The effect on mortality of having a Chief Executive Officer position: An analysis of Swedish data from 1997–2009

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Abstract

In this thesis, data on 203 702 CEOs in Sweden from the time period 1997 to 2009 is combined with death data and company information to compare CEOs' mortality between different groups. This study compares survival analysis results using Cox, Gompertz and GEE-logistic parametric models. The Logrank test is used to compare the survival curves between the groups obtained by the Kaplan-Meier method. Firstly, results show that CEOs have a significantly lower mortality in ages 40–69 compared to board members. Secondly, results show that CEOs for big companies have a significantly lower mortality than CEOs in small companies. Thirdly, the industry comparisons show that CEOs of service companies and finance companies have a higher mortality compared to manufacturing companies and other companies, respectively. In the parametric models, a gender variable is used as covariate to account for mortality differences established in previous research. This paper seems to be the first in Sweden to examine a CEO effect on mortality.

Keywords: CEO, hazard ratio, life expectancy, mortality, survival analysis

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Contents

1 Introduction

Being a CEO is one of the jobs with the greatest responsibilities within a company. CEOs of big companies are well paid and often receive extraordinary benefit packages from the company. Aside from monetary rewards they receive social rewards in terms of recognition, praise and status. But there are also drawbacks of the work. CEOs normally work longer hours and have a responsibility to a greater extent than an average employee. They seem to be subject to psychological pressure in a greater degree considering the number of stakeholders of the company that aim to influence them. It is clear that the job of a CEO is demanding in many aspects and that the lifestyle can significantly differ from the daily life of a person not holding such a position. The job characteristics of being a CEO, the high demands, responsibility and being at the top position in the hierarchy, are in this study hypothesized to change the mortality risk negatively as it is believed that the rewards do not affect health positively in the same amount as the responsibilities affect health negatively.

One of the core questions in finance theory is how to convince managers to work for investors. Agent theory suggests that CEOs can benefit from working in companies at shareholders' expense. If the work of a CEO has an enhancing or decreasing effect on life expectancy, a personal cost or benefit, it would have implications on how investors can motivate CEOs. In other words it has to be taken into consideration when calculating the compensation to the CEO. A decreasing life expectancy should increase the risk compensation and an increased life expectancy should potentially decrease the compensation. A difference in life expectancy for the CEO group could have impact on pensions, as life expectancy tables are used in calculations by insurance companies. Moreover, a deviation in either direction will raise the question of whether the structure of CEO responsibilities is designed in an appropriate way, especially if there are differences between industries or sizes of firms.

Research about life expectancy has increased remarkably in the last decade. Studies have shown how factors such as education, socio-economic status and displacement affect life expectancy [1, 2, 3, 4]. Other researchers have focused on health effects on promotion [5]. Most studies have examined the mentioned factors and no research paper has thus far analyzed how the CEO position, which is characterized by many of the mentioned factors, affects mortality. The main reason for this is because it is uncommon in many countries to have complete records on deaths associated with a personal identity number. If these records exist they are often difficult to link with firm level data. By using Swedish death and company data from 1997 – 2009, this thesis is the first to examine whether being CEO affects mortality or not and if there are differences in CEO mortality between different groups of companies.

The data is restricted by only including companies over a certain size. Companies with less than 10 employees, less than 10 million SEK in revenues and less than 10 million SEK in total assets are excluded. Moreover, only limited liability companies (“Aktiebolag”), and non-subsidiaries are included in the dataset. The reason behind this is to reduce the number of companies where the CEO potentially has another job as main occupation or has work characteristics very similar to the work of coworkers. A panel data set for the remaining observations, between 1997 and 2009, is created to use in mortality tests.

With the aim of studying the mortality of CEOs, the study is divided into three main areas: the general CEO effect, the CEO size effect and the CEO industry effect. In order to extract the general CEO effect, CEOs are compared to board members, who are assumed to be people with similar socio-economic status, education and background. Thereafter an analysis is done within the CEO group, comparing big and small companies, to extract the effect of greater responsibility, pressure from different stakeholders and compensation packages that comes with bigger companies. To further investigate if the CEO effect is more significant in one industry compared to another and to extract the effect of a more stressful environment and other sector variables, the mortality of CEOs in different industries are compared.

Different survival analysis methods are used on the retrieved panel data in order to analyze the differences in hazard ratios, survival functions and odds ratios in regression models. Kaplan-Meier curves and log-rank tests combined with Cox, Gompertz and GEE-logistic regression are used to draw statistical inferences of the sample. The regression models use the gender variable to account for gender differences in mortality.

The Kaplan-Meier curves indicate a difference in mortality between CEOs and board members, CEOs in the finance industry against the non-finance industry as well as for the CEOs in the service against the non-service industry. In the logrank tests, it is shown that there is a significant difference in mortality for the size study group (1% significance) and the finance industry group (5%). There is some significance for the service group (10%) and almost significance for the CEO against board-group (p-value = 0.1017). No significance is shown for the trade group. Therefore the study dismisses the trade variable as an explaining factor of the CEO mortality.

To quantify the difference of the study groups from the Kaplan-Meier curves and logrank tests, regressions are used. The survival analysis Cox regression supports the logrank test of the size (1% significance) and the finance variable (5%); moreover it supports significance for the service (5%) and the CEO variable (1%). The results suggest an increased hazard ratio of 46% for the small company group, 26% for the finance group and 20% for the service group. The CEO variable is shown to decrease the hazard ratio by 16%.

Furthermore, the study tests the results for robustness across other regression models, which are shown to yield similar results. The GEE logistic model and the Gompertz distribution survival analysis model support the results of a decreased mortality of CEOs and higher mortality of CEOs in small companies, the finance industry and the service industry. However, among the main data issues faced in the research is the possibility that a person, who in the data set only shows up as a board member, has been CEO previously. Another important potential bias in the study is that hazard ratios can be biased upwards if there are big differences in death rates in early ages. An assumption of the study is that board members are similar to CEOs in education, socio-economic status and income.

The paper is structured in the following manner. First, a general background on mortality, CEOs and boards are discussed. Secondly, previous research on mortality and CEOs is presented. A description of the data is then provided, followed by the methods used in the study. The method section is divided into three sections: descriptive statistics, GEE-logistic regression and survival analysis. Assumptions of the models are presented in this section. The results section contains both descriptive results as well as regression results. Tests of robustness are then discussed. Finally, the conclusion section summarizes the results, discusses implications as well as potential further research on the topic.

2 Background

To provide an overview of the central definitions used in this research paper, the following section provides a brief overview of mortality trends, mortality measures as well as the roles of CEOs and board members in Sweden.

2.1 Mortality trends

The death distribution of ages has changed remarkably during the last decade in Sweden. The expansion of human life in the last hundred years and its socio-economic implications has stimulated efforts to analyze and forecast mortality trends which are guided by insights gained from mortality models [6]. This conclusion further supports the interest in the topic of this study.

2.2 Mortality measures

The commonly used definition of mortality is death rate, which is often expressed as the number of deaths per 1000 people. Comparing mortality between groups can be done with several other measures, some more specific than others. Often the data used in survival studies is right censored, which means that one cannot observe all the deaths of the research group. This is accounted for by the basic principle behind all survival analysis tools, which is to calculate how long a person is expected to live at a certain age or point in time, i.e. expected remaining lifetime.

Survival analysis is the statistical tools for analyzing longitudinal data on the occurrence of events, often deaths. It is special in the sense that it takes into account right censoring and the time factor of a data set. In regression models of survival analysis, it is possible to specify a distribution of the data and the Gompertz distribution is normally used for adult death analysis [35, 36].

