5

The Impact of Social Factors on Excess Winter Mortality in Denmark

5.1 Introduction

5.1.1 The Data of Denmark

This chapter analyzes the impact of social factors on seasonality in mortality in Denmark, focusing on winter excess mortality. Denmark has been chosen deliberately. No other country in the world has collected more data on its population [112]. Information on almost every aspect of life is computerized and stored in several hundred administrative, official statistical and in research registers. For example, these registers contain information on vital events as well as on tax records, medical records, etc. [7, 96]. These individual-level registers can be linked via a 10-digit unique person identifier [349]. This allows for reconstructing the life-course of every Danish individual for all registered events. The prime tool for demographers is the Danish Demographic Database [287] which already contains the most often used demographic variables such as birth date, sex, education, date of death, cause of death (if applicable), etc. This database starts on 01 January 1980 and is updated regularly.

5.1.2 (Seasonality in) Mortality in Denmark

Besides the unchallenged data-quality, Denmark is appealing to mortality researchers also because it does not follow the mortality patterns of its neighboring countries. The linear increase observed in record life expectancy throughout the world for women as well as for men suggests an annual increase of 0.246 (women) and 0.222 (men) years [279]. In Denmark, however, life expectancy at birth rose slower than in most other OECD countries since the 1970s [74]. Chenet et al. [46] calculated an increase for the 11 year-period between 1979 and 1980 of 0.9 years for men whereas 2.442 could have been expected from the study of Oeppel and Vaupel [279]. Sweden, which neighbors Denmark, exhibited an increase of 2.6 years. The lag in the development of female life expectancy is even more alarming: In contrast to the 2.673 years suggested by record life expectancy, Danish women could only expect to live 0.35 years longer in 1990 than in 1979 [46]. The causes of death contributing most to the differential development of life expectancy in Denmark and Sweden were malignant neoplasms — especially respiratory cancer — and cerebrovascular diseases [46]. This previous study which compared Denmark and Sweden suggested that "mortality rates are sensitive to even minor differences in social and cultural factors across countries". There has been much debate which "social and cultural" factors are to be blamed. As Jacobsen et al. [173] discovered, the observed decelerated mortality rates are explained better by cohort than period effects: women born between the two World Wars constitute the most unfortunate birth cohort. The lack of the same effect for men rejects the intuitive hypothesis that early life conditions are mainly responsible. The generally accepted explanation is the high smoking prevalence of women born during these years. In the beginning of the 1990s the proportion of smoking women was higher in Denmark than in any of the other 86 countries analyzed. Simultaneously, smoking-related causes of death increased since the 1950s, whereas the number of people dying from "non-smoking causes" steadily declined in Denmark during the same period [181].[1] Other factors such as the relatively high alcohol consumption can also play a major role in the lagging behind of survival improvements in Denmark [10].

Less is known about seasonal mortality and the impact of social factors. So far, only one study investigated seasonal mortality exclusively in Denmark [302]. There are, however, two major drawbacks: The analysis was based on a random sample of the Danish population. This shortcoming is relatively minor as the sample size of 46,293 individuals was still relatively large. The major problem was the lack of any variables apart from sex, age, and cohort. Three other studies examined seasonal mortality in Denmark briefly in conjunction with other European countries [62, 147, 252]. Compared to the UK, this number of publications is very small.

Overall, seasonal mortality in Denmark is on the European average. Nevertheless, differences between winter and summer mortality are higher there than in other Scandinavian countries or in neighboring Germany [147, 252]. The only study which investigated the impact of social factors on seasonal mortality so far which used Danish data is Healy's study [147]. Unfortunately, his analysis was not based on individual-level data but rather on cross-country comparisons using ecological data. Hence, his conclusions can only be applied in the form of "countries with high housing quality experience low excess winter mortality", not permitting statements on the influence of social factors within a country. This topic remains, thus, an uncharted territory for Denmark.

[1] It should be noted that the high smoking prevalence of Danish women has seriously been tried to be explained by the bad role model effect of the Danish queen — a well known smoker [193]. Others, however, have heavily criticized this suggestion on methodological grounds as well as on common sense [174, 236].

5.1.3 Research Questions

As a consequence of the lack of research on seasonal mortality in Denmark, we analyzed whether the findings from other countries can be applied to Denmark, too. In addition, we also tested hypotheses which have not been put forward previously in the field of seasonal mortality at all. Our research questions were:

- **Age.** As individuals grow older, their mortality increases. Various biological theories offer explanations ("error catastrophe", "Hayflick limit", "free radical damage" .... For an overview, please consult: [247, 398].) The result is a *shrinking* resistance against a *given* environment. The environment, however, is not constant. The seasonal mortality pattern with its peak during winter shows also that certain periods of the year are more stressful than others for the human body. If susceptibility of the individual is increasing *and* the adverse effects of the environment are also seasonally changing, we should anticipate an increase in seasonal mortality with age. This expectation has been met by most of the studies of seasonal mortality by age — starting with the pioneering analysis of Quetelet [300] for Belgium in 1838. However, the basis of the data in many previous studies was questionable in drawing conclusions on the relationship between seasonal mortality and age as shown by Rau and Doblhammer [302, p.199].[2]
- **Sex.** Sex, beside age, is the most important determinant in mortality differentials. At least since the middle of the 18^{th}century [e.g. 66] it is well known that women live longer on average. The survival advantage of women is founded biologically as well as behaviorally [227, 229]. As environmental hazards are seasonally oscillating we can raise the conjecture that men face higher excess mortality in winter due to lower biological resistance to adverse effects of nature. In addition, their behavior such as a higher smoking rate at higher ages, for instance, increases their chances to die of typical seasonal illnesses like cardiovascular diseases, too [421].
  Results of many previous studies were surprising: If a differentiation by sex has been performed in the analysis, typically no significant differences were found [98, 121, 262, 419]. Rau and Doblhammer [302] found slightly larger seasonal mortality fluctuations for men than for women. This tendency, however, was not statistically significant.
- **Wealth.** Income, education and occupational status are regarded as the most influential factors in determining socioeconomic mortality differentials [371]. In the present study "wealth" was used as an indicator for socioeconomic status. It is a composite index on the household level, taking any monetary transfer into account. As we analyzed almost exclusively only retired people (age 65+), wealth seems to be a good proxy for measuring income as well as occupational status. Since the classic study of Kitagawa and Hauser [195], an inverse relationship has been regularly found

[2] See also Section 4.5.2 on page 110.

between income and occupational class on the one hand, and mortality on the other hand [e.g. 210].[3] Higher socioeconomic status reduces the risk of many diseases via lower occupational risks, lower stress, better diets, more exercise as well as more information and better access to health care [314]. The literature is divided whether socioeconomic status matters with respect to seasonal mortality. Various studies found no support that lower socioeconomic groups face higher excess mortality during winter [121, 214, 215, 342]. Contradictory evidence has been discovered as well in several studies [79, 147, 251]. Donaldon and Keatinge [79], for example, point out that "[c]old related mortality in the retired (65–74) age group was generally higher in men of class 5 (unskilled) than class 1 (professional), or other classes, with little difference between men, and women or housewives" [79, p. 790].

Most of these findings can be criticized methodologically as their analyses are based on ecological data on the electoral ward level [e.g. 214, 342], or even on the national level [147]. Neglecting the cross-country comparison, the divergence of the outcomes is surprising as all of the studies were based on data from the UK. This chapter can thus expand the present knowledge in two ways: First, it is based on data from a whole population on the individual level; secondly, with the use of Danish data, a country is analyzed which has not been studied before.

- **Education.** Another indicator which is often used to measure socioeconomic differences in mortality is educational attainment [e.g. 103, 124, 195, 210, 219, 296, 374]. This variable has several desirable characteristics [cf. 374]. For example, education is better suited than occupation-related indicators as it stays constant even in retirement. Typically an inverse relationship is found: the lower the educational level, the higher are the mortality risks.

  Apart from the analysis in Chapter 4, studying the impact of education on seasonal mortality fluctuations represents a novel approach. We assume to find a similar finding as in the United States where people with a college degree showed lower excess winter mortality than people with relatively little formal education.
- **Housing Quality.** The quality of housing is closely related to socioeconomic status. Its pre-dominant position in the field of seasonal mortality does not allow it to be subsumed under this category, though. Marsh et al. [245] reviewed the impact of housing conditions on health. A shortened and slightly modified version of their overview is given in Table 5.1.

  It clearly shows that most housing problems increase mortality risks — especially for diseases which are highly seasonal such as respiratory diseases, ischaemic heart diseases and strokes. The most important factor is

[3] Following Rogers et al. [314], already Friedrich Engels observed in his publication "Die Lage der arbeitenden Klasse in England", written in 1844, that factory workers in Manchester had relatively high mortality.

Table 5.1. Housing Problems and their Health Consequences

Housing Deficiency	**Health Consequence**
Overcrowding	• increased risk of infectious disease • increased risk of respiratory disease
Damp and Mould	• respiratory problems • asthma
Indoor pollutants and infestation	• asthma
Cold	• diminished resistance to respiratory infection • hypothermia • bronchospasm • ischaemic heart disease, myocardial infarction and strokes

Source: Marsh et al. [245, p. 6], shortened and slightly modified

probably cold as "man is a tropical animal"[209, p. 338]: mortality is at a minimum between 18 and 20 °C [37, 79, 98]. Consequently it is not surprising that central heating is a focal point in avoiding cold-related mortality and that the decrease in seasonal mortality fluctuations over time is attributed to its widespread use [16, 54, 57, 76, 77, 81, 98, 147, 187, 220, 251, 252, 253, 280, 340, 404]. Only Kunst et al. [208] doubt whether the increasing use of central heating is that important. They assume that socioeconomic progress in general is responsible for the decrease in winter excess mortality.

- **Car Ownership.** Nevertheless, "Warm housing is not enough" [186]. Donaldson and Keatinge [78, p. 90] point out that "outdoor cold stress has been independently associated with high excess winter mortality." They argue that the best protection from indoor cold is useless if people face stress from cold outdoors. It is a recurrent finding that people in colder regions show less excess winter mortality [e.g. 135, 147, 252]. The larger proportion of people wearing several layers of clothes in conjunction with avoiding time spent outdoors in those countries explains a large proportion of this reduced cold-related death toll [81, 97, 98]. For example, in Yakutsk — the coldest city in the world with an average temperature of −26.6°C between October and March — people are not experiencing excess winter mortality, an outcome of wearing very warm clothing outdoors and spending as much time as possible indoors [76]. As suggested by Donaldson and Keatinge [77], increased car ownership in southeast England helped in reducing the number of excess winter deaths as people spent less time outdoors. Thus, we used the information, whether people own a car or not, as an indicator whether avoiding outdoor cold stress is of importance for seasonal mortality in Denmark.

- **Marital Status.** Marital status is another important factor in differential mortality research. Comparable to the results by age, sex, wealth, and housing quality, mortality differentials by marital status are known for more than 150 years with Farr's observations on the "Influence of Marriage on the Mortality of the French People" published in 1858 [125]. It is unanimously accepted that married people live longer than widowed, divorced or never married people [223]. The differences are much bigger for men than for women [129]. Among the three unmarried groups, divorced people face the highest mortality risks [163].

  Typically two potential causal pathways (being not exclusive of each other) are offered on how marital status affects mortality [see for an overview: 125, 223]: The first explains the lower death rates of married people by a *protection* effect. Married people are less prone for risky, unhealthy behavior; they suffer less from stress-related diseases and are helped by their respective partner when ill. From an economical perspective, marriage correlates with better general living conditions by pooling financial resources. The second explanation proposes a *selection* effect into marriage. In the words of Lillard and Panis [223, p. 314]: "The argument is straightforward: Persons with observably poor health, and those with chronic conditions or dangerous or unhealthy lifestyles [...], may find it more difficult to attract a spouse than do healthy, relatively settled individuals [...]. By a similar argument, those in good health may be better able to maintain a marital relationship and thus have lower dissolution rates."

  Despite this wealth of literature on the impact of marital status on mortality and its consistent findings, no study so far has addressed the question whether marital status also matters for annual fluctuations in mortality. Without predecessors, our study presents an exploratory first step. We hypothesize that married people show less vulnerability to cold stress. Two reasons can be given to support this idea: First, married people are more robust on average than others due to the selection effect into marriage. Secondly, the protective effects of marriage by avoiding unhealthy behaviors should give them a survival advantage during winter.
- **Living Alone.** There is evidence in the literature that people who are living alone tend to have higher mortality [201]. This variable is often treated as a sub-factor of marital status (usually it is assumed that married people are not living alone). Rogers et al. [314], for example, calculated that the mortality risk of US adults who are not married and are living alone is roughly 50% higher than for married people who live with their spouse and two children.[4] Also Rogers [313] discovered elevated mortality for people who live alone — regardless of whether they were previously married or not.

  In a society like the Danish, however, one can not generalize that being married automatically means not living alone and being not married means

[4] This study controlled, of course, for other factors such as sex, age, race, income.

living alone. As a consequence, we treated this binary variable extra and controlled simultaneously for marital status. Only one recent study exists which investigates the question whether people who are living alone have an excess risk of dying in winter as compared to people who share their household with at least one more person [405]. They were, however, not able to detect any significant differences.

