuing care positive population. The difference is much larger for survivors, where same implied difference in health status is likely the primary cause. The survivor graph (Figure D.8) also demonstrates why caution is warranted in reaching general conclusions about age from segmented results. Although conditional hospital spending is relatively flat in each of the subsamples, for the whole population (represented by the blue line) it rises steadily with age. This is due to the fact that the probability of positive continuing care utilization rises strongly with age and more of the population is in the positive continuing care category (the blue line) at older ages.
Figure D.5: Predicted Hospital Probability of Positive Utilization, Whole Population versus Subsamples with Continuing Care Spending = 0 and > 0, by Age, 1996-1999 Data, Decedents (TTD=1)
Figure D.6: Predicted Hospital Probability of Positive Utilization, Whole Population versus Subsamples with Continuing Care Spending = 0 and > 0, by Age, 1996-1999 Data, Survivors (TTD>3)
Figure D.7: Predicted Hospital Expenditures Given Positive Utilization, Whole Population versus Subsamples with Continuing Care Spending = 0 and > 0, by Age, 1996-1999 Data, Decedents (TTD=1)
Figure D.8: Predicted Hospital Expenditures Given Positive Utilization, Whole Population versus Subsamples with Continuing Care Spending = 0 and > 0, by Age, 1996-1999 Data, Survivors (TTD>3)

The age derivative of predicted hospital expenditures remained fairly consistent for decedents between the two study periods (see Figure E.1). However, there is a clear reduction in the age derivative for survivors, particularly the more elderly ones (Figure E.2). In the case of continuing care, survivors and decedents present an interesting contrast with respect to their changes in the age derivative from the earlier to later time period (Figures E.3 and E.4). As noted earlier, the age derivative is strongly positive and rises with older ages for both decedents and survivors. For decedents, the effect of age grew stronger at younger ages and weaker at older ages between the two time periods. For survivors, the effect was reversed, with a strengthening in the age derivative at the older ages and weakening at younger ages.

Turning to medical spending (Figures E.5 and E.6), we see a similar contrast between decedents and survivors as with continuing care, but in the opposite direction. The effect of age on survivors grows more positive at younger ages and more negative at older ages. For decedents, the effect grows more negative at younger ages and is unchanged at older ages. The age derivative for drug spending (Figures E.7 and E.8) is quite similar to medical spending, though the time changes are more distinct and, for older-aged decedents, there is a definite strengthening (less negative) in the age effect.
Figure E.1: 95% Confidence Intervals for Age-Derivative of Expected Hospital Expenditures, Females, by Age, 1991-94 vs. 1996-1999 Data, Decedents (TTD=1)

Figure E.2 95% Confidence Intervals for Age-Derivative of Expected Hospital Expenditures, Females, by Age, 1991-94 vs. 1996-1999 Data, Survivors (TTD>3)
Figure E.3: 95% Confidence Intervals for Age-Derivative of Expected Continuing Care Expenditures, Females, by Age, 1991-94 vs. 1996-1999 Data, Decedents (TTD=1)

Figure E.4: 95% Confidence Intervals for Age-Derivative of Expected Continuing Care Expenditures, Females, by Age, 1991-94 vs. 1996-1999 Data, Survivors (TTD>3)
Figure E.5: 95% Confidence Intervals for Age-Derivative of Expected Doctor Billings, Females, by Age, 1991-94 vs. 1996-1999 Data, Decedents (TTD=1)

Figure E.6: 95% Confidence Intervals for Age-Derivative of Expected Doctor Billings, Females, by Age, 1991-94 vs. 1996-1999 Data, Survivors (TTD>3)
Figure E.7: 95% Confidence Intervals for Age-Derivative of Expected Pharmaceutical Expenditures, Females, by Age, 1991-94 vs. 1996-1999 Data, Decedents (TTD=1)

Figure E.8: 95% Confidence Intervals for Age-Derivative of Expected Pharmaceutical Expenditures, Females, by Age, 1991-94 vs. 1996-1999 Data, Survivors (TTD>3)