An important concept in survival analysis is the hazard ratio [37], which measures how often deaths happen in one group compared to another group. Hazard ratios are often used to calculate the risk of dying at a certain point in time, given being alive at the beginning of the time period. A hazard ratio of one means there is seemingly no difference between the groups whereas a hazard ratio of 0.8 indicates that the odds of dying at any point in time are 20% lower compared to the reference group.

Another concept is the odds ratio [38], describing the relative odds of the occurrence of death. It measures the association between two binary values, in this study death to no-death. An odds ratio of deaths being 2.0 means that for every no-death (living) occurrence there are two cases of deaths. The difference between the hazard ratio and the odds ratio is that the former represents an instantaneous effect which says more about whether there is an effect or not while an odds ratio is a measure of the magnitude of the effect [37].

In survival studies, functions of survival rates can easily be shown, showing the number of surviving individuals at a specific time to the number of living at the beginning of the study period. That briefly describes the computation of the Kaplan-Meier curve and is often used in survival analysis to give an overview of the mortality data and compare differences between study groups.

2.3 The roles of CEOs and board members in Sweden

The roles of CEOs and board members in Sweden are governed and regulated by the Swedish Corporate Governance Code and "Aktiebolagslagen".

The code states the primary responsibilities for the board as having the ultimate responsibility for the firm's organization and the management of the firm's business including choice of strategic direction, delegation of authority, appointment of CEO and to provide the CEO with guidelines. Moreover, the board is obliged to follow directives from the annual shareholders' meeting.

The CEO's main responsibility is the day-to-day management of the company. The CEO is obliged to follow the directives given by the board. If there are matters of unusual nature not considered to be a part of the day-to-day management of the company, the CEO has to report to the board.

Clearly, a CEO has a more direct responsibility of the company than the board. The board will come up with strategic directions which differ significantly from the operational and staff responsibility of a CEO. The CEO can easily be accounted for mistakes of running the company, whereas it is harder to blame the type of decisions a board can make. Furthermore, bonuses connected to the performance of CEOs are generally more common than for board members. Seemingly, the work of a CEO is more recognized and symbolizing status than the work of board members.

3 Empirical research

Because of the rare existence and availability of complete data on companies combined with complete death statistics, no research has thus far examined if being a CEO, at all or in a certain industry, will affect the mortality rate of that person.

Many research papers examining mortality have studied how different environmental and heritage effects affect mortality [1,2,3,4]. Studies have shown that education may increase life expectancy by several years [7]. Additionally, scholars argue for a correlation between socio-economic status and life expectancy. In the medical field, genes, although not specified which combination or certain gene, play a big role in life expectancy. Other aspects are diet and lifestyle, which are argued to play a big role as well, although they are more difficult to measure. Almond [8] has provided evidence showing that conditions in the womb affect long-term health and other life outcomes. Growing up in poverty has also shown to have negative impact on long-term on adult outcomes [9]. Further research shows that job characteristics may impact health in different ways [10]. Fletcher (2012) finds limited evidence to support that blue-collar jobs have lasting health implications when controlling for siblings [11]. Despite the way in which the technical details in measuring mortality rates vary between the research papers, the basic structure of their data is the same. The mentioned research papers use panel data in order to calculate mortality and life expectancy.

3.1 Factors possibly affecting CEO mortality

The CEO work is regarded as a position with high status and is characterized by high levels of stress, control and responsibility. Also, CEOs often find themselves at the center of attention, receiving recognition and sometimes praise. Aside from these aspects, one needs to consider the differences between companies of different industries and sizes, which may influence how prominent the characteristics mentioned above are in each type of company.

Previous studies have found that people with high occupational status have low rates of premature mortality. However, a later study suggests that it is not the promotion causing the better health, but rather healthy people get promoted in a higher extent [5]. Becoming a CEO requires, in most cases, several promotions before reaching the top. Based on the aforementioned research, there may be reasons to believe that CEOs are more likely to stay healthy than other people. This may be a reason for a higher life expectancy and better conditions to be chosen as CEO. The issue of endogeneity will be discussed further in the data issues section. One may also argue that the amount of intrinsic rewards, such as recognition and the feeling of meaningfulness, creates a state of mind that has positive effects on health.

Stress and pressure combined with heavy workload may lead to burnout. Researchers have proven a link between cardiovascular diseases and burnout [12]. A group of people suffering to a larger extent of burnout will most probably have a higher mortality ratio as cardiovascular disease is a serious illness today that causes large numbers of deaths each year. Linked to characteristics described in the previous research paper and highly relevant for this study is a research on a large sample on Swedish males examining whether job characteristics have an association with subsequent cardiovascular disease [34]. Hectic and psychologically demanding occupations were increasing the risk of disease in the study. However, low-decision-latitude (low intellectual discretion and low personal schedule freedom) was positively correlated to the same diseases [13].

Being in a leading position may also lead to higher mortality risk. Other researchers have found dominance among male chimpanzees to lead to higher mortality risk, which is caused by a higher degree of metabolic stress because of higher energetic expenditure in their roles [14]. A large amount of medical studies, in addition to those mentioned above, have found that stress and unhealthy lifestyles decrease life expectancy. These studies suggest that people in stressful and demanding positions have a higher mortality rate than a group with less stressful occupations. Thus, from this research, it seems CEOs should have a higher mortality.

There is a vast amount of literature showing that people with low income, low education and low socio-economic status die earlier than others [15]. For the United States, the National Longitudinal Mortality Study shows that more education and high income reduce mortality [16]. Cutler and Deatons research show indirect evidence of the relationship between socio-economic status and physical health. Cutler et al. also mention the well-established concept of psychosocial stress, i.e. the wear and tear of having subordinate status in a social setting and having little control over one's own life [15]. This concept suggests that there are stress-related symptoms, which emerge in hierarchies and are related to an individual's rank instead of individual characteristics. There is biological research supporting this theory (Cutler et al.). It has been shown that the immune system changes negatively in mice when being subject of subordinate stress in certain contexts [17]. The individuals with subordinate status may feel less in charge of handling demands, resulting in subordinate stress. Theorizing, CEOs may have closer relationships to the board, and a feeling of equality, which includes the CEO in the decision making process of the demands on the CEO. The link between social status and health is complex, but still relevant for this study.

In conclusion, one can state that previous research has found many factors that affect the mortality hazard. Even though many of these factors can be found as characteristics of the CEO position no clear-cut correlation can be determined for certain. Previous research have mostly focused on the factors affecting mortality and not taken a next step to see if the CEO position, which has many of the factors affecting mortality present, affects mortality. This research aims first to investigate if there exists a “CEO effect” on mortality. Second, it examines if the effect is larger in certain industries or company sizes.

4 Data

4.1 Processing of data

The data used in the study is collected from PAR AB and Dödsboken, providing observations on people being CEO or board member for a Swedish company as well as company financials and death data for the Swedish population during the period 1997–2009. The data is further limited to CEOs and board members for which complete personal identity numbers are available, which consist of ten digits that are unique for each person.

The focus has been set on firms over a certain size. Firms with the following characteristics: less than 10 employees, a turnover of less than 10 million Swedish crowns and an asset base of less than 10 million Swedish crowns, have therefore been excluded. This definition excludes the smallest micro-companies, which are companies with up to 10 employees and approximately 20 million in assets and turnover [39] and keeps a reasonable number of companies in the data set. Furthermore, companies with missing information on any of those numbers as well as subsidiaries and companies with a legal structure other than AB have been discarded. This is based on the assumptions that CEOs for subsidiaries do not have all the responsibilities a CEO for a group or a parent company has to bear. Moreover, CEOs in firms less than a certain size and of a different structure have a different role than the traditional CEO for a limited liability company.