5.1.4 Summary

Danish data provide a rich data-source for the analysis of mortality in general and of seasonal mortality in particular. Thanks to the availability of linkable person-registers, individual life-courses can be reconstructed on almost any relevant aspect of life with unmatched precision on the timing of the event as well as on the quality of the data.

Denmark shows different mortality patterns than most other Western European countries. Especially the slow increase of life expectancy during the last thirty years has been of concern for epidemiologists and politicians. The relatively high smoking prevalence among Danish women born between the two World Wars is quite likely the root cause. Not much is known on seasonal mortality in Denmark. Compared to other European countries, Danish seasonal mortality is “mid-table”. It fares, however, worse than its neighboring countries. Not much is known so far about the impact of social factors on cold-related mortality.

Our study asks the following questions:

- How does seasonal mortality change with age?
- Can we find different susceptibility to cold stress for women and men?
- Can we shed more light on the ambiguously discussed topic of the impact of socioeconomic status on seasonal mortality? We use wealth (on the household level) and highest attained education (on the individual level) as indicators for socioeconomic status.
- Do people who own a car face less cold stress outdoors and have consequently lower seasonal mortality fluctuations?
- Are the typical mortality differentials by marital status also mirrored in the seasonal mortality pattern?
- Are individuals who are living alone more vulnerable to the environmental hazards during winter than people who share the household with at least one other person?

5.2 Data and Methods

5.2.1 Data Description

The base population are all people who were 65 years or older in Denmark between 01 January 1980 and 31 December 1998. If we bind the age-axis at a certain point, our base population is a rectangle in the Lexis diagram. There are three ways of entering our data-set:

- people were 65 years or older on 01 January 1980
- people become 65 years old between 02 January 1980 and 31 December 1980
- people immigrated into Denmark between 01 January 1980 and 31 December 1998 being 65 years or older

Likewise there were also three possibilities to exit the data-set:

- people who died between 01 January 1980 and 31 December 1998 being 65 years or older
- people who were 65 years or older and alive on 31 December 1998
- people who emigrated out of Denmark between 01 January 1980 and 31 December 1998 being 65 years or older

As already mentioned in the introduction of this chapter, Denmark's population registers are unique in the world concerning quantity and quality of the information provided. The focal point is a unique person-identifier called "CPR". In its original version it consists of a ten-digit number. The first six numbers indicate the birth date. The remaining four digits contain a serial number, sex of the individual (♀: even number; ♂: odd number) and some controls [349]. While it is true that one CPR refers uniquely to one person, it is possible under rare circumstances that one person has more than one CPR [289]. As pointed out by Petersen [289], the person-number ("PNR") used in the Danish Demographic Database [288] eradicated this problem: one person corresponds to one person-number and exactly vice-versa.

Table 5.2. Population Registers used in Our Analysis

Register-Name	Time-Span Covered	Key-Variables
`idperson`	1980–98	birth data, sex
`mortality`	1980–98	date of death, cause of death
`bil`	1992–98	car ownership
`dwelling`	1991–98	housing information: installations size per person; age of house
`education`	1980–98	highest educational level attained
`household`	1980–98	number of people living in the same household
`maristat`	1980–98	marital status
`wealth`	1980–96	wealth quartile on family level based on all kinds of of income (pension, rent, ...)

Table 5.2 shows the population registers used in our analysis: The data-set `idperson` consisting of 1,842,377 individuals serves as our base population. Out of them 999,605 died during the observation period and are contained in the data-set `mortality`. For 93% of them at least one cause of death was available (931,526).[5] These mortality data reflect nicely the high-quality of the population registers in Denmark: Only three individuals from this million had values outside the possible range of 01 January 1980 – 31 December 1998. One particular problem was the changing coding scheme for causes of death. Until the end of 1993, Danish authorities used ICD-8 for coding causes of death. Afterwards they switched directly to ICD-10. This step induced problems. First, conversion tables are usually only available from one revision to the next. Secondly, and more importantly, ICD-10 introduced an alphanumeric coding scheme whereas previous revisions were purely numerical. The problematic task of producing comparable time-series for causes of death was impeded even further. Fortunately, it was possible to reconstruct comparable data for the three causes which are high-risk diseases for seasonal mortality, and which have been used in the most in-depth analysis of winter excess mortality so far [98]: Ischaemic Heart Disease, Cerebrovascular Diseases and Respiratory Diseases. The following table (Table 5.3) shows the coding for these three causes by coding scheme (ICD-8 vs. ICD-10):

Table 5.3. Coding of Causes of Death in Denmark by Coding Scheme

Cause of Death	**ICD-8**	**ICD-10**
Ischaemic Heart Disease	410–410	I20–I25
Cerebrovascular Diseases	430–438	I60–I69
Respiratory Diseases	460–519	J00–J98

Starting in 1992, a car register (data-set `bil`) was installed. Each record in this database gives information about the registration, the de-registration (if applicable) the kind of car and the person who registers for every car in Denmark. We simplified this data by ignoring changes from one vehicle to another one. We coded a dummy variable which only indicates whether a person owns a car at a certain point of time or not. Out of the 1,8 Mio. people in the base population, 502,455 individuals were coded to be car-owners following this coding convention. Surprisingly, it happened that people were registered for a car for some time after their deaths. Rather than excluding those illogical cases from the analysis completely, we rather assumed that the relatives de-registered the car simply awhile later.

The `dwelling` register (started in 1991) contains various information about the size of the dwelling, its age and its installations. In contrast to most other

[5] The Danish Demographic Database contains information on primary, secondary, and tertiary cause of death.

databases in the Danish registers, housing information is annually available, and not on a daily or monthly basis. As previous seasonal mortality literature is mainly concerned about the housing quality, we relied on the information given for installations. Denmark is a relatively homogeneous country with relatively similar living standards. Therefore we only made a distinction between people who have the maximum number of installations (toilet, central heating, bath) versus the rest (versus not stated). 91.92% of the apartments of the individuals had the maximum number of installations, 6.52% had less than the maximum and 1.56% were not possible to be assigned.

Education (data-set `education`) measures the highest educational level attained by any individual and is available for the whole time period (1980–1998). Education is coded using eight digits to reflect any possible combination of educational pathways. Coordinating with Jørn Korsbo Peterson — he is the maintainer of the Danish Demographic Database — this abundance of information[6] was grouped into three categories which is the typical approach taken by researchers using Danish register data.

Table 5.4. Educational Categories

Code	Danish Description	English Description	ISCED Code†	Share
1	Almenuddanelse	Lower Secondary Education or less	0–2	61.42%
2	Gymnasie og erhvervsgaglige uddannelser	(Upper) Secondary Education, post secondary non tertiary education, skilled manual worker	3–4	27.75%
3	Videregående og ph.d.	Tertiary education or higher	5–6	10.83%

† ISCED is the International Standard Classification of Education [370].

Table 5.4 describes which categories were used for the coding of education, how large their proportion is and to which ISCED categories [370] the present classification corresponds. People who attended primary school only or in conjunction with lower secondary school were assigned to category 1 ("lower education"). 61.42% of the people belonged to this group. Roughly 28% of the people have an intermediate level of education (Code 2, "middle"). They attended upper secondary education and/or are skilled manual workers. People with an academic degree, regardless of whether it a Bachelor, a Master or a Ph.D., are members of the highest educational group. About 11% of all individuals in the data-set are in this third category ("high").

The data-set `household`, which is updated annually, contains information on the number of people having the same household identification

[6] The actual number of possible education levels was 436.

number. This was used to assess how many people are living in the same flat/apartment/house. Although the actual number of people is known, we used a binary variable to indicate whether a person is living alone or not. At the time of death (or censoring) 53.55% were living alone, for the remaining 46.45% at least one more person was living in the same household.

In the data-set `maristat`, the marital status of the population is recorded. Every person at any point of time is assigned to exclusively one of the following categories: Married, divorced, widowed, unmarried, registered partnership, revoked registered partnership and "longestliving of two partners". The last three categories constitute combined less than 0.03% of all cases and have been excluded from any further analysis.

The data-set `wealth` is a special measure of socioeconomic status. It includes not only the salary measured in income but also other kinds of revenue. A typical example is receiving rent from a house one owns. Finally, the complete income is annually measured in Danish Krones. One important advantage of this variable is that it is measured on the family level. This implies, for instance, that a woman who has no income of her own but is married to a millionaire is not classified as poor. Wealth has already been transformed into four categories by Statistics Denmark. Those four groups represent quartiles of wealth (0–25%, 25–50%, 50–75%, 75–100%). This variable was available only for the time period 1980 until 1996. Any analysis involving this variable was, thus, restricted to the first 17 years of our observation period.

5.2.2 Method

Introduction: Why Logistic Regression?

Event-history analysis represents the appropriate framework to study the time-to-failure distribution of events of individuals over their life course. In demographic applications "Failure" can not only be death but also transition to the first child, re-entry into the labor-market, etc. Traditional approaches like the linear OLS model are not appropriate for these kind of data for several reasons. For example, lifetimes are (necessarily) positive, the assumption of a normal distribution for the error term in the OLS model does not hold because the normal distribution is defined from $-\infty$ to ∞.[7] The problem of *censoring* is more serious. This appears when the event of interest has not happened until the last moment of observation (e.g. if a person survived until a certain point of time which marks the end of the study period) [56]. Event-history models, sometimes also coined survival models, are able to incorporate these special data characteristics. While most event-history models are designed for continuous time, we have decided to employ a logistic regression model which can be considered as a survival model for discrete time [cf. 85]. Various reasons can be brought up to support such an approach [cf. 5, 6, 418]. The decisive ones

[7] This drawback could be mediated by taking the log of the lifetime.

for our analysis were: first, it allows to incorporate time-varying covariates easily. Secondly, an important "consideration concerns the number of *ties* in the data. Events are tied when two or more subjects in the sample have events at the same time" [418, p. 16]. In our application it is, of course, possible that individuals die during the same month at a certain age. "The presence of ties can lead to serious bias in parameter estimates when using Cox's method for proportional hazards models [...]. On the other hand, discrete-time models can handle ties without introducing bias in parameter estimates" [418, p. 16–17]. The third reason is especially important for our huge data set: The calculation takes considerably less time with logistic regression than with the Cox-Model which appears to be the default choice in most applications. In practice, the results between the methods differ only marginally. A comparison between a continuous and a discrete time model in the appendix of Rau and Doblhammer [302] shows almost indistinguishable regression coefficients for a seasonal mortality analysis. The major practical difference between the two approaches is found in modeling the duration dependency. For example in the common proportional hazards regression, a baseline hazard is estimated (non-parametrically in the case of a Cox-Model) and the effect of the covariates shifts this baseline duration dependency proportionally up or down.[8] In the case of logistic regression, this time dependency has to be entered as a covariate (or as covariates) into the model.

The Model

The logistic regression we used is outlined in Equation 5.1:

$$\log\left(\frac{P_{it}}{1-P_{it}}\right) = \alpha + \beta_{\text{Winter}} x_{1;ti} + \beta_{\text{Spring}} x_{2;ti} + \beta_{\text{Fall}} x_{3;ti} + \\ + \sum_{\text{age}} \gamma_{\text{age}} x_{\text{age};ti} + \sum_{\text{period}} \delta_{\text{period}} x_{\text{period};ti} + \text{further covariates} \tag{5.1}$$

where:

$$x_1 = \begin{cases} 1 & \text{if current month is Dec, Jan or Feb} \\ 0 & \text{otherwise.} \end{cases}$$

$$x_2 = \begin{cases} 1 & \text{if current month is Mar, Apr or May} \\ 0 & \text{otherwise.} \end{cases}$$

[8] Also in the other common approach, the accelerated failure time models (AFT), a baseline hazard is estimated. The main difference to the proportional hazards model (PH) is the effect of the covariates which does not work on the hazard function but on the failure time [141].

$$x_3 = \begin{cases} 1 & \text{if current month is Sep, Oct or Nov} \\ 0 & \text{otherwise.} \end{cases}$$

The log of the odds-ratio (which is the probability that individual i experiences death at time t divided by one minus this probability) is related to an intercept denoted by α and a set of time-fixed and time-varying covariates. The coefficients β_{Winter}, β_{Spring} and β_{Fall} are of primary interest in our analysis as they correspond to the influence of the covariates $x_1, x_2,$ and x_3 which indicate as binary variables the seasons Winter, Spring, and Fall. The obtained estimates have to be interpreted therefore in relation to the reference group summer which has been left out.
The effect of age on mortality is captured in the set of regression coefficients denoted by γ_{age}. The age-groups corresponding to the set of dummy-variables $\sum_{\text{age}} x_{\text{age}}$ are (in years): 65–69 (Reference Group), 70–74, 75–79, 80–84, 85–89, 90–94, 95–99, 100 and older.
Possible period effects are accounted for by the set of dummy-variables δ_{period} which measure the influence of the period dummies denoted by $\sum_{\text{period}} x_{\text{period}}$.
The dummies for the periods were the following calendar years: 1980–84, 1985–90, 1991–93 (Reference Group), 1994–96, 1997–98.[9]
Controlling for other effects has been denoted in Equation 5.1 above by "further covariates". That means, for example, that in a model where the influence of living arrangements (living alone yes/no) has been investigated, we controlled for education, marital status and wealth in addition to season, age, and period. The actual variables belonging to "further covariates" are given in every estimated model presented in latter parts of this chapter.

Interpreting Results from the Applied Logistic Regression Model

- **Odds-Ratios vs. Relative Risks**
  Strictly speaking, the exponentiated regression coefficients (e.g. $e^{\beta_{\text{Winter}}}$) have to be interpreted as odds-ratios. If the probability of the event is rather small, however, these odds-ratios are close to the relative risks known from standard event-history models and can be interpreted as such [28, 159, 257, 414]. This approximate equality of odds-ratios and relative risks in the case of events which are relatively rare is explained in the following example.
  In our data we have roughly 1 Mio. deaths but more than 180. Mio person-months lived. This situation is shown in Table 5.5 in a simplified manner. With these data, we want to calculate the relative risk as well as the odds-ratio for death among women in relation to men.

[9] The unequally spaced distinction across the periods has been chosen as these years (apart from 1984/85) reflect changes in the availability of data (cf. Section 5.2.1 starting on page 131).

Table 5.5. Hypothetical Example: Survival Status by Sex

	Survived?		
	Yes	No	$\sum$
Women	100×10^6	0.5×10^6	100.5×10^6
Men	80×10^6	0.5×10^6	80.5×10^6
$\sum$	180×10^6	1.0×10^6	181.0×10^6

Following Woodward [414], a risk is defined by the number of cases who experienced a certain event divided by the number of cases at risk. The relative risk (RR) of death of women compared to men is therefore:

$$RR = \frac{\frac{0.5\times10^6}{100.5\times10^6}}{\frac{0.5\times10^6}{80.5\times10^6}} = \frac{0.004975}{0.006211} = 0.800998 \tag{5.2}$$

In contrast, the odds are defined as the number of cases who experienced a certain event divided by the number of cases who did not experience the event [414]. The odds-ratio (OR) is therefore:

$$OR = \frac{\frac{0.5\times10^6}{100\times10^6}}{\frac{0.5\times10^6}{80\times10^6}} = \frac{0.005}{0.00625} = 0.8 \tag{5.3}$$

The relative risk RR in this example is 0.800998. The odds-ratio OR is 0.8. We can therefore conclude for our application where events are relatively rare, that odds-ratios are approximating relative risks very closely.

- **Interpreting Our Models**
  The regression coefficient which is used mainly in our results is β_{Winter}. Due to the size of the data-set we estimated separate models for the different groups of interest. Therefore, the point and confidence estimates given (or plotted) have to be interpreted always in relation to the specific reference group which is summer. An example might clarify this: Given that we want to analyze the effect of education which is measured in three levels (low, middle, high), we estimated a separate model for each educational group. Let's assume we have a point estimate for people with high education of 0.2 and a standard error for this coefficient of 0.02. The 95% confidence interval for this coefficient is therefore: $0.2 \pm 1.96 \times 0.02 = 0.2 \pm 0.0392$. If we exponentiate these estimates, we obtain a point estimate for the odds-ratio/relative risk of $e^{0.2} = 1.2214$ and confidence estimate of $e^{0.2-0.0392}$; $e^{0.2+0.0392} = 1.1745; 1.27023$.

  A valid interpretation is:
  – For people with high education, the relative risk of dying in winter is significantly higher than during summer because the confidence interval does not include 0 (or 1 in the case of $e^{\beta_{\text{Winter}}}$).

– The regression results indicate a relative risk of dying which is 22% higher during winter than during summer for people with high education.

Given we have parameter estimates for people with middle education of 1.30 (lower 95% CI), 1.325 (point estimate), and 1.35 (upper 95% CI), we can not make any inferences whether the excess risk during winter is *significantly* higher for people with middle education than with high education. This drawback is less serious than it may appear at first sight: Because of the size of our data-set, it is quite likely that even the smallest differences between two parameters turn out to be significant. But even if a difference, for example, between 1.23 and 1.24 turns out to be significant, one has to question whether this significant difference is of actual practical relevance. Sachs [321] distinguishes, therefore, in his textbook between statistical significance and practical significance.[10]

5.2.3 Problems of the Data Analysis

Timevarying Covariates

It should be pointed out that age, period, and current month have been coded properly as time-varying covariates. Other covariates have been assumed to be time-constant despite their inherent time-varying nature. The main reasons are computational resources. In typical applications there is no problem to represent time-varying covariates adequately, as they change rarely and/or the number of individuals covered in the data-set is of manageable quantity. In our application however, every person-month lived is a new record. Our 1.8 million subjects in the base population survived roughly 100 months on average. Consequently, the data-set contains 180 million person-months lived and the same number of records.[11] To obtain a final data set with all the (time-varying) information, one needs to calculate data-sets with these 180 Mio. records for each variable separately, as they are all given in single data-sets linkable via the PNR. Even if the base population is broken down by sex and into 5 year birth cohorts, the data-sets are too large to be sorted and merged together.[12] The actual approach was to use time-constant covariates instead of time-varying covariates by taking the last observed realization of the covariate for each individual. The question is then, of course: How much does this simplification reduce the quality of the analysis? In most cases the loss of information is of minor importance for several reasons:

[10] "Weiter sei noch auf den zuweilen nicht beachteten **Unterschied zwischen statistischer Signifikanz und "praktischer" Signifikanz** hingewiesen: praktisch bedeutsame Unterschiede müssen schon mit nicht zu umfangreichen Stichproben erfaßt werden können" [321, p. 187; boldface in source document].

[11] There are precisely 186,271,440 person months lived. 106,322,677 person-months were lived by women and 79,948,763 by men.

[12] A trial dataset for one sex and five birth years resulted in a file, which was larger than 3GB.

- At advanced ages, variables like wealth (measured in quartiles on the family level), education, and housing quality are changing their values only very rarely. Thus, an approach where these variables are coded as time-constant on the one hand, and as time-varying on the other hand, should both give approximately the same results because neither the number of exposures nor the number of occurrences change.
- Some variables like housing quality or wealth are only available on an annual basis. Thus, in some cases it would not even be possible at all to code the change into the month when it actually happened.[13]
- The annually measured variables are only available if the person has survived until the end of the year. Consequently, nothing is known at the moment of death about those covariates. The closest information one could obtain is the one from the previous year which we used in our approach.
- For the variable of car ownership the validity can be doubted, as it measures only the registration of the car but not its use. In many cases the car got de-registered several months after the death of the person. While it is impossible for the deceased to use a car after her/his death, one can neither assume that the person used the car during the month(s) preceding death.

The two remaining variables which are intrinsically time-varying even at those advanced ages are “marital status” and “living alone yes/no”. Our approach used the last information available, which means that the number of events is correct. The exposure time, however, is biased. For the variable “living alone yes/no”, people who were alone at the end of their lives have probably not lived throughout the whole observation period alone. Thus, the exposure time for this category in our models is too large and regression estimates would result in even higher values for those people if the variable was coded as time-varying. Reciprocally, the exposure time for people who were not alone is too large which should result in lower mortality estimates if the variable was coded more precisely. Marital status is more problematic. The number of events in our models for each category is entered correctly. The exposure time is exact only for the group “never married / single”. The categories “widowed” and “divorced” contain too many exposures, while “married” contains less exposure time (It is likely that the people who are widowed and/or divorced in our data have spent some time during the follow-up being married). As a consequence, the mortality estimates for the categories “divorced” and “widowed” should be higher than in our results and the ones for “married” should be lower.

Summing it up, using time-constant covariates instead of time-varying covariates, because of technical resource problems, appears less of a problem than it first suggests. Many variables are approximately time-constant anyway

[13] Typical approaches would assume that the changes take place either in the middle or in the end of the year. Those implementations are arbitrary and would influence our model estimates severely as we are interested in the actual month of death.

at ages over 65. The impact of variables like "marital status" and "living alone yes/no" is also manageable if the results are carefully interpreted. This view gains some support from a paper recently published in the British Medical Journal. In their study "Vulnerability to winter mortality in elderly people in Britain: population based study", Wilkinson et al. use exclusively time-fixed covariates — also for the question whether somebody was living alone or not [405].

Competing Risks

We analyzed mortality for various causes of death. It can be assumed that the risk of dying from one cause is not independent from the risk of dying from another cause in the case of human mortality [61]. Therefore it appears to be most natural to estimate a competing risks model. We are, however, faced with a dilemma: [196, p. 51–52, emphasis in source document]:

> "In competing-risks modeling we often need to make some assumptions about the dependence structure between the potential failure times. Given that we can only observe the failure time and cause and not the potential failure times these assumptions are not testable with only competing risks data. This is called the *identifiability dilemma*. [...] This means that given what we actually see, (T, δ), we can never distinguish a pair of dependent competing risks from a pair of independent competing risks."[14]

As pointed out by Allison [6], not much can be done about this dilemma. Although it is "possible to formulate models that incorporate dependence among event types but, for any such model, there's an independence model that does an equally good job of fitting the data" [6, p. 209].

If independence (or quasi-independence [cf. 61]) is assumed, one can follow either one of the following two approaches: either one is estimating a model with all causes *simultaneously*, or one is estimating a model for each cause of death *separately*. Both approaches are statistically equivalent. It has been shown, for example in Prentice et al. [293], Kalbfleisch and Prentice [183] and Allison [6], that the likelihood function for all causes together (i.e. simultaeoeusly for j causes of death) can be factored into separate likelihood functions for each of the j causes of death. The only advantage of a simultaneous estimation therefore is "to reduce the number of statements needed to specify the models" [6, p. 188]. On the contrary, there are some advantages of estimating models separately: First, one does not have to specify the same functional form and not the same set of covariates for all causes of death. Secondly, "a further implication is that you don't need to estimate models

[14] In the quotation above, T indicates the duration (e.g. age); δ denotes the last observed status of the subject (e.g. alive/censored, death from cause a, death from cause b, ...).

for all event types unless you really want to. If you're only interested in the effects of covariates on deaths from heart disease, then just estimate a single model for heart disease, treating all other death types as censoring. Besides reducing the amount of computation, this fact also makes it unnecessary to do an exhaustive classification of death types. You only need to distinguish the event type of interest from all other types of events" [6, p. 188]. These advantages, in conjunction with the identifiability dilemma, let us choose to run models separately.

5.3 Results

5.3.1 Descriptive Results

The upper panel in Figure 5.1 gives an overview about the distribution of deaths during the observation period from 1980 until 1998 for both sexes. Each gray vertical bar represents the monthly number of deaths (adjusted to a standard length of 30 days) in Denmark at ages 65 and higher. Clearly, a distinct seasonal pattern can be observed. Each January is marked by a black triangle, whereas August is illustrated by a black square. With a few exceptions, these two months represent typically the maximum and the minimum in numbers of deaths in every year. With regard to the heavy media coverage after the summer of 2003 on heat-related mortality, it should be stressed that deaths during summer were always below the average number of deaths during the whole observation period of 19 years.

The seasonal pattern for the whole time period can be described by the "Winter / Summer-Ratio", which has been discussed in Chapter 3 as seasonality index φ_1 (see page 41). This index results in a value of 1.17, which means that 17% more people are dying during winter than during summer. In contrast to the initial description in Chapter 3, the months which served as nominator and as denominator have been slightly changed: December, January and February are the months with the highest numbers of death as shown in the two lower panels of Figure 5.1. To have a year whose seasons are divided into four consecutive parts of equal length, summer was defined for the months June, July, August.

The two lower panels in Figure 5.1 show the same data aggregated into one year, separated by sex and converted into monthly contributions given in percentages; women's seasonality of deaths is displayed in the lower left panel with a gray barplot, the lower right panel depicts the corresponding pattern for men in black. For clarification, in both panels a horizontal line has been drawn at 8.3% to indicate the value of a uniform distribution.

The differences in the Winter/Summer Ratio (φ_1) are relatively small among the two sexes. Women's seasonality measured by φ_1 is 1.18, men's $\varphi_1 = 1.17$. For both sexes the six months with the highest number of deaths is followed by the six months of lowest deaths. Consequently, Hewitt's test for seasonality

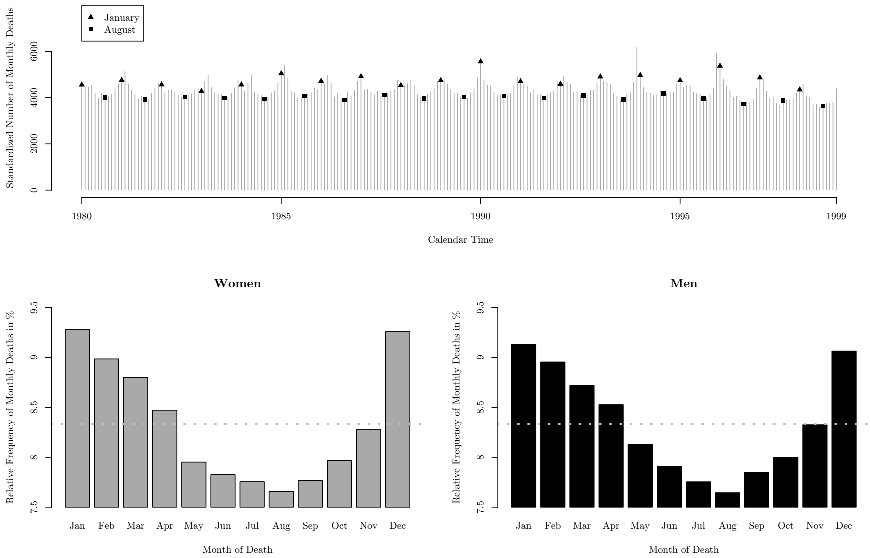

Fig. 5.1. Monthly Distribution of Deaths Above Age 65 in Denmark, 1980–1998 and Its Aggregation into Twelve Months by Sex (standardized for length of month)

resulted in a maximum rank sum of 57 which corresponds to significance on the $\rho = 0.013$ level which is the lowest possible value for this nonparametric test (cf. Chapter 3 (page 39), 150, 395).[15]

5.3.2 Absolute Level of Mortality

Using our discrete-time event-history approach, we are mainly presenting relative mortality risks.[16] To get an overview about the absolute differences between winter and summer mortality, a seasonal life-table has been calculated. To estimate a life-table, two inputs and one assumption are required:

Occurrences: The occurrences in our application are deaths at a certain (integer) age in a specific month for either women or men.