The companies are then joined using company identification numbers with the CEO data in order to see who and how many people are or have been CEOs for these companies. The board members of these companies are included for later use as a control group. CEOs are defined as any people in the data set who has had or currently holds a CEO position in the study period. As some individuals are active in several firms at the same time, those duplicates are dropped in order to only keep one observation of each unique individual each year.

Lastly, the file containing CEOs and company information are joined with the Swedish mortality data in order to get the year of death and the number of deceased CEOs and board members in our sample.

For each year, from 1997, observations for each person are present and a death variable shows if this person was alive or deceased. This continues for each year until 2009. If a person dies during the study period, then the time series end at the year of death, as further observation would be irrelevant. For example, if a person is observed to die in 2003, this person has observations from 1997 to 2002, each stating that this person was alive that year. In year 2003 this individual has an observation stating that this person dies and no further observations are recorded.

The final dataset used for analysis contains a total of 2 619 844 observations, 203 702 unique CEOs and board members, and a total of 6 662 deceased. A total summary can be seen in Table 1a (Appendix table 1a). A CEO group is further created without the board members in order to analyze the industries and sizes between CEOs more efficiently. Moreover, as the SNI1 codes, which show the primary industry of the firm, are incomplete some more observations are excluded from the CEO group. The dataset is still large enough to provide reliable results. (Appendix table 1b-e)

The finished formatted data set is panel data grouped by person number during 13 years. The panel data is not balanced as observations are excluded on already dead people. However, the observations are discretely equally spaced with one year between each observation and do not have any gaps. An advantage with having panel data is the possibility to control for factors that vary across people and not over time, factors that could cause omitted variable bias and unobserved data. Education is a typical variable which does not typically change over time, which means that analysis over time already accounts for that variable if it is not collinear with the variable tested.

The SNI[3] codes are used to define the industry groups. A summary of the biggest industry groups can be seen in the appendix (Appendix table 2). Groups of companies that are believed to have similar characteristics are grouped within the same group. The definition of industries used is based on the SNI code 2002 definitions. When grouping into broader industry groups the codes have been used as a starting point and then grouped to fit the data in the best way possible. In the end, the definitions of the industry groups used in this research are very similar to the broader industry groups suggested by SCB[4]. However, there are smaller groups of companies that do not have similar characteristics. These companies are, in this study, summarized in the group other industries (Appendix table 2). If a CEO has been active in both industry groups, it is counted twice. This explains the difference in the count of unique individuals across the industry group tests.

The industry groups, which we have chosen to investigate, are further selected based on the number of observations, because a bigger group contains more cases of death and thus gives more reliability in estimates. They are also based on the common classification of industries, which is based on differences in characteristics, for example between service and manufacturing. The testing of trade, financial and service companies was enabled because of the large amount of observations in each group.

[3] Svensk Näringsgrensindelning (Statistical Classification of Economic Activities in Sweden)
[4] Statistiska Centralbyrån (Statistics Sweden)

4.2 Control group

In order to have a control group as similar to the CEO group as possible, data of board members is used. This is to minimize the effects of education, socio-economic status and income on mortality [18]. In this study, board members are assumed to be similar to CEOs in these respects. Another reason to do this is because it minimizes, if not eliminates, the healthy workers effect. The healthy workers effect is, as formulated by Last (1995) [19], that workers usually exhibit lower overall death rates than the general population because the severely ill and chronically disabled are ordinarily excluded from employment. It can be seen as a sort of endogeneity problem where more healthy workers are favored, thus giving people with occupations a seemingly better life expectancy. By comparing two very similar groups, where the members of both groups are employed, the healthy workers effect is minimized. However, in an ideal setting the CEOs would have been compared to non-CEOs holding fixed all other parameters affecting mortality.

5 Methodology

5.1 Descriptive models

The descriptive models allow for an easy interpretation of the mortality difference between the study groups. Averages, medians, and standard deviations are calculated for key factors such as age at the beginning of the study period, death age and gender. Mortality ratios, female ratios and other ratios are calculated. A more detailed description of the tables is presented in the appendix (Appendix table 1a-e).

Standardized mortality ratios (SMRs) are used to easily see differences between groups, using age groups to achieve more relevant results because of too few deaths at each age. SMRs compare the number of death cases to the expected death cases based on the control group. An SMR of one indicates that there is no difference in death rates between the groups; an SMR of 1.25 indicates that 25% more deaths are observed in the first group compared to expected deaths based on the reference group. The SMR is calculated as

$$\frac{Death\ rate\ of\ study\ group}{Death\ rate\ of\ reference\ group * Study\ group\ population}.$$

To facilitate further analysis of the data and in order to manage the censoring problem (see section 7 on potential biases in the study), the data is declared in Stata as survival analysis data to form a basis for the different survival analysis models. It also means that personal identity numbers are seen as group identifiers, which follow the subjects over time. Coping with the problem of people dying at the first year in the study period, the study period is shifted in time one year right to the observation period, which means that a person is assumed to be observed from the beginning of the studied year and that observed deaths occur in the end of the year.

Kaplan-Meier curves [20] are used to show the survival rates for a study group at each age. This makes it easy to compare the groups and see where the censoring is most emphasized. Kaplan-Meier curves do take into account censoring but may result in misleading results if the amount of censored data differs largely between the two groups. The curves are estimated using a maximum-likelihood method of the probability, S(t), of having a lifetime exceeding a certain year t_i. The model is on the form:

$$\hat{S}(t) = \prod_{t_i<t} \frac{n_i - d_i}{n_i}$$

where n_i is the number of survivors prior to year t_i minus the number of censored observations and d_i is the number of deaths during year t_i. When comparing the Kaplan-Meier curves of two groups the difference in slope explains the differences in survival rates.

The curves are combined with the non-parametric logrank [21, 22, 23] tests to see if, at the early stage, there are any significant differences in hazard functions between the groups. The logrank test is most powerful when the proportional hazards assumption holds. To assess whether the proportional hazards assumption holds, in order to see whether the groups are relevant for the logrank test, the Cox and the Gompertz regression models, a log scale of survival rates is used. If the lines of the two groups are close to parallel in such a test, the parameters have the effect of multiplying the hazard rate by a constant and then the proportional hazard assumption is valid.

5.2 Regression models

The Cox regression model [22] is a semi-parametric model and follows up the shown differences in the logrank tests. The model is argued by Cox to have significant advantages over the parametric models, partly because it does not need a specified mortality distribution. The model's only assumption is the one of proportional hazards – that parameters affect the hazard rate by a multiplied constant. The proportional hazards assumption does, however, not often hold in practice [24] but one solution is using time-varying coefficients. If the proportional hazards assumption does not hold, accelerated failure time models can be used instead.

The general estimation equation model, GEE, is applied since the data is longitudinal and the number of observations is large [25, 26]. It is a semi-parametric model which uses a generalized quasi-score function estimate for the regression coefficients, and moment estimates for the correlation parameters [26]. A reason to use GEE is the aim to examine population-averaged differences between the study groups. Instead of using the probability ratio directly, the logarithm of the odds ratio is used,

$$\ln \frac{p_{it}}{1 - p_{it}}$$

where p_{it} is the probability of dying at a certain age t for a person i, given living at the beginning of that age. The formula is normally called the log odds of death or logit. Including the parameters in the model, the model is as follows

$$\ln \frac{p_{it}}{1 - p_{it}} = \alpha + \beta_{i,f} D_{i,f} + \beta_{i,CEO} D_{i,CEO} + \beta_{Age} x_{it} + \varepsilon_{it}$$

where $D_{i,f}$ is a dummy variable of one if the person is female and $D_{i,CEO}$ is a dummy of one if the person has ever been CEO.