Exposures: In our case, the exposures are women and men who are at risk of dying during a certain (integer) age in a specific month.

[15] Also, any other test, which was presented in Chapter 3, resulted in highly significant values for these Danish data.

[16] To be precise, we will present odds-ratios. But as pointed out before and also shown, for example, by Woodward [414], odds-ratios are often a good approximation to the relative risk. Since the number of events in our application is relatively rare to the number of exposures, we can safely use this approximation.

Assumption: The function $a(x)$ usually specifies the "mean number of person-years lived in the interval by those dying in the interval" [297, p. 43]. In our case, we give a value of 0.5 as the mean number of person-months lived in the interval (a month) by those dying in the interval in an integer age. This value of 0.5 corresponds to the assumption that deaths occur in the middle of the month.

We picked the death rates — usually denoted by m_x — as our life table function of choice. These standard rates for mortality from all causes have been plotted by age in Figure 5.2 on page 146 in the upper left panel for women (gray) and men (black). The other three panels show the results from ischaemic heart disease (upper right), cerebrovascular diseases (lower left), and respiratory diseases (lower right). The death rates for these three causes have been estimated using a multiple decrement lifetable approach as outlined in Preston et al. [297] on pages 71ff. Accordingly, the rates ${}_m m_x^i$ at age x in month m for cause-of-death i are:

$$ {}_m m_x^i = \frac{{}_m d_x^i}{{}_m L_x}. \tag{5.4} $$

The number of people dying at age x in month m from cause i is denoted by ${}_m d_x^i$. The people who are exposed to the risk of dying are denoted by ${}_m L_x$.

We plotted the resulting death rates ($m(x)$) by age in Figure 5.2 on page 146. The upper left panel shows results for mortality from all causes. The remaining three panels contain information on the seasonal pattern for the selected causes of death: ischaemic heart disease (upper right), cerebrovascular (lower left) diseases and respiratory diseases (lower right). Several interesting features can be discovered in the four panels:

- All four causes of death show a distinct difference between summer and winter mortality. Albeit on a lower overall level, these differences are larger for respiratory diseases than for ischaemic heart disease and cerebrovascular diseases.
- On the plotted log-scale, we observe for mortality from all causes, from ischaemic heart disease and from cerebrovascular diseases, a linear increase in mortality with age. This corresponds to an exponential increase in mortality.
- For all-cause-mortality, three reference lines have been plotted to give an impression on how much winter mortality is exceeding summer mortality. Winter mortality for women at age 80 can be seen at the intersection of the gray dashed vertical line and the gray dashed horizontal line. The equivalent for men is shown at the intersection of the gray dashed vertical line and the black dashed horizontal line. Following the horizontal reference lines to the right, we can see that summer mortality reaches the level of winter mortality two years later for women and three years later for men.
- At first glance it is surprising that the mortality curves for women and men are converging (all-cause-mortality, ischaemic heart disease) or even

are crossing over. This does not reflect what is observed in reality. It is an outcome of pooling data for the years 1980 to 1998. Since mortality is lower for females than for males, the average (calendar) time was earlier when women died at those high ages where converging mortality is displayed. Due to the progress in survival chances, men are catching up. In any graph which is aggregating mortality information over several units of time, the plotted gap between female and male mortality is therefore smaller than the one measured at one unit of time.

The following sections present the results of our discrete-time event-history analysis. To condense the information, the regression coefficients are given in a figure and in a table only for the first analysis. For the remaining analyzed variables, only the graphs are included in the main text. The corresponding tables can be obtained from the author.

5.3.3 Seasonal Mortality by Sex and Cause of Death

In a first step, seasonal mortality has been analyzed by sex and cause of death. Separate logistic regressions have been conducted for men and women for mortality from all causes, ischaemic heart disease mortality, cerebrovascular diseases and respiratory diseases.
The odds-ratios and the 95% confidence intervals for the parameter estimates from this discrete-time event-history analysis are shown in four panels in Figure 5.3. By looking at Figure 5.3 a), one can recognize that the differences between women and men for seasonal mortality from all causes are rather negligible. Although we can detect that the excess in mortality during winter is higher for women than for men, the differences are relatively small. Women's relative mortality risk (RMR) in winter is 18 percent higher than in summer. Men's excess is 16 percent. Excess mortality from Ischaemic Heart Disease (Figure 5.3 b) is slightly higher for both sexes than from all causes. Again, women's RMR is higher than men's ($e_{♀}^{\beta_{\text{Winter}}}$: 1.235; $e_{♂}^{\beta_{\text{Winter}}}$: 1.204). Male cold-related excess mortality surpasses women's only for cerebrovascular diseases in all seasons (Figure 5.3c). Similarly important for high winter excess mortality are respiratory diseases. Although the share of ischaemic heart disease combined with cerebrovascular diseases among all diseases is larger (IHD & Cerebrovascular Diseases: $\approx$ 40%; Respiratory Diseases: $\approx$ 7%), the excess from respiratory diseases is considerably higher (see Figure 5.3d). Men's risk of dying from respiratory diseases is 36.5% higher in winter than in summer. Women's risk is elevated by more than 55%. It should be emphasized, however, that we are using relative mortality measurements. Therefore it is not possible to filter out whether winter mortality is extremely high or summer mortality is extremely low.

Relatively similar results for winter excess mortality for both sexes with a slight "advantage" for women have been reported previously for all-cause

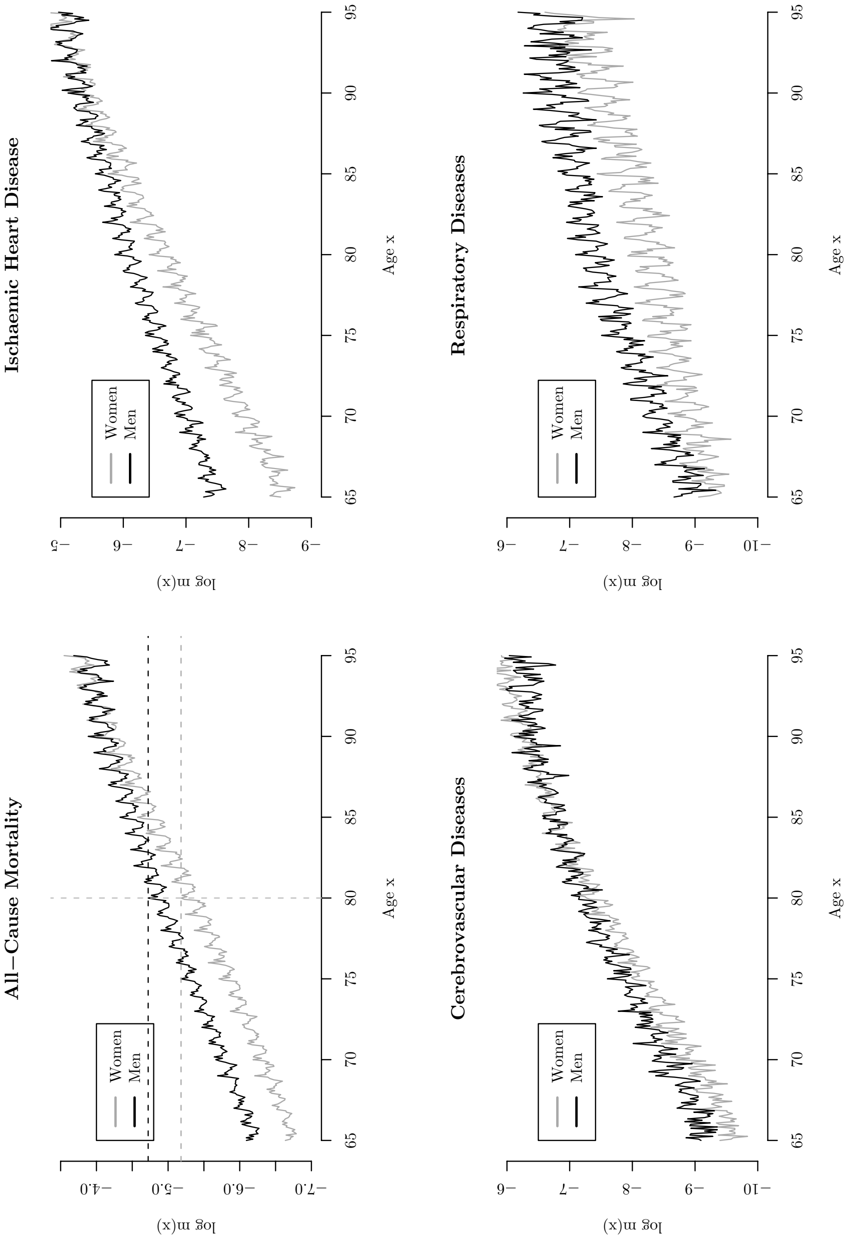

Fig. 5.2. Age-specific Mortality Rates by Cause and Sex

mortality [37, 98, 121, 419], as well as for heart diseases [246].[17] Our results are contradictory to findings from mortality research in general where women typically have lower mortality rates at all ages. These results should be interpreted with care for two reasons:

- If the analysis does not correct for age, those differentials might be the outcome of an age effect: due to higher life-expectancy of women, the mean age in a female population should be higher than in the corresponding male population. In conjunction with the increase of seasonality with age as previous articles stated [e.g. 102, 251, 300], women's seasonality could simply be larger because of their higher susceptibility to cold climate at advanced ages. Our analysis, however, controlled for possible confounding with age.
- A possible solution for this surprising finding might be the specific Danish situation: As already outlined in the introduction to this chapter, life expectancy in Denmark rose slower than anywhere else in comparable countries — especially for women. The main reason for the decelerated increase in life expectancy was the high smoking prevalence among females in Denmark. This reasoning might also apply to seasonal mortality in our analysis. When looking at the results from respiratory diseases (Fig. 5.3 d), it can be easily detected that women and men both display substantial excess mortality during winter. Women's relative risk of dying during the cold season is even higher than that of men. This might be traced back to the cohort of heavily smoking women who were born between the two World Wars and which is strongly represented in our data. But not only this compositional effect of a large proportion of smoking women in Denmark can be brought up to explain the higher excess mortality of women than of men in Denmark. There are also indications for a direct sex-effect of smoking between women and men. Although "it is too early to conclude that women may be more sensitive than men to some of the deleterious effects of smoking" [238, p. 787], several articles from Prescott et al. point into the direction that smoking has more severe effects on health for women than for men [e.g. 294, 295]. In one of her studies which is based on data from Denmark, Prescott et al. [295] show that this differential among women and men was visible in particular for the relevant seasonal diseases (cardiovascular, cerebrovascular and respiratory diseases) but not for cancer [295].

5.3.4 Winter Excess Mortality by Age, Sex, and Cause of Death

Age is the most important single determinant of mortality. Therefore, we calculated seasonal mortality for five-year age-groups in a second step. To fa-

[17] This finding of larger seasonal variations of coronary heart disease in New Zealand by Marshall et al. [246] only applied to the Non-Maori population.