Assumptions of the GEE model are that the dependent variable is linearly related to the parameters (1), that the number of clusters is relatively high, possibly more than 30 [33] (2) and that the observations in different clusters are independent (3). The first assumption is accounted for by the specified logit link in the model. The second assumption holds since there is at least 24 886 unique people in every study group. The third assumption holds since one person does not normally affect the time of death of another person. This assumption seems reasonable for the data, since the age effect on mortality can be estimated to be linear (4). However, the correlation structure is not very relevant for the results, but for the tests of the method, i.e. the standard errors may be estimated incorrectly if the assumed correlation structure is not correct. Robust standard errors are reported using observed data variability instead of predicted variability by an underlying survival function. A drawback is that the model does not take censoring into account.

By using log odds instead of probability, the range of results varies between negative infinity to positive infinity instead of 0.0 – 1.0. Moreover, the logistic regression allows a linear relationship to the explanatory variables. Another advantage is the easier interpretation compared with other possible models to use.

The probit model was considered, however, the logit model was chosen because of its flatter tails, corresponding better to the age-concentrated nature of death. A result of this is a more robust model regarding errors in the data or inaccuracies in the underlying model. Also, the logit model allows a more intuitive comprehension with log odds as well as results in slightly higher log likelihood in this study compared to the probit model. A higher polynomial age variable has been shown to not significantly alter the results, which is why a linear age variable is used [31].

According to Miller [28], parametric results are likely to be more accurate than semi-parametric models when the data is known to follow a certain hazard function, e.g. the Gompertz, Weibull or exponential function. Miller also argues that the Kaplan-Meier curve is inefficient and that parametric models should be used whenever possible. However, Meier [30] later argued that Miller's conclusions were incorrect. To examine potential drawbacks of the descriptive and semi-parametric models and to increase robustness, the parametric proportional hazards model is further used in this study.

In the parametric model maximum-likelihood estimation is used assuming a Gompertz distribution of the survival data. The Gompertz distribution has been shown in several studies to be the best fitting survival distribution [4, 29, 31]. It is the most celebrated distribution model of adult age-specific mortality in which the rate of mortality exponentially rises with age [24]. It is frequently used in medical research when calculating mortality ratios.

The models used in the study have drawbacks, for example, the standard error of the Cox regression may be too large and the GEE-logistic model may produce too large prevalence of death [32]. However, in the same article, it is shown that the models produce negligible differences of point estimates for the parameter tested.

6 Potential biases in the study

The potential biases in the research are mainly associated with data structure issues but also result from simplification necessary to conduct the research.

As data of CEOs and board members is only available for the time period 1997 – 2009 a potential concern is that the dataset does not cover data on individuals holding their position (CEO/board member) before the study period, which implies that an individual, who was CEO before 1997 and became board member after this period, shows up as only board member in the data. This may affect the difference observed between the CEO group and the board member group. It is believed that this bias may cause the difference shown in this study to be smaller than it is in reality. This is because it is common to become a board member after having been CEO, thus showing up in the data as a board instead of a CEO. As this study is mainly to establish any difference between the groups, this bias will not significantly affect the results, though it will be important in future studies if the aim is to quantify the difference more exactly.

Another concern is that self-selection bias may be present in the data. An example is a CEO who became CEO because of his or her personality, or other personal features. However, this bias is difficult to control for and there is little research on whether parameters like this affect mortality. There is also the endogeneity problem that people who have good genes may get the best conditions of becoming CEO. Among many factors when selecting a CEO for a company, one can be health; the recruiter may ask if the person is healthy enough to handle the responsibilities of being a CEO. A good health status may indicate good genes and in turn lead to a longer life-span. The selection bias here would therefore be that people with higher life expectancy are selected as CEOs and not that the responsibilities of being a CEO lead to a longer life-span. This effect, the healthy CEO effect, has been observed in other research articles as well under the name: "Healthy worker effect (HWE)" in research articles such as Last 1995 [19]. Related to this are also other factors that are hard to distinguish using the dataset in this research paper. These factors include, but are not limited to, education, personal income, family background, and socio-economic background. By comparing CEOs with board members or only CEOs of different groups with each other an assumption is made that these factors are relatively similar across the groups, which should be a valid assumption. However, it is still important to question how good of a proxy the board group is. As mentioned before a perfect comparison group would be where environmental, socio-economic and other factors could be observed. There is the risk that the board group has characteristics not found in the CEO group, apart from the fact that they are not CEOs which could bias the results.

Data on cause of death would have been interesting to have in an analysis of mortality like this since the parameter effect can be examined further. Cause of death may help further studies to determine whether the CEO effect is present only for certain diseases or only increasing the age of natural death. This study uses two different age groups, 40–69 years old and 70–103 years old, in order to separate premature deaths from natural deaths.

In some cases, the death year of people in the data is before the end of the tenure, which may be due to closure or registration error in the companies' records. Naturally, it is solved in the study by using the death year to indicate the end of the CEO tenure as well as time of death.

Moreover, facilitating, the study does not differ between being a CEO one year or ten years. Being CEO for a longer period could reasonably have a larger effect given that there is a CEO effect, which can be linear or exponential in nature. This would be interesting to investigate further but in this research, focus was to see if there is any CEO effect at all. Also, there was too much uncertainty in the data regarding start and end dates in the position. Therefore, as long as an individual has been CEO, this person will be grouped into the CEO group. A further concern is that the number of deaths is small in the early part of the study period, which is 1997–2009. This is because there should be few CEOs and board members who die in their position or slightly after quitting. Using the survival rate in a Kaplan-Meier curve solves some of the concerns.

Since the data has an upper year-limit of 2009, there is a right censoring of people dying after this year, which refers to people surviving the whole study period. To avoid the censoring problem, the study has primarily used survival analysis regressions, standardized ratios and graphs to make inferences about the sample.

The data is collected following different cohorts during the study period, the sample could be viewed as either a Swedish time sample, thus which is not randomly chosen, or the population in Sweden for this time period. It may be argued that the results in this study are mostly applicable to Swedish CEOs. However, this is left to examine in further studies.

To make statistical inferences from this data, it must be assumed that cohort effects are minor, which means that time passage does not affect the effect of being CEO on mortality. More specifically, for the study sample, the assumption is that different years of birth (birth cohorts) may not significantly affect the age of dying. In order to control for cohort effects, the data was further divided in two time periods, from 1997–2005 and 2005–2009, respectively.

Another important issue to mention is the SNI codes and how reliable they are. The groups seen in the appendix had to be manually divided into bigger groups. A more exact division of the industry groups could certainly be made, although the crude industry groups seen in this research should give an idea of if any difference may exist. To make the results of the industry variables more robust, it would have been useful to compare the mortality of the general population within a certain industry to account for the pure sector effect. However, that type of data was not available in the study.

Another potential bias affecting the difference in hazard ratios in the tests can be early deaths. The reason is that the hazard rate is very low in the beginning as a result of few cases of deaths, for example the death rate for one group can be 0.007. If the death rate for the other group were 0.014, which also is very low, it would imply a hazard ratio of 2.0 compared to the first group. In real terms the difference is very small, but as difference in hazard ratio is reported in terms of percentage it may seem that the difference is actually much bigger than what it is. This is especially important when measuring the overall hazard rate, as the hazard rates towards the end can be 14 % compared to 24 %. In terms of percentage the difference is smaller than in the first example, however, in real terms the difference is bigger in this example.

7 Results

The main result in this research is that there exists a difference in mortality for CEOs, which the first comparison shows. The results from the other tests are mainly to see if the CEO effect is concentrated to a specific type of companies. This section is constructed by presenting the results of the general CEO-effect first, i.e. CEOs compared to boards. Next, the results for the CEO's company size are presented and lastly the industry comparisons. In each section the descriptive results are first presented followed by regression results.

7.1 CEOs compared to boards

The first descriptive table (Appendix table 1a) shows that the average ages for CEOs and boards, respectively, are the same, which indicates a good base a for mortality comparison. The table shows a big difference in mortality ratio, 1.93% for CEOs compared to 3.47% for board members, however, the average age of death is 64.01 years versus 68.47 years. These findings suggest opposite relations of mortality between the groups. If a group has a high quota of females, then it is expected to have a higher life expectancy. The table shows that the cause of the higher average age of death could be that the board group has a three times higher ratio of females. However, the opposite relation for the mortality ratio is not explained by this. Instead, it may be explained by the fact that the ratio of old people is bigger in the board member group. The ratio of people above 70 years old in the data is 6% for CEOs and 11% for board members. (Appendix table 3) The lower average age of death for the CEO group may indicate earlier deaths or a data issue as the board group has a higher degree of elderly people and thus more people who die at higher ages as seen in the maximum age at death, 103 years in the board data and 97 in the CEO data.

The seemingly low average death age, compared to the life expectancy of the population in Sweden (SCB), is because of the data structure, as death of people in high ages is not observed in our observation groups to a large extent. This is because the big majority of our observations survive the whole time period. The logic behind this is that the observations are exclusively people who have been either board member or CEO at a certain point in time during the study period. The conclusion that can be drawn based on the descriptive statistics is that there seems to be differences between the groups, suggested by both the mortality ratio and average death age. However, the results are ambiguous and it is too early to make any certain conclusions about differences in mortality before further tests.

The SMRs for CEOs show there are 18% fewer cases of death in ages 40-69 and 20% fewer cases of death in ages 70-90 (Appendix table 4). Age groups are used in order to get enough death observations to draw conclusions and to separate premature deaths from natural deaths. The results are interesting since they give a first hint on the magnitude of the difference in mortality. They indicate that CEOs have a lower risk of death compared to boards. However, at this stage, it is hard to say anything about the difference between the SMRs of the age groups with a small difference of 2 percentage units. But the results between CEOs and board members strongly suggest a difference, which makes it important to test it further in order to see if they are consistent.

In order to observe the differences in more detail, a Kaplan-Meier curve combined with a logrank test are used, as it is able to show differences across different ages as well as how significant the overall difference is (Appendix Table 5). The curve shows differences across the groups and the logrank test confirms that this difference is interesting to further analyze, since it is close to significant with a p-value of 0.1017. To further quantify the significance and relevance of the differences regression tests are run.

The proportional hazard test (Appendix Table 7) shows the hazard is proportional between the two groups when the number of observations is higher. This allows for the use of a Cox regression. It shows that the CEO group's overall hazard ratio is 16% lower than for board members, at a 1% significance level. The difference seems to originate from the difference in mortality for the ages 40 – 69, which is assumed to indicate premature deaths. For the ages 70 – 103 there is no significant change in hazard ratio. The results are further supported by the robustness checks in time spans, showing significance for both 1997–2005 and 2006–2009 (Appendix Table 8). Both the Gompertz regression and GEE regression support these results. (Appendix Table 9, 10)

A reason for the lower mortality among CEOs in the lower age group may be that the work in fact decreases the rate of premature deaths. Perhaps CEOs are generally more concerned about keeping a healthy lifestyle because of consciousness of their own health's influence on their job. It is also hypothesized that a CEO may be required to have a more physically active role in the organization since it involves many different responsibilities. Anyhow, research supports that lack of psychosocial stress plays a role in mortality determination, meaning that the CEO feels control over his or her life and the daily work. The lack of the mentioned stress factors may be reducing the general stress in the CEO's life and therefore a result is less stress-related diseases and thus less premature deaths. Also theories about that healthy people are promoted and that high-occupational status decreases mortality could be possible explanations. It is important to note that this is speculation about the reasons behind the results and would be interesting to investigate in further research.

7.2 Big company CEOs compared to Small company CEOs

The table 1b summarizes the descriptive results of small company CEOs and big company CEOs. The average ages for the two groups are similar, 41.62 and 43.09 years. The mortality ratio is

1.84% for big companies compared to 2.70% and the average age of death is slightly higher for big company CEOs, 64.19 compared to 63.87. (Appendix Table 1b) Both the mortality ratio and average age of death suggest CEOs of big companies to have a longer life expectancy. Because the female ratio is similar in the two groups the difference should not be due to a skewed distribution of females across the groups. One hypothesized possible explanation is that instability in smaller companies could increase stress and therefore mortality. The relative standard deviation of sales is used as a proxy and measure of company stability. As seen in table 1b, the volatility for big companies is higher than for small companies, thus this possible explanation can be dismissed.

The SMRs for CEOs in small companies show that there are 16 % more cases of death in the ages 40 – 69 and 87 % fewer cases of death in the ages 70 – 90. The first case is more reliable as it contains more observations. At this stage it is too early to draw any conclusions regarding the differences in mortality, however, one can state that there seems to be differences depending on age interval. (Appendix Table 4)

The Kaplan-Meier function shows that a difference in mortality can be seen in the ages 60–80, where small company-CEOs have a lower survival rate (Appendix table 5). The logrank test further shows a strong significance in the difference, a significance level of 1 %. (Appendix table 4).

The proportional hazard test shows the proportional hazard assumption seems valid for the group comparing company sizes since the lines are approximately linear. It means that the Cox regression model can be used. The Cox regression shows a 46% higher overall hazard ratio for CEOs of small companies compared to CEOs of bigger companies at a significance level of 1%. In ages 40 – 69, small company CEOs have an increased hazard ratio of 70% at a significance level of 1%. However, for the age interval 70 – 103, the hazard ratio for small company CEOs is increased by 3.6% compared to big company CEOs, but the result is not significant. This difference may suggest the big-small effect mostly affects premature deaths. But the insignificance may also depend on fewer deaths for higher ages in our data. The Gompertz and GEE regressions confirm the results which may suggest that there is no difference between the hazard rate of the two groups after the age of 70, further enforcing the hypothesis of increased premature mortality hazard for small company CEOs (Appendix Table 8, 9, 10).

When adding *female* to the model, it is shown that company size affects mortality more than gender in regards to the magnitude of the difference (Appendix Table 8), which is interesting results.

There may be several important other factors affecting the mortality results, for example the fact that bigger companies in a higher extent can choose CEOs with more education and thus receive higher life expectancy. Unfortunately, that data is not available in the study.

7.3 Service Company CEOs compared to Manufacturing Company CEOs

The third descriptive graph comparing company CEOs of manufacturing and service companies show small differences in mortality ratios, 2.11% and 2.03%, with a slightly higher mortality ratio for the service group. The data also shows a lower average death age for the service group, 63.92 compared to 64.81 years. Both these factors indicate a lower life expectancy for CEOs in service companies. (Appendix table 1c)

The SMRs for CEOs in the service industry show no difference in cases of deaths in ages 40–69 and 34 % more cases of deaths in the age interval 70–90 (Appendix Table 4). Further the Kaplan-Meier curve show what seems to be a slightly lower mortality for manufacturing firms that is consistent across different ages. (Appendix table 5) The logrank test confirms that the difference between the two groups is significant at a 10% level (Appendix table 6). The proportional hazard assumption seems to hold at the interval with the most observations and not to hold at few observations.