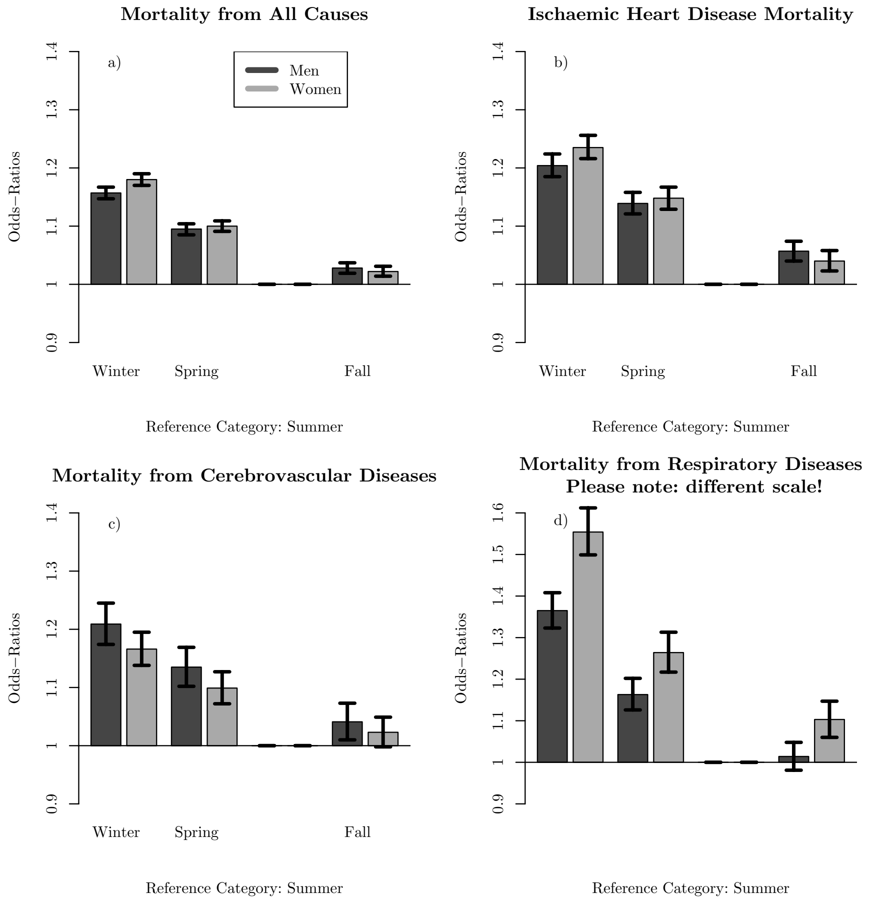

Fig. 5.3. Seasonal Mortality by Sex and Cause of Death (Odds-Ratios and 95% Confidence Intervals)

cilitate interpretation, only the estimated winter odds-ratios have been plotted in Figure 5.4. The results for winter excess mortality from all causes are shown in Fig. 5.4 a) for women and men. For women as well as for men, seasonal mortality increases with age. Between ages 65 and 69 the risk of dying in winter is about 10% higher for women as well as for men ($e_{♀}^{\beta_{\text{Winter}}}$: 1.102; $e_{♂}^{\beta_{\text{Winter}}}$: 1.095). Winter excess mortality is increasing with age. Danish people face excess winter mortality of about 15% in their mid 70s ($e_{♀}^{\beta_{\text{Winter}}}$: 1.146; $e_{♂}^{\beta_{\text{Winter}}}$: 1.149). When Danish people survive until 90 years of age, women's risk of dying is about 23% higher in winter than in summer; for men, the risks are slightly higher (90–94 years: 26.2% ; 95–99 years: 28.0%). Although the Danish data are of high quality, results for centenarians should

Table 5.6. Regression Results, Seasonal Mortality by Sex and All Cause Mortality

Women

Covariate		β	e^{β}	s.e.	ρ
Intercept (α)		-6.618		0.007	<.0001
Winter		0.165	1.180	0.004	<.0001
Spring		0.095	1.100	0.004	<.0001
Summer (RG)		-	-	-	-
Fall		0.022	1.022	0.004	<.0001
Age (in Years)	65-69 (RG)	-	-	-	-
	70-74	0.444	1.558	0.006	<.0001
	75-79	0.931	2.536	0.006	<.0001
	80-84	1.473	4.363	0.006	<.0001
	85-89	2.016	7.511	0.006	<.0001
	90-94	2.529	12.537	0.007	<.0001
	95-99	2.918	18.499	0.009	<.0001
	100+	2.815	16.695	0.021	<.0001
Period	1980-84	0.033	1.034	0.005	<.0001
	1985-90	-0.004	0.996	0.005	0.377
	1991-93 (RG)	-	-	-	-
	1994-96	-0.007	0.993	0.005	0.149
	1997-98	-0.066	0.936	0.006	<.0001

Men

Covariate		β	e^{β}	s.e.	ρ
Intercept (α)		-6.102		0.006	<.0001
Winter		0.146	1.157	0.004	<.0001
Spring		0.090	1.095	0.004	<.0001
Summer (RG)		-	-	-	-
Fall		0.027	1.028	0.005	<.0001
Age (in Years)	65-69 (RG)	-	-	-	-
	70-74	0.443	1.557	0.005	<.0001
	75-79	0.893	2.441	0.005	<.0001
	80-84	1.298	3.662	0.005	<.0001
	85-89	1.679	5.361	0.006	<.0001
	90-94	1.997	7.365	0.007	<.0001
	95-99	2.026	7.586	0.013	<.0001
	100+	1.004	2.729	0.036	<.0001
Period	1980-84	0.107	1.113	0.005	<.0001
	1985-90	0.041	1.042	0.005	<.0001
	1991-93 (RG)	-	-	-	-
	1994-96	-0.030	0.971	0.005	<.0001
	1997-98	-0.105	0.900	0.006	<.0001

Table 5.7. Regression Results, Seasonal Mortality by Sex and Ischaemic Heart Disease

Women

Covariate		β	e^{β}	s.e.	ρ
Intercept (α)		-8.448		0.014	<.0001
Winter		0.211	1.235	0.008	<.0001
Spring		0.138	1.148	0.008	<.0001
Summer (RG)		-	-	-	-
Fall		0.040	1.040	0.009	<.0001
Age (in Years)	65-69 (RG)	-	-	-	-
	70-74	0.647	1.910	0.014	<.0001
	75-79	1.285	3.615	0.013	<.0001
	80-84	1.927	6.870	0.013	<.0001
	85-89	2.522	12.458	0.013	<.0001
	90-94	3.068	21.492	0.014	<.0001
	95-99	3.466	31.992	0.018	<.0001
	100+	3.309	27.347	0.041	<.0001
Period	1980-84	0.299	1.348	0.009	<.0001
	1985-90	0.168	1.183	0.009	<.0001
	1991-93 (RG)	-	-	-	-
	1994-96	-0.200	0.819	0.011	<.0001
	1997-98	-0.382	0.682	0.013	<.0001

Men

Covariate		β	e^{β}	s.e.	ρ
Intercept (α)		-7.449		0.011	<.0001
Winter		0.186	1.204	0.008	<.0001
Spring		0.131	1.140	0.008	<.0001
Summer (RG)		-	-	-	-
Fall		0.056	1.057	0.008	<.0001
Age (in Years)	65-69 (RG)	-	-	-	-
	70-74	0.470	1.599	0.010	<.0001
	75-79	0.942	2.564	0.009	<.0001
	80-84	1.352	3.866	0.010	<.0001
	85-89	1.753	5.769	0.011	<.0001
	90-94	2.092	8.103	0.014	<.0001
	95-99	2.174	8.792	0.024	<.0001
	100+	1.116	3.052	0.069	<.0001
Period	1980-84	0.323	1.381	0.009	<.0001
	1985-90	0.171	1.186	0.009	<.0001
	1991-93 (RG)	-	-	-	-
	1994-96	-0.214	0.807	0.011	<.0001
	1997-98	-0.392	0.676	0.013	<.0001

Table 5.8. Regression Results, Seasonal Mortality by Sex and Cerebrovascular Diseases

Women

Covariate		β	e^{β}	s.e.	ρ
Intercept (α)		-9.346		0.023	<.0001
Winter		0.154	1.166	0.013	<.0001
Spring		0.095	1.099	0.013	<.0001
Summer (RG)		-	-	-	-
Fall		0.023	1.023	0.013	0.077
Age (in Years)	65-69 (RG)	-	-	-	-
	70-74	0.766	2.152	0.024	<.0001
	75-79	1.506	4.507	0.022	<.0001
	80-84	2.226	9.261	0.021	<.0001
	85-89	2.800	16.438	0.021	<.0001
	90-94	3.220	25.023	0.023	<.0001
	95-99	3.385	29.518	0.031	<.0001
	100+	2.998	20.053	0.078	<.0001
Period	1980-84	0.090	1.094	0.014	<.0001
	1985-90	-0.004	0.996	0.013	0.776
	1991-93 (RG)	-	-	-	-
	1994-96	-0.167	0.846	0.015	<.0001
	1997-98	-0.306	0.736	0.018	<.0001

Men

Covariate		β	e^{β}	s.e.	ρ
Intercept (α)		-8.945		0.023	<.0001
Winter		0.190	1.209	0.015	<.0001
Spring		0.127	1.135	0.015	<.0001
Summer (RG)		-	-	-	-
Fall		0.040	1.041	0.016	0.010
Age (in Years)	65-69 (RG)	-	-	-	-
	70-74	0.679	1.973	0.021	<.0001
	75-79	1.352	3.866	0.020	<.0001
	80-84	1.896	6.662	0.020	<.0001
	85-89	2.293	9.903	0.021	<.0001
	90-94	2.562	12.960	0.026	<.0001
	95-99	2.440	11.471	0.046	<.0001
	100+	1.157	3.181	0.147	<.0001
Period	1980-84	0.134	1.144	0.016	<.0001
	1985-90	-0.001	0.999	0.016	0.946
	1991-93 (RG)	-	-	-	-
	1994-96	-0.236	0.790	0.019	<.0001
	1997-98	-3868.000	0.000	0.022	<.0001

Table 5.9. Regression Results, Seasonal Mortality by Sex and Respiratory Diseases

Women

Covariate		β	e^{β}	s.e.	ρ
Intercept (α)		-9.077		0.025	<.0001
Winter		0.441	1.554	0.019	<.0001
Spring		0.234	1.264	0.020	<.0001
Summer (RG)		-	-	-	-
Fall		0.098	1.103	0.020	
Age (in Years)	65-69 (RG)	-	-	-	-
	70-74	0.355	1.426	0.023	<.0001
	75-79	0.633	1.882	0.023	<.0001
	80-84	0.953	2.595	0.023	<.0001
	85-89	1.310	3.706	0.024	<.0001
	90-94	1.750	5.755	0.028	<.0001
	95-99	2.188	8.920	0.042	<.0001
	100+	2.014	7.495	0.106	<.0001
Period	1980-84	-0.443	0.642	0.021	<.0001
	1985-90	-0.244	0.784	0.019	< .0001
	1991-93 (RG)	-	-	-	-
	1994-96	-0.222	0.801	0.021	<.0001
	1997-98	-0.081	0.922	0.023	0.000

Men

Covariate		β	e^{β}	s.e.	ρ
Intercept (α)		-8.750			<.0001
Winter		0.311	1.365	0.016	<.0001
Spring		0.151	1.163	0.017	<.0001
Summer (RG)		-	-	-	-
Fall		0.014		0.017	0.413
Age (in Years)	65-69 (RG)	-	-	-	-
	70-74	0.548	1.730	0.020	<.0001
	75-79	1.077	2.936	0.019	<.0001
	80-84	1.431	4.183	0.020	<.0001
	85-89	1.729	5.632	0.022	<.0001
	90-94	1.941	6.969	0.029	<.0001
	95-99	1.854	6.383	0.054	<.0001
	100+	0.979	2.661	0.139	<.0001
Period	1980-84	-0.096	0.909	0.018	<.0001
	1985-90	-0.023	0.977	0.017	0.163
	1991-93 (RG)	-	-	-	-
	1994-96	-0.220	0.803	0.020	<.0001
	1997-98	-0.137	0.872	0.022	<.0001

be interpreted with great care: As indicated by the large confidence intervals, not many people belong to this category. Consequently, just a few erroneous cases of people who died after their 100$^{\text{th}}$ birthday, may have a large impact on the estimated regression coefficients.

Further insights can be gained by investigating the patterns for the three selected causes of death: ischaemic heart disease, cerebrovascular diseases and respiratory diseases (Fig. 5.4 b,c,d). The relatively close resemblance of mortality from ischaemic heart disease with mortality from all causes should not be surprising as this cause of death alone contributes about 30% to all deaths. Also cerebrovascular diseases which contribute about 10% display an increase with age, albeit the slope is less smooth than for Figures 5.4 a) and b). While the relative risks of dying from ischaemic heart disease during winter is higher for women, men's relative risks are higher for cerebrovascular diseases. This is in contrast with the susceptibility to these diseases for mortality in general: Men's mortality rate from ischaemic heart disease is typically higher than women's, whereas the chance of dying from stroke (cerebrovascular disease) is greater for women.[18]

Winter excess mortality caused by respiratory diseases (cf. Fig. 5.4 d) does also increase with age for women. The development for men does not show any clear trend. Although the relative risk of dying from respiratory diseases is higher for men when they are 85–89 years old than for men 65–69 years ($e^{\beta_{\text{Winter}}}_{\text{♂}65-69y}$: 1.283; $e^{\beta_{\text{Winter}}}_{\text{♂}85-89y}$: 1.504;), the odds-ratio decreases for men in their late 90s $e^{\beta_{\text{Winter}}}_{\text{♂}85-89y}$: 1.263;). Due to the large 95% confidence interval for this estimate, one should be careful with its interpretation.

Generally speaking, our analysis supports the results from previous research. We obtained a general trend which has been observed by Quetelet from as early as 1838 [300]: the seasonal amplitudes in mortality are increasing with age. This has been also regularly found in former studies [eg. 102, 121, 251, 268, 302]. One could argue that with increasing age, the susceptibility towards adverse environmental conditions gains in relevance. Public health policies aiming to reduce the annual number of cold-related deaths should therefore be aimed at the most vulnerable group: the very old. The general advice to keep a warm indoor climate, avoid exposure to cold outdoors, ... is particularly important to people at advanced ages.

Our analysis can not answer the question conclusively whether the previously discovered higher excess winter mortality for women than for men (cf. Fig. 5.3) can be generalized. The differential age-composition of women and men in the population can not be the reason as shown in Fig. 5.4 a). In most age-groups women and men differ only marginally in the extent of winter excess mortality. It can be assumed that female excess winter mortality is caused by factors which are specific for Denmark. Respiratory diseases con-

[18] Information about mortality in general has been derived from own calculations based on the WHO database located at `http://www.who.int/whosis`. Data were taken for Denmark for the year 1998.