The Cox regression shows an increased overall hazard ratio of 20.3% for the service company CEOs with a significance level of 5%. It also shows a 35.8% higher hazard ratio for the service group in the ages 70 – 103 years with a significance level of 10%. Both the Gompertz regression and GEE regression confirm these results. (Appendix 8, 9, 10)

7.4 Trading Company CEOs compared to Other Company CEOs

The descriptive table 1d shows a lower mortality ratio, 1.90% compared to 2.22%, for CEOs in trading companies against CEOs in non-trade companies. This suggests a higher life expectancy for a trading company CEOs. The theory is further enhanced by the average death age factor, 66.59 years compared to 63.62 years, where trade company CEOs shows a higher average death age. (Appendix table 1d)

The SMRs of trading company CEOs show 16 % less cases of death in the ages 40 – 69 and 27 % more cases in ages 70 – 90. To further compare the differences a Kaplan-Meier curve is plotted to see differences across ages. However, no clear difference can be seen in the graph. This is confirmed by the logrank test, which states that there is no significant difference between the industry groups. However, it is still interesting to examine if there are significant differences between certain age groups. Therefore further regression analysis is made. (Appendix Table 4, 5, 6)

Neither the Cox, Gompertz or GEE regression show any significant results for any difference between the mortality of CEOs in trade companies and the mortality of CEOs in other companies. (Appendix Table 8, 9, 10)

7.5 Finance Company CEOs compared to Other Company CEOs

The final descriptive table comparing finance and administration company CEOs and other company CEOs show a lower mortality ratio for finance and administration companies, 1.95% compared to 2.12%. However, the average age of death is slightly lower for finance and administration company CEOs, 63.61 years compared to 64.36 years. The median on the other hand is equal between the two groups, 63 years. The information from the descriptive table is ambiguous but suggests a slightly higher life expectancy for CEOs in finance and administration companies. (Appendix table 1e)

The SMRs for CEOs in finance companies show 15 % more cases of death in the ages 40 – 69 and 27 % more cases of death in the older age group, 70 – 90. (Appendix Table 4)

The Kaplan-Meier curve shows the opposite of what the earlier descriptive tables seem to , the curve suggests that CEOs of Finance companies have a higher mortality. This is further confirmed by the logrank test at a 5% significance level. This discrepancy may be a result of differences across age groups. Therefore further regression analysis is made. The proportional hazards assumption seems to hold well at most ages.

The Cox regression shows a 26% higher overall hazard ratio for the finance group at a 5% significance level. Regarding the specific age groups it shows a 69% higher overall hazard ratio for the ages 70 – 103 years at a significance level of 5%. To have in mind is though that only 23 people over 70 years old in the finance industry were declared dead during the whole time period, which is a small sample and can be misleading in the results. Both the Gompertz regression and the GEE regression confirm the results of the Cox regression. (Appendix table 6, 7, 8)

7.6 Robustness

Estimating the GEE model and the Gompertz model yield results which are very similar to the results of the Cox model, but GEE showing odds ratio differences between the groups. (Appendix Table 9, 10)

The GEE-logistic tests show CEOs have a 16% lower mortality odds ratio compared to board members with 1% significance. CEOs of small companies are reported to have an increased odds ratio by 47% on the 1% level. GEE-logistics also show that CEOs in the service industry compared to other industries have a 20% higher odds ratio on the 5% significance level. CEOs in the finance industry had an increased odds ratio, by 25%, compared to the non-finance industry on a 10% significance level. CEOs in the trade industry did not differ significantly in mortality.

The Gompertz model shows the CEO-variable has a 14% lower mortality on a 1%-significance level. The size variable shows an increased mortality of 45% (1% significance), finance by 26% (5%) and service by 20% (5%).

8 Conclusion

The purpose of the study is to examine whether being CEO affects mortality and to see if there is a subgroup, depending on size or industry, where the effect is larger. As seen in the results, the conclusion is that CEOs in general have a lower mortality and that this effect is most prominent for big companies. The effect seems to be larger for CEOs in manufacturing companies. CEOs in finance and administration companies are seen to have higher mortality. This conclusion is based on the following test results.

The first test, to see whether CEOs in general have a different mortality, shows a lower mortality for CEOs when comparing to board members. The most interesting result shows that CEOs have a lower hazard ratio of 14–16% (1% significance), which is robust across several measures and models. Surprisingly, the effect is only significant in the age interval 40–69 for the parametric models. The results may have biases if being CEO is correlated with education and income compared to board members. However, the marginal effect of education and income should reasonably be small since board members are a group of individuals with relatively high socio-economic status. Furthermore, there may be biases in self-selection and differences in the ratio of old people between the groups. Also the bias of early deaths for the hazard ratio can affect the results. Still, the robustness across descriptive methods, semi-parametric results and regressions support that there is an actual difference in mortality between CEOs and board members.

The second test, CEOs in small companies compared to CEOs in big companies, shows that small companies have a higher mortality risk compared to big companies. Regarding the industry group tests, the results show that CEOs of service companies and finance companies have a higher mortality risk compared to the control groups. The differences are mainly seen in the ages 40–69 where the differences are mostly significant. No mortality difference was found for CEOs in the trade industry, which is notable since the other industries showed quite clear differences. This might be due to few characteristics of the trade industry considering stress and other health-related factors. No previous study has, to our knowledge, been examining effects of being CEO on mortality, which makes the results particularly interesting.

The conclusion differs from our original hypothesis of lower life expectancy for CEOs. In contrast, the results imply a decreased risk of premature deaths among CEOs. The authors of this thesis believe it might be explained by having the top position in the hierarchy, which means less subordinate stress causing certain diseases. A lower mortality in bigger companies may come from the fact that employees in bigger companies possibly have more education and higher income, which from previous studies are evident to have a positive impact on life expectancy. This factor could not be accounted for since data on education and income was not available. However, the results for company size may also be affected of the theory of psychosocial stress, being a CEO of a big company might imply a feeling of higher control than that of being CEO of a small company. Moreover, the observed CEO effects could be due to the impreciseness of the control groups, which are assumed to proxy characteristics for the CEO group except for the variable tested. In a perfect world where factors such as genes, education and background can be fully observed and controlled for the result would be more reliable.

Further research of the causes of the CEO effect on mortality would be of high value to CEO mortality studies. It would also be interesting to look further into what kind of mortality is affected, for example using death cause data to determine which death causes seem to be delayed by being CEO. Comparing CEO mortality against mortality of top managers, such as CFOs and COOs would also gain further insight. An additional idea is to examine whether CEOs of several companies at the same time have a differing mortality.

Examining the CEO effect more specifically can be done by looking at how early the effect takes place and if CEO tenure matters. Lastly, an overview of CEO mortality in other countries than Sweden and other time spans than 1997–2009 could increase the reliability of the results. Lastly, if the results in this study are confirmed by further studies, then the controversial discussion on the remuneration of CEOs could get a new twist.

9 References

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10 Appendix

Table 1a
CEO and Board member descriptive data

The following table provides information on the CEO and Board data set. A person is defined as a CEO if he/she has been a CEO for at least one year between 1997-2009. The ratio of observations describes how big the groups are compared to each other. Total unique observations list each individual person once. Total observations lists the same person up to 13 times, from 1997-2009 at the most. Average ages are computed by calculating the ages of the people in each group in 1997. The median, standard deviation, minimum and maximum are also based on year 1997. The number of deceased is based on the total number of deaths regardless of year in the period 1997-2009. Mortality ratio is calculated by dividing the number of deceased in our time period with the total unique number of observations in our data. Deaths per thousand is based on the mortality ratio, to show how many in a group of 1000 that would be expected to be deceased based on the mortality ratio. Average, median, standard deviation, minimum and maximum of death are based on the total number of deceased. The seemingly low average death age is because of the data structure, as death of people in high ages is not observed in our observation group as many of our observations survive the time period. Female ratio is calculated by dividing the number of unique individuals with the total number of unique individuals in the data.

	CEOs	Board members
Ratio of total observations	13%	87%
Total observations	338 261	2 281 583
Total unique observations	26 214	177 488
Average ages	42.37	42.17
Median age	42	42
Standard Deviation of average age	10.58	12.81
Minimum age	8	1
Maximum age	93	95
Number of deceased	593	6157
Mortality ratio	1.93%	3.47%
Number of deaths per thousand	19.26	34.69
Average age of death	64.01	68.47
Median age of death	63	69
Standard Deviation of age of death	11.34	12.85
Minimum age of death	35	24
Maximum age of death	97	103
Female ratio	10%	33%
Number of female deaths	28	1238
Ratio of female deaths	5.54%	20.11%
Average age of death for males	64.23	68.74
Average age of death for females	63.99	67.39

Table 1b
Big and Small company CEO descriptive data

The following table provides information of the big and small company CEOs in the dataset. A company is defined as a big company if it has over 20 employees while at the same time has over 50 million Swedish crowns in turnover and assets. A company CEO is listed as a CEO for a big company if his company has been defined as a big company for at least one year during the period 1997-2009. The data is listed and constructed in the same way as table 1a. Compared to table 1a all board members are dropped which is because this dataset only contains the CEO observations comparing CEOs of big companies and small companies. Additional statistics regarding relative standard deviation, number of employees, turnover and amount of assets are added. The relative standard deviation is calculated by dividing standard deviation of sales with the mean of sales to adjust for differences in size.

	CEOs of big companies	CEOs of small companies
Ratio of total observations	51%	49%
Total observations	173 040	165 221
Total unique	13 381	12 833
Average ages	43.09	41.62
Median age	43	42
Standard Deviation of average age	9.89	11.21
Minimum age	13	8
Maximum age	93	91
Number of deceased	246	347
Mortality ratio	1.84%	2.70%
Death per thousand	18.38	27.04
Average age of death	64.19	63.87
Median age of death	64	63
Standard Deviation of age of death	10.87	11.68
Minimum age of death	35	36
Maximum age of death	97	95
Female ratio	9%	11%
Number of female deaths	10	21
Ratio of female deaths	4%	6%
Average age of death for males	64.48	63.64
Average age of death for females	57.40	67.48
Relative standard sales deviation	7.46	5.23
Average number of employees	566.46	18.22
Median number of employees	57	14
Average turnover	1 200 000	22 655
Median turnover	110 000	16 530
Average assets	2 000 000	16 037
Median assets	63 008	8 042

Table 1c
Service industry and Manufacturing industry descriptive data

The following table provides information on service companies and manufacturing companies. A company is sorted into each group based on the SNI code, which indicates their primary industry. Compared to table 1b observations containing no SNI code are dropped. If a CEO has been active in both service and manufacturing companies during the period, then they are counted in both groups, which explains why the number of unique observations are slightly higher compared to table 1b. The data is listed and constructed in the same way as for table 1a and 1b.

	CEOs in the service industry	CEOs in the manufacturing industry
Ratio of total observation	61%	39%
Total observations	188 155	111 035
Total unique observations	15 760	9 954
Average ages	44.12	45.26
Median age	44	46
Standard Deviation of average age	9.87	9.96
Minimum age	14	15
Maximum age	91	90
Number of deceased	332	202
Mortality ratio	2.11%	2.03%
Death per thousand	21.07	20.29
Average age of death	63.92	64.81
Median age of death	63	64
Standard Deviation of age of death	11.62	10.52
Minimum age of death	35	42
Maximum age of death	95	97
Female ratio	11%	7%
Number of female deaths	22	4
Ratio of female deaths	7%	2%
Average age of death for males	63.85	64.95
Average age of death for females	64.91	58.25
Relative standard sales deviation	8.85	11.07
Average number of employees	416.66	245.08
Median number of employees	27	26
Max employees	230 000	99 322
Average turnover	520 000	290 000
Median turnover	41 170	31 096
Average assets	860 000	440 000
Median assets	20 365	19 174

Table 1d
Trade industry CEOs and other industries CEOs descriptive data

The following table provides information on trading company CEOs and CEOs in other companies. The sorting is based on the SNI codes. The listing and structure of the statistics is identical to 1c.

	CEOs in the trade industry	CEOs in other industries
Ratio of total observations	23%	77%
Total observations	62 966	236 224
Total unique observations	5 835	19 051
Average ages	42.43	43.02
Median age	42	43
Standard Deviation of average age	10.61	10.28
Minimum age	15	8
Maximum age	84	93
Number of deceased	111	423
Mortality ratio	1.90%	2.22%
Death per thousand	19.02	22.20
Average age of death	66.59	63.62
Median age of death	67	63
Standard Deviation of age of death	12.2	10.91
Min age of death	36	35
Max age of death	94	97
Female ratio	9%	10%
Number of female deaths	5	21
Ratio of female deaths	5%	5%
Average age of death for males	66.47	63.67
Average age of death for females	69.2	62.62
Relative standard sales deviation	7.31	9.57
Average number of employees	130.42	410.89
Median number of employees	23	28
Max employees	53 430	230 000
Average turnover	260 000	470 000
Median turnover	51 904	32 267
Average assets	160 000	20 995
Median assets	840 000	19 474

Table 1e
Finance and administration industry CEOs and CEOs in other industries descriptive data

The following table provides information on CEOs in Finance and Administration companies and other companies. The sorting is based on the SNI codes. The listing and structure of the statistics is identical to 1c.

	CEOs in finance and administration industries	CEOs in other industries
Ratio of total observations	18%	82%
Total observations	43 445	255 745
Total unique observations	4 521	20 996
Average ages	43.50	42.80
Median age	44	43
Standard Deviation of average age	9.8	10.43
Minimum age	15	8
Maximum age	74	93
Number of deceased	88	446
Mortality ratio	1.95%	2.12%
Death per thousand	19.46	21.24
Average age of death	63.61	64.36
Median age of death	63	63
Standard Deviation of age of death	9.90	11.50
Minimum age of death	35	36
Maximum age of death	93	97
Female ratio	10%	9%
Number of female deaths	5	21
Ratio of female deaths	6%	5%
Average age of death for males	63.60	64.39
Average age of death for females	63.80	63.90
Relative standard sales deviation	5.67	10.38
Average number of employees	955.64	156.4
Median number of employees	60	27
Average turnover	1 500 000	260 000
Median turnover	82 748	33 366
Average assets	3 000 000	320 000
Median assets	58 015	17 583

Table 2
Descriptive data on the main industries in the data

The following table shows the main industries identified by using the SNI codes. (Statistical Classification of Economic Activities in Sweden.)

Industries	**Number of observations**	**Percentage**
Public sector	6 389	2.1%
Health and social care	5 721	1.9%
Construction	10 994	3.7%
Advertising	5 543	1.9%
Repairs	4 048	1.4%
Financial sector	10 164	3.4%
Agriculture, forestry and extraction	3 709	1.2%
Textile and paper sector	15 030	5.0%
Manufacturing	43 825	14.6%
Trade	62 966	21.0%
Land and construction, including water and gas supply	22 299	7.5%
Transport, hotel and catering	22 649	7.6%
Real Estate	15 627	5.2%
IT and telecommunication	17 028	5.7%
Law, management and audit	33 281	11.1%
Other industries	19 917	6.7%
Total	299 190	100.0%

Table 3
Descriptive data for older people in each test group

The following table shows data produced in order to test the causes of results and further investigate potential biases. The ratio of older people in a certain group can for example significantly alter the average age of death.