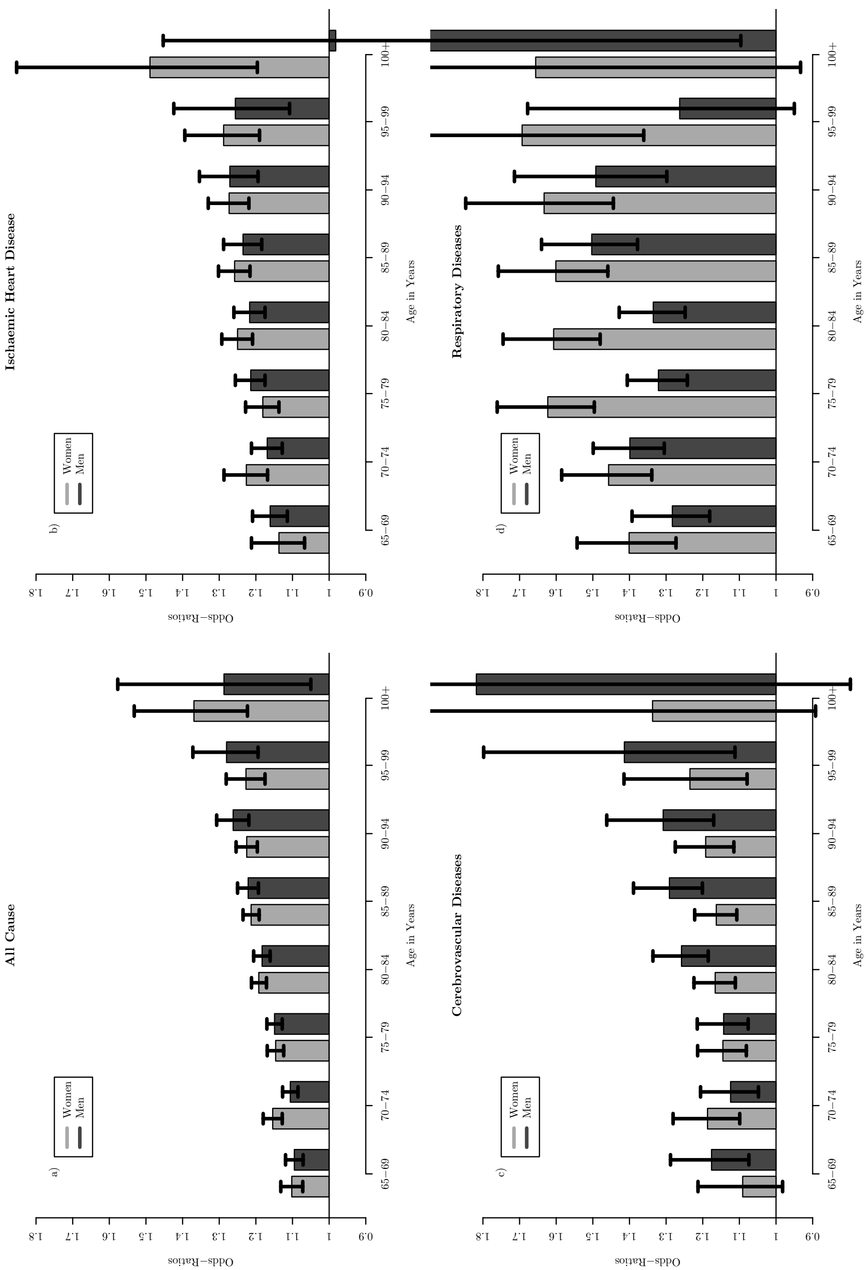

Fig. 5.4. Winter Excess Mortality by Sex and Age and Cause of Death (Odds-Ratios and 95% Confidence Intervals)

tribute only about 6–7% to all deaths. Nevertheless the differences between women and men with respect to winter excess mortality is especially large for that cause of death. The high smoking prevalence among Danish women in general can be offered as an explanation. This line of argumentation wins further support when one considers that the only significant differences in winter excess mortality from all causes is among people between 70 and 74 years of age. This is also the age-group with the largest differences between women and men in any age-group for ischaemic heart disease, and the only age-group where women exceed men in winter excess mortality from cerebrovascular diseases. Both causes of death are associated with smoking [3, 248, 294]. It has been analyzed previously that women born between the two World Wars show a high mortality most likely caused by a high smoking prevalence [173]. It can be therefore assumed that we observe rather a cohort effect than an age effect because these women constitute an important part in our data-set.

5.3.5 Seasonal Mortality by Sex, Wealth and Cause of Death

Socio-economic factors, besides age and sex, are important determinants of mortality differentials. The first indicator we analyzed was wealth which was measured on the household level and categorized into quartiles. In our model we controlled for age and period, marital status, education and the question whether somebody was living alone or with at least one more person. The coding was performed as outlined in section 5.2.1 starting on page 131.[19] The estimates for winter excess mortality for this variable are plotted in Figure 5.5 with summer serving as reference category. The four panels show the results for all-cause mortality (upper left panel), ischaemic heart disease (upper right panel), cerebrovascular diseases (lower left panel), and respiratory diseases (lower right panel) for women (left side in each panel) and men (right side in each panel). The poorest people are plotted in dark gray, people richer than 25% but poorer than 50% of the population are indicated by shaded bars in dark gray. The wealth quartile 50% –75% is shown in light gray and the richest 25% are in shaded light gray. Results for the poorest people should be interpreted with great care. Not many old people belong to this category (∼3.4%), hence the relatively large confidence intervals.

The general finding is that a social gradient is not observable. It is hard to track down visually any differences among the four social groups, for example, for winter excess mortality for female all-cause mortality (Figure 5.5a)) shows that the point estimates differ only marginally with a range from 1.181 (Quartile 1) to 1.202 (Quartile 4). Unfortunately, the statistical software used for the analysis (SAS) had problems with the estimation of seasonal mortality from all causes for men (Figure 5.5b). The results should therefore be

[19] The reference groups for the respective covariate-groups were: 65–69 Years (Age); 1991–93 (Period); Married (Marital Status); Alone (Living Alone Yes/No); Medium Education (Education).

interpreted with care. Nevertheless, the same tendency can be observed as for women: differences in excess winter mortality between the richest and the poorest people are rather negligible ($e_{\text{Q1}}^{\beta_{\text{Winter}}}$: 1.171; $e_{\text{Q4}}^{\beta_{\text{Winter}}}$: 1.187).

For the remainder of this section, results for the poorest quartile are not taken into account anymore as the number of deaths from ischaemic heart disease, cerebrovascular diseases and respiratory diseases in that social group is relatively small.

Figure 5.5 c) and d) portrays the seasonal nature of ischaemic heart disease for women (left) and men (right). Basically one can observe the same pattern as for all-cause-mortality: the risk of dying in winter is elevated by roughly the same amount across the three wealth quartiles. Men's risk of dying in winter rather than in summer is 27% higher in Quartile 25%–50% and 26% higher among the wealthiest. Women show a slight trend with an unexpected gradient where the richest face a relative risk of 28% in winter and women belonging to Quartile 25%–50% only of 21%. This tendency is, however, not statistically significant as the 95% confidence intervals overlap.

Results for the analysis of winter excess mortality for cerebrovascular diseases are displayed in Figure 5.5 e) and f). Not surprisingly, deaths from cerebrovascular diseases show a very similar pattern to deaths from ischaemic heart disease: Again, no significant (95%-level) differences have been estimated. From an overall perspective, the estimated values are somewhat smaller for cerebrovascular diseases than for ischaemic heart disease. While the relative risk of dying was 25.9% higher for the latter cause of death among men in the richest wealth quartile, it was only elevated 23.3% for the cerebrovascular diseases. It is interesting to note that the ordering of the wealth quartiles by winter excess mortality is the same for both causes of death: If we can speak of any social gradient for women at all, the slope is in the opposite direction than what would be expected. The wealthiest women face again a higher relative risk than women from poorer social strata.

The results for deaths from respiratory diseases are illustrated in Figure 5.5 g) and h). The first impression reiterates the finding from Figure 5.3d. Women's excess winter mortality is considerably higher than men's. But again there is no social gradient present.

Socio-economic factors have been established as an important determinant in mortality differentials [195, 210, 314]. Indeed, in many countries those differences are even increasing over time [e.g. 29, 71, 243, 284] — also in Denmark [233]. The lack of an effect of wealth on seasonal mortality is not surprising, though. It is rather a common finding that there is "no clear evidence of a relationship between socioeconomic status and seasonal mortality" [121, p. 274]. Several of those studies are, however, based on ecological data on the ward level [cf. 214]. This lack of correlation on the aggregated level must not necessarily correspond to a lack of correlation on the individual level

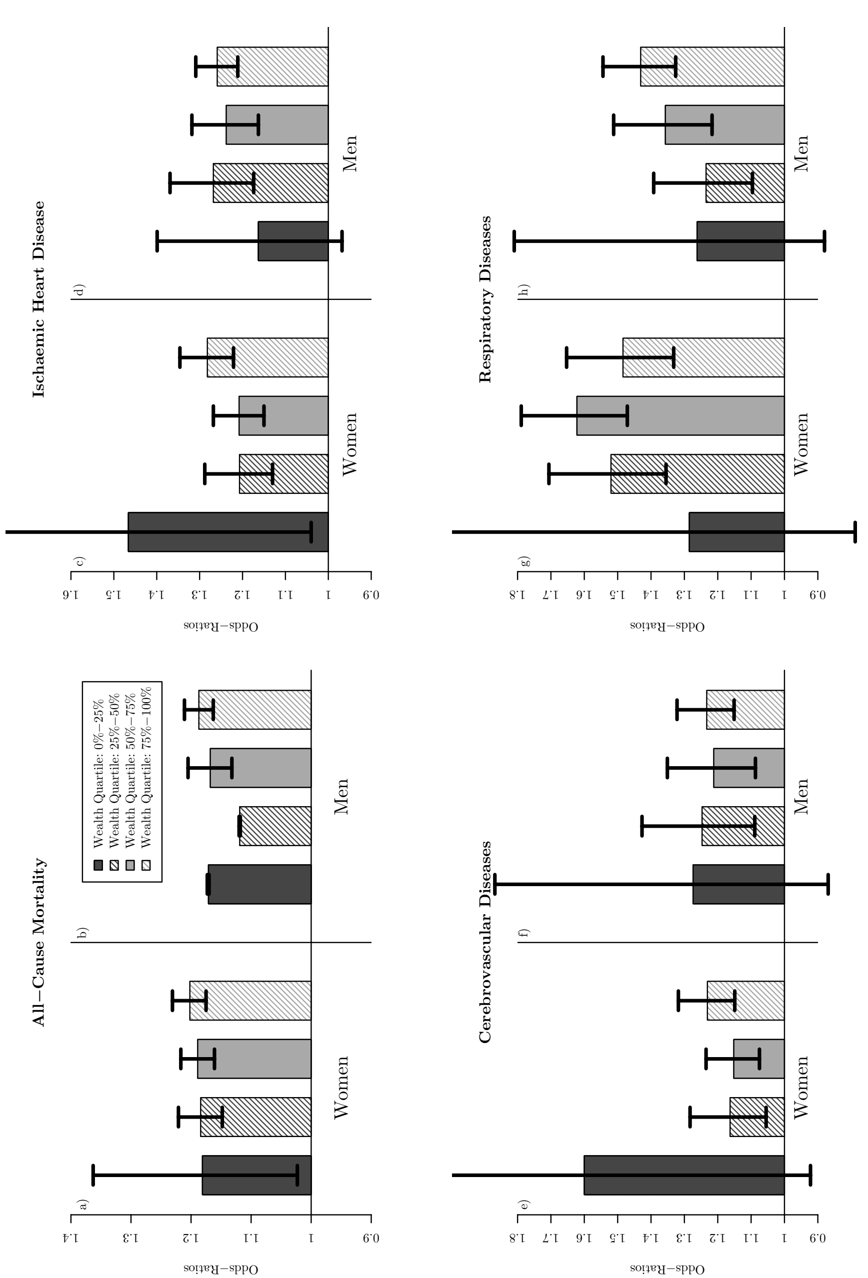

Fig. 5.5. Winter Excess Mortality by Sex, Wealth, and Cause of Death (Odds-Ratios and 95% Confidence Intervals)

[311].[20] If studied with individual level data, there are some first indications that socio-economic status does actually matter for seasonal mortality. Donaldson and Keatinge found that "cold related mortality in the retired (65–74) age group was generally higher in men of class 5 (unskilled) than class 1 (professional), or other classes, with little differences between men, and women or housewives" [79, p. 790]. The question which arises then is: why did we not find any impact of wealth in Denmark despite the high-quality of the Danish data on the individual level?

It is likely that the lack of any evidence is associated with the specific situation of Denmark. For example, the health system is tax-financed and open to everyone for free [171, 336].[21] Consequently, access to health care is independent of income and wealth which might be particularly important in the case of seasonal mortality. Despite the aspect of access to health care via economic resources, there is also a behavioral aspect for the relation between socio-economic status and mortality: "poor people behave poorly" [230, p. 809] with higher rates of smoking, less physical activity, poorer nutritional habits .... The amount of poor people in Denmark is, however, lower than anywhere else in Europe. Only 3.9% of the people in Denmark earn less than half of the mean income [162].[22] This implies that the absolute differences between the four wealth quartiles in Denmark are relatively small. Consequently, the socio-economic differences measured by wealth in the population which could be important for cold-related mortality [cf. 79] are rather negligible in the Danish context. Wealth (or income) is, however, only one approach to measure socio-economic status. Since we have shown in the previous chapter that an educational gradient exists in seasonal mortality in the United States, we will investigate the impact of formal school education on winter excess mortality in Denmark in the following section.

5.3.6 Winter Excess Mortality by Sex, Education and Cause of Death

Another approach to measure socio-economic status is by education. While weakening health can influence the income and wealth of a person, the highest educational level achieved remains unaffected. In addition, it is almost constant in the age-range analyzed here and it is better suited than measurements

[20] It should be mentioned that not all recent studies which discovered no impact of socio-economic factors on seasonal mortality used aggregate level data. For example, the analysis of van Rossum et al. [376] used individual level data. Their analysis was however aimed at a relatively homogeneous population: male civil servants.

[21] As pointed out by the Danish "Indenrigs- og Sundhedsministeriet" [171], this is not perfectly correct. Private expenditures for health care have to be given for some medicinal products, dentistry, and physiotherapy.

[22] Other European countries show much larger values. E.g. Portugal 24.5% , France 14.7%, UK 14.8%.

derived from occupational status, as the study population is 65 years or older and therefore most of them are no longer actively working anymore and are retired [374]. In addition, education is less related to *financial aspects* (like wealth), yet it is rather linked to behavioral aspects of health.

Figure 5.6 shows the results from the logistic regression analyzing the impact of education on winter excess mortality from all causes. The estimated odds-ratios for women are displayed on the left side (Fig. 5.6 a), winter excess mortality for men on the right side (Fig. 5.6 b). The results by cause of death are plotted in the Appendix in Figure D.1 on page 185. In this approach we controlled for age, period, marital status and wealth (we used the highest wealth quartile as the reference group).

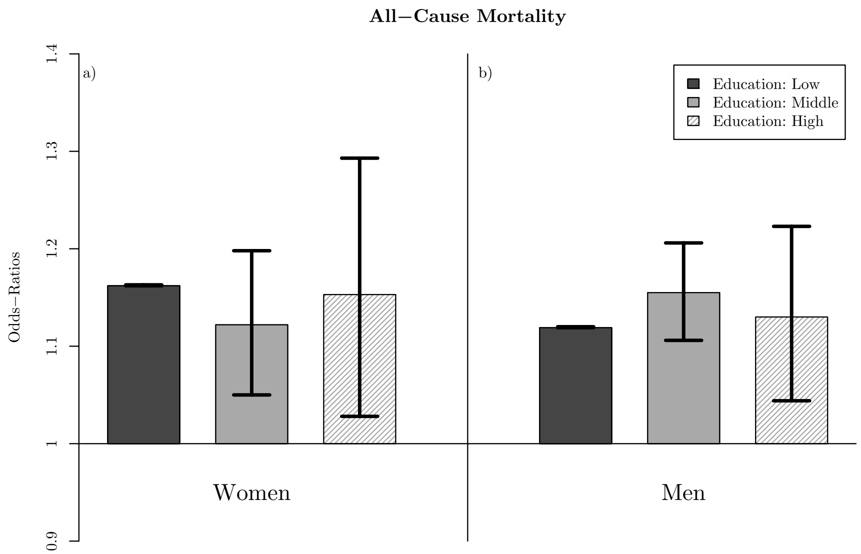

Fig. 5.6. Winter Excess Mortality by Sex, Education, All Cause Mortality (Odds-Ratios and 95% Confidence Intervals)

The results for winter excess mortality by educational attainment iterate the findings from the analysis of socio-economic status measured via wealth: no clear social gradient is observable neither for women nor for men. The relative risk of dying during winter is elevated by about 16% for females of the lowest educational group and roughly 15% for females of the highest educational group. This lack of a tendency can be also observed for men with slightly lower values (low: 1.120, high: 1.130). Although the problems of the software to estimate standard errors for women and men with the lowest education should lead to careful interpretations, the results for causes of death such as ischaemic heart disease and respiratory diseases (Fig. D.1, 185) support the view of a lack of a social gradient.

No previous literature exists so far which analyzed the impact of educational level on seasonal mortality. Only the analysis in the previous chapter (Chapter 4, page 83) touched this subject. In the analysis in the previous chapter using data from the United States, we have found an apparent social gradient: Generally speaking, people with higher education showed lower seasonal fluctuations in mortality. A lack of a differential of mortality in general by educational group can not be offered as an explanation. Actually, educational differentials in adult mortality do not only persist but even increase in both countries [103, 233, 296]. Errors in the coding of education in the data-set should not be the explanation either, Typically, an educational gradient was found when controlling for education in other analyses. For example, the regression model which resulted in Figure 5.5 a) for the richest women (shaded, light gray bar) controlled for age, period, marital status, living alone yes/no and education. Intermediate level of education served as reference category. People with lower education showed higher mortality (odds-ratio: 1.117) and vice versa (odds-ratio: 0.900). One can therefore conclude that education is not well-suited as a good proxy variable in a homogeneous country to determine seasonal mortality differences. This implies that behavior which is known to increase the risk of dying (for example, wearing not appropriate clothes outdoors) [80] is in Denmark independent from the knowledge people have acquired in school.

5.3.7 Winter Excess by Cause of Death and Housing Conditions

Housing conditions are closely related to socio-economic status. Omitting an analysis by housing quality after not finding any results for wealth and education would not be appropriate because of the crucial role housing conditions play. Poor housing conditions are a major health risk [245] — especially for typical seasonal diseases such as cardiovascular, cerebrovascular, and respiratory diseases [54, 121, 404]. Therefore a separate analysis has been conducted which examined whether housing conditions are of major relevance also in Denmark.

The results for winter excess mortality from all causes, ischaemic heart disease, respiratory diseases, and from cerebrovascular diseases, are plotted clockwise in Figure 5.7 starting in the upper left panel. In each panel, the left side shows the estimated odds-ratios for women, the right side for men. The dark gray color indicates bad housing conditions and barplots in light gray good housing conditions. We controlled for age, period, marital status, living alone and education. The influence of wealth has not been included because the data on housing conditions started only in 1991 and the availability of information on wealth finished in 1996.

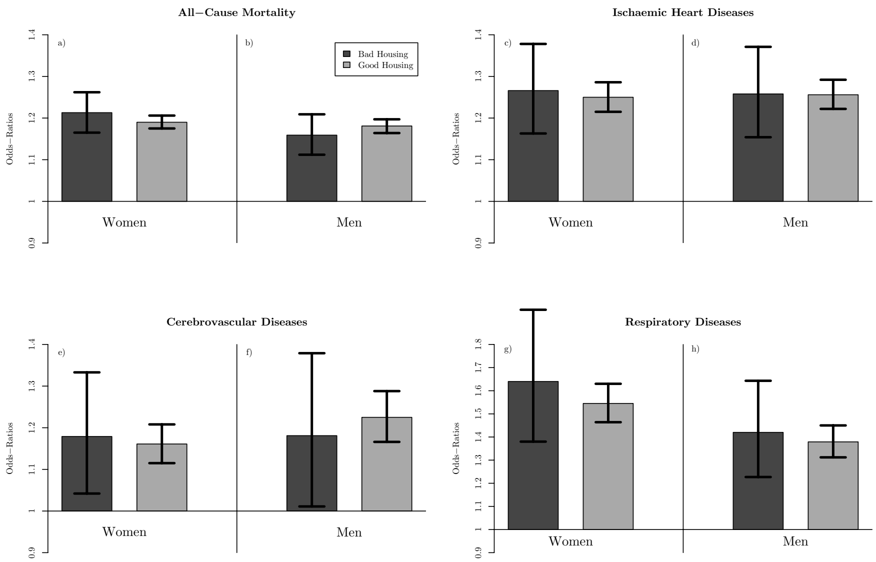

Fig. 5.7. Winter Excess by Sex, Cause of Death and Housing Conditions (Odds-Ratios and 95% Confidence Intervals)

The differences in winter excess mortality from all causes are rather small between people living in good housing conditions on the one hand and people living in less favorable houses and apartments on the other hand. The risk of dying during winter is elevated by 21% in poor housing conditions for females. Women who live in better houses and apartments have a lower relative risk; the differential is, nevertheless, relatively small (19%). A difference of two percentage points is also observed among men. Surprisingly, the direction is in the opposite direction: While men in poor housing face a relative risk of 16%, people in better housing show slightly higher odds-ratios (1.18). These differences are, however, not statistically significant on a 95% level. Cerebrovascular diseases show the same tendency, whereas the differences for ischaemic heart disease are even more minor: the odds-ratios are 1.266 for women during winter in poor housing and 1.250 in good housing conditions. For men, the corresponding values are 1.258 and 1.256. Albeit not statistically significant either, the only cause of death where good housing conditions appear to favor both sexes are respiratory diseases. The relative risk of dying for women during winter is 64% higher during winter than during summer if they live in relatively poor housing. In good housing conditions, the risk is only elevated by about 55%.

Although "warm housing is not enough" [186], it has often been singled out as a major determinant to avoid winter excess mortality [e.g. 16, 54].

It is therefore surprising that we did not find conclusive evidence for such a housing effect on winter excess mortality in Denmark. The key to answer this question lies probably again in the remarkable homogeneity of the Danish population on a high absolute level. "97–99 percent of those aged 70+ who live in ordinary housing are in houses with kitchen, toilets, central heating, and hot water " [128, p. 26]. Almost no apartments exist in Denmark without central heating, whose absence has often been described as the main factor triggering cold-related mortality [e.g. 16, 75, 77, 188, 251, 324, 325, 340]. Contrastingly, elderly people in the United Kingdom, the country in which most of these previous studies have been conducted, face severe housing problems [47]. For example, the 2001 census showed that more than 10% of all households in England still do not have central heating.[23] We can therefore not conclude that housing conditions are of minor importance for winter excess mortality. If the population is, however, rather homogeneous and on a high level in housing terms like in Denmark, the amount of excess mortality attributable to poor standards in houses and apartments is rather negligible.

5.3.8 Winter Excess Mortality by Cause of Death and Car Ownership

Whether one owns a car can be interpreted as another measurement of socio-economic status. We employ this indicator in our analysis following the suggestion of Donaldson and Keatinge [77]. They argue that increased car ownership reduced the annual amplitude in mortality by exposing less and less people to the cold outdoors. Consequently, one should assume that people with a car should show less winter excess mortality than the ones without.

The results for women and men are shown in Figure 5.8 for all-cause mortality as well as for ischaemic heart disease, cerebrovascular diseases and respiratory diseases. We controlled for age, period, marital status, living alone and education.[24]

For mortality from all causes, risks are elevated by 20% during winter for women if they did not own a car. In case of a car the risk was 22%. Men showed a similar value in the absence of a car (20%); their risk decreased if they owned a car. The same pattern can be observed for both sexes for cerebrovascular diseases: an increase for women and a decrease for men in the presence of a car. For ischaemic heart disease, almost no change was detectable (odds-ratio for women without car: 1.268, with car: 1.254; odds-ratio for men without car: 1.267, with car: 1.243). Respiratory diseases showed even a slight increase in winter excess mortality if a car was present. But none of these results was significant.

[23] Result based on own calculation derived from data available online at the Statistical Office of the United Kingdom [265]

[24] Like in the analysis for housing conditions, we excluded the variable wealth from our analysis for similar reasons: the car register provided data starting in 1992 and wealth was only available until 1996.

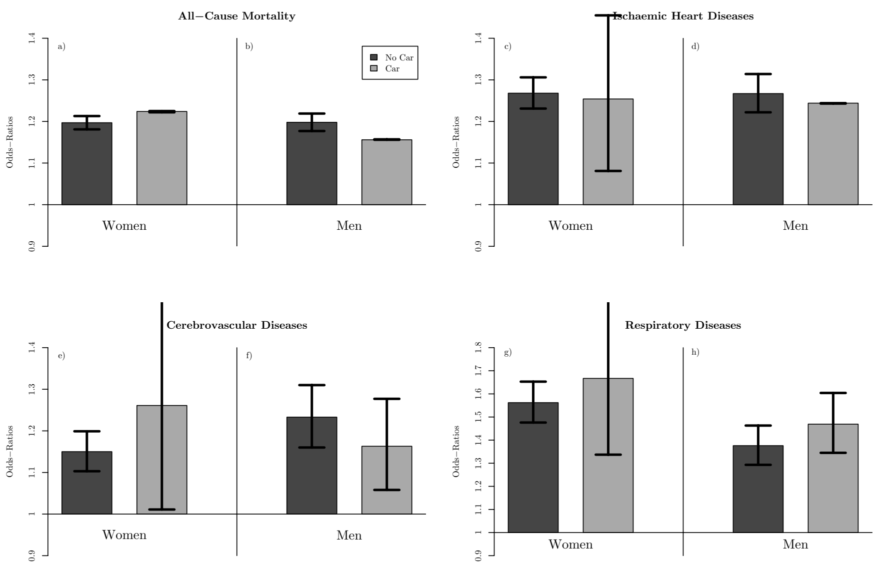

Fig. 5.8. Winter Excess Mortality by Sex, Cause of Death and Car Ownership (Odds-Ratios and 95% Confidence Intervals)

The suggestion whether increased car ownership decreased the amount of cold-related deaths during winter has never been analyzed so far in an empirical investigation. Our results indicate that the question whether one owns a car or not is rather irrelevant for the relative risks of dying in winter in Denmark. This could either mean that the availability of a car is of minor importance for excess winter mortality or another explanation could be that the system of public transportation in Denmark is of high quality. Buses operating on a regular basis and windproof bus shelters, as suggested by Keatinge and Donaldson [186], help in reducing exposure to outdoor cold. Consequently, being owner of a car or not is less important for seasonal mortality.

5.3.9 Winter Excess Mortality by Sex, Marital Status and Cause of Death

The impact of marital status on seasonal mortality is examined in Figure 5.9. The four panels show the results for all-cause mortality (upper left), ischaemic heart disease (upper right), cerebrovascular diseases (lower left), and respiratory diseases (lower right). Each of the four panels is divided into a left part for women and into a right part for men. In these subpanels the exponentiated regression coefficients are plotted for widowed (dark gray), divorced (dark gray, shaded), married (light gray), never married / single (light gray, shaded) people. The respective reference season in each case is summer. In this analysis we controlled for age, period, being alone, education, and wealth.

At a first glance no consistent pattern giving a straightforward interpretation is present. None of the four presented marital statuses shows consistently higher or lower values of winter excess mortality than the other ones. For "All-Cause Mortality" the odds-ratios for winter excess mortality for women vary between 1.157 for "divorced" and 1.205 for "widowed". The estimates for men are in a similar range (divorced: 1.127; never married: 1.203). Almost non-observable differences exist for mortality from ischaemic heart disease for women and especially for men (odds-ratios for women: widowed 1.243, divorced 1.210, married 1.226, never married 1.245; odds-ratios for men: widowed 1.243, divorced 1.260, married 1.257, never married 1.257). Larger differences do exist for cerebrovascular diseases and in particular for respiratory diseases.

Marital status is a well established factor to determine mortality differentials. International comparisons [e.g. 163] have shown that married women and men have lowest age-specific mortality rates compared to people in any other marital status. Typically divorced people face the highest mortality risks. It is a common finding that men benefit more from being married than women [129]. Two strains of causal explanation are usually given: selection effects and protection effects. A selection effect postulates that mentally and physically healthier persons are more likely to marry. Among other factors, a protection effect hypothesizes that married people have more emotional and social support, have better access to medical information and health services due to a higher income per person and it also reduces risk taking behavior, encouraging healthier lifestyles. [124].

Our study could not detect any advantage for married women and men in terms of winter excess mortality. While it is usually not the category showing highest winter excess mortality, it is neither displaying consistently lower cold-related mortality. We should be, however, careful with the interpretation of these variables as there is a bias towards not enough exposure time for married people and too many exposures for widowed and divorced people.

If our results were true, an explanation could be that better access to medical care via a higher income per head is irrelevant in Denmark where medical services are open for everyone. Another reason could be that in this analysis by marital status we controlled — among other factors such as age, period, wealth, and education — also for the question whether somebody was living alone or not. If marital status operated for excess winter mortality via emotional and social support and fast help in case of an emergency, it was unlikely that this analysis yielded any significant results. Therefore we analyzed in a final step the question whether living arrangements matter for cold-related mortality.

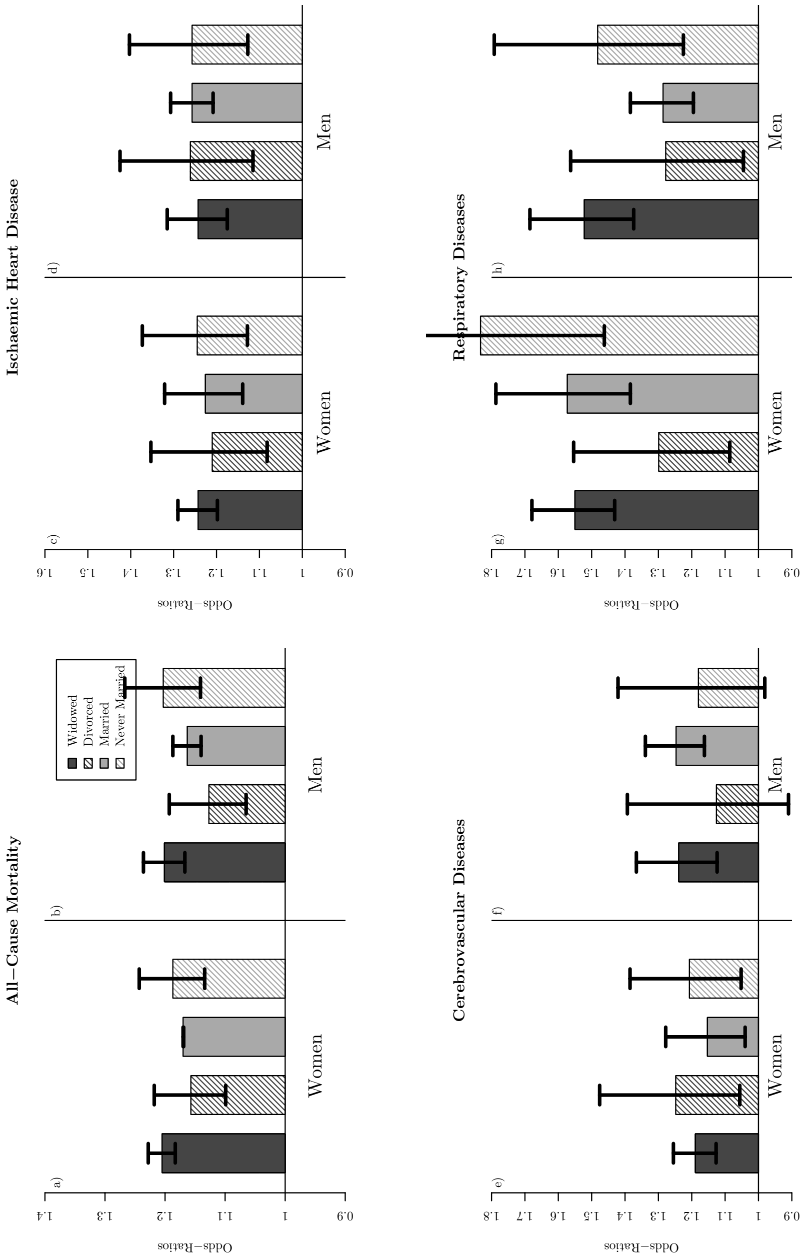

Fig. 5.9. Winter Excess Mortality by Sex, Marital Status, and Cause of Death (Odds-Ratios and 95% Confidence Intervals)

5.3.10 Winter Excess Mortality by Cause of Death and Living Alone

In Figure 5.10 the odds-ratios are plotted for winter excess mortality for people who either lived alone or not. Starting in the upper left panel in a clockwise direction the results are shown for mortality from all causes, ischaemic heart disease, respiratory diseases and cerebrovascular diseases. We controlled for age, period, marital status, wealth and education.

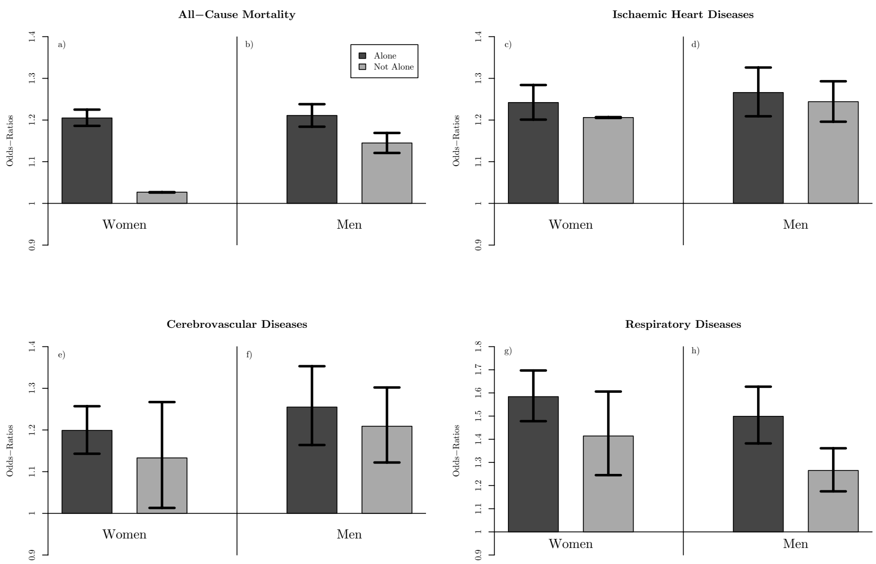

Fig. 5.10. Winter Excess Mortality by Sex, Cause of Death and Living Alone (Odds-Ratios and 95% Confidence Intervals)

For mortality from all causes, the relative risk of dying is 21% higher in winter than in summer for women as well as for men who are living alone. If men had at least one more person present in the household, the relative risk of dying during winter is 14.5% which is significantly lower (95% confidence level).[25] Also the differences are not significant for the selected causes of death. The same tendency can be detected for ischaemic heart disease, cerebrovascular diseases as well as for respiratory diseases: People who live alone are more prone to dying during winter than people who do not live alone.[26]

[25] The results for women should be interpreted with care as the software had problems with convergence. The value of 1.027 is probably too low.

[26] It should be noted that the smaller differences for ischaemic heart disease than for cerebrovascular diseases reflect the fact that in case of stroke it is much more

Respiratory diseases display the largest slope of all of these causes. If women live alone their relative risk of dying during winter is 58.4% higher than during summer; in presence of a partner, the risk was only 41.4% higher than during summer. For men, the differences in the odds-ratios is even larger (odds-ratio alone: 1.499; odds-ratio not alone: 1.265).

The empirical evidence in the literature suggests that there is a strong positive effect on mortality if people live alone rather than with a partner [15, 23, 123, 180, 226]. In the case of seasonal mortality, two studies exist measuring the impact on seasonal mortality. The one which investigated the effect on winter excess mortality could not detect any significant differences [405]. One study analyzed the question for heat-related mortality during extreme heat waves [267]. Their paper reflected also our finding: If people are living alone during periods of adverse environmental conditions, it is better not to live alone but together with a partner to avoid mortality. The possible linkage is probably via emotional and social support. Also the possibility that somebody is present in the case of an emergency to provide first aid and call for an ambulance can have a considerable influence.

5.4 Summary

The aim of this chapter was to analyze the determinants of excess winter mortality in Denmark. Denmark was chosen mainly because of its data. No other country in the world has as much information available about the whole population in a longitudinal dimension as Denmark. These population register data have been analyzed using a discrete time event-history approach. In our analysis several findings from the literature were tested for the first time in a longitudinal perspective for an entire population on the individual level. As the data were available as individual life course histories, we used a discrete-time event-history model for our analysis.

Denmark follows the typical pattern of developed countries in the Northern hemisphere with the highest annual numbers of death in December and a minimum in August. Winter deaths exceed summer deaths by about 17%. We have shown that winter excess mortality becomes more pronounced with increasing age. The oldest people tend to be the most vulnerable group not only in terms of overall mortality but also in their amount of cold-related deaths. Women seem to have higher fluctuations between winter- and summer-mortality than men. Previous literature suggested that there are no sex-related differences in excess winter mortality. Our finding could be caused by the specific situation in Denmark with a relatively high prevalence of smoking among women which has an impact on typical seasonal diseases. Especially for respiratory diseases we detected considerably higher winter excess mortality for women than for

important to have quick help available than in the case of myocardial infarction [347].

men.

The lack of impact of socio-economic status on cold-related mortality has been reported previously in the literature. Neither wealth nor education seems to be correlated with excess winter mortality. Again, this could be caused by the homogeneity of the Danish population where the differences between relatively poor and relatively rich people are smaller in absolute terms than in other countries. Also housing conditions are less problematic for an increased risk of dying during the cold season in Denmark than in the UK, which was most often the country of analysis in previous studies. In socio-economic terms, Denmark is not only homogeneous. This homogeneity is, in addition, also at a very high level. Really poor housing conditions are hard to find; more than 90% of all households have the maximum number of installations which are recorded in the housing.

We did not find any association between car ownership and excess winter mortality. This means that car ownership is either not a good proxy to measure exposure to outdoor cold during winter or that there are only marginal differences in time spent outdoors for old people who own a car and who don't (maybe due to high standard of public transportation). Despite its importance for mortality analysis in general, we could not find any effect of marital status on excess winter mortality. More crucial are the living arrangements: If somebody is living alone, the relative risk of dying during winter is much higher for him or her than people who share the apartment with at least one more person.

Many studies as well as our results point in the direction that socio-economic conditions do not have an impact of excess winter mortality. This does not imply that they do not differ in general. Many previous studies used aggregate level data which do not allow to make inferences on the individual level. And, indeed, when looking at the individual level, it has been observed that people of lower socio-economic status face higher mortality risks during winter than in summer compared to people from higher social strata (cf. Chapter 4, page 83 or Donaldson and Keatinge [79]). The lack of findings for Denmark for socio-economic status can probably be attributed to the homogeneous character of the country at a relatively high level. Or as Peter Høeg observed in his novel: "Seen from my perspective, Denmark's entire population is middle-class. The truly poor and the truly rich are so few as to be almost exotic" [151, p. 25].