	CEOs	Board members	CEOs in small companies	CEOs in the finance industry	CEOs in the service industry	CEOs in the trade industry
Number of unique individuals above 70 years old	1 600	19 273	814	205	862	348
Number of unique individuals	26 214	177 488	12 833	4 521	15 760	5 835
Ratio of unique individuals above 70 years old	6.10%	10.86%	6.34%	4.53%	5.47%	5.96%
Number of deceased unique individuals above 70 years old	165	2 874	94	23	95	42
Number of unique individuals surviving the whole time period	25 621	171 419	12 486	3 240	14 300	4 770

Table 4
Standardized mortality ratios for all test groups

The following table shows the Standardized Mortality Ratios (SMR) for two age groups: 40–69 years old and 70–90 years old. The results are shown across all study groups in the sample and during the study period of 1997–2009. SMR is calculated by taking the number of observed deaths in the study group compared to the expected deaths. The number of expected deaths is computed from the rate of death in the reference group times the number of living in the study group the year before. The reference group for the study group CEOs is board members and the reference group for CEOs in finance companies is the group of CEOs in non-finance companies etc. Death rate in the reference group is the number of deaths divided by the number of living the year before. Age groups are used to get at least one person dying in each year for each group, however, this was not possible to achieve with the CEOs in the finance industry in reasonable age groups. A relative death of -18% in the age interval 40–69 years for CEOs means that this group experienced 18% less cases of death compared to the reference group.

Standard Mortality Ratios (SMR), age group

	CEOs	CEOs in small companies	CEOs in the finance industry	CEOs in the service industry	CEOs in the trade industry
Observed deaths, 40–69	420	249	64	230	67
Expected deaths, 40–69	511	215	56	230	80
SMR, 40–69	0.8225	1.1578	1.1496	0.9982	0.8375
Relative death, 40–69	-18%	16%	15%	0%	-16%
Observed deaths, 70–90	157	89	22	84	40
Expected deaths, 70–90	196	701	17	63	32
SMR, 70–90	0.8005	0.1269	1.3096	1.3399	1.2698
Relative death, 70–90	-20%	-87%	31%	34%	27%

Table 5
Kaplan and Meier curves of each study group

Kaplan-Meier curves of the study groups showing the survival rate, the fraction of people living, at each age. A survival rate of one indicates that all individuals in the group are alive and zero that all individuals have died. Lines consistently crossing each other indicate there is no difference in mortality between the two groups. The reason to why the curves get horizontal steps of an increased size at the end of the ages is that very few people are left in the data at that age. That means most people have died and there is little data on the deaths of the remaining sample. The text box under each graph tells which study group it is. For example, small=0 signalize that it is not a small company and ceoever=1 signalize that it is the CEO group.

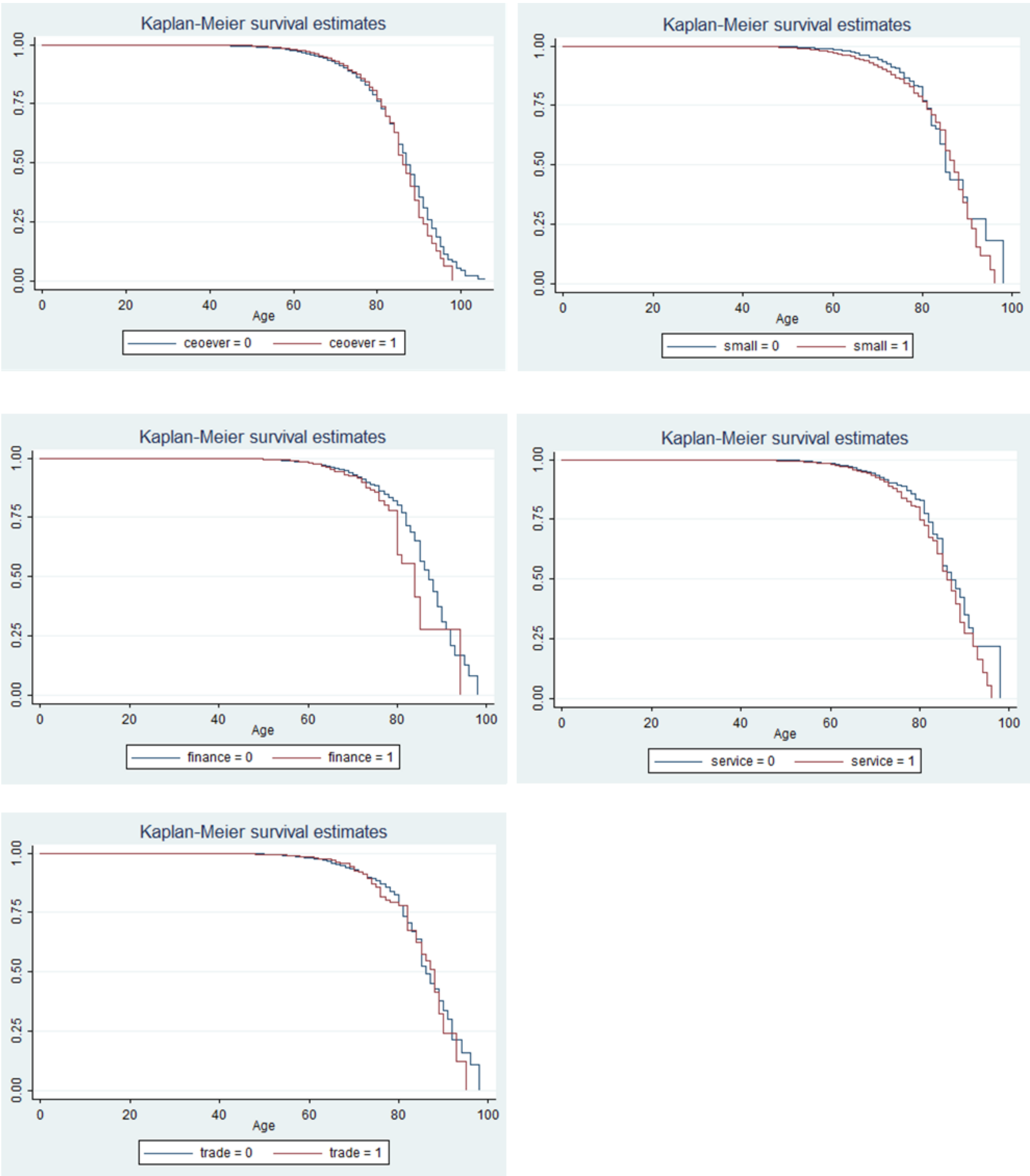

Table 6
Logrank tests of all study groups

The logrank test shows the p-value of the null hypothesis of the two compared groups in each study group. It shows that the mortality of the variable groups ceo, small, finance, and service differ from their control groups quite significantly. It means those variables are seemingly suitable in a mortality regression. Small differences in mortality are not accounted for in the logrank test; however, the Cox regression is quantifying the difference if the assumption of proportional hazards holds.

Logrank test statistics of difference in mortality ratios 1997–2009

	CEOs	CEOs in small companies	CEOs in the finance industry	CEOs in the service industry	CEOs in the trade industry	Females
P value	0.1017	0.0000	0.0483	0.0597	0.6069	0.0000

Table 7
Proportional hazard tests of each study group

Proportional Hazard Assumption tests showing reasons to believe the Proportional Hazard Assumption holds if the lines are parallel and does not cross each other significantly. The finance and small variables are holding. The others seem to hold as well, especially when there are many observations (in the middle of the line). The text box under each graph shows which study group it is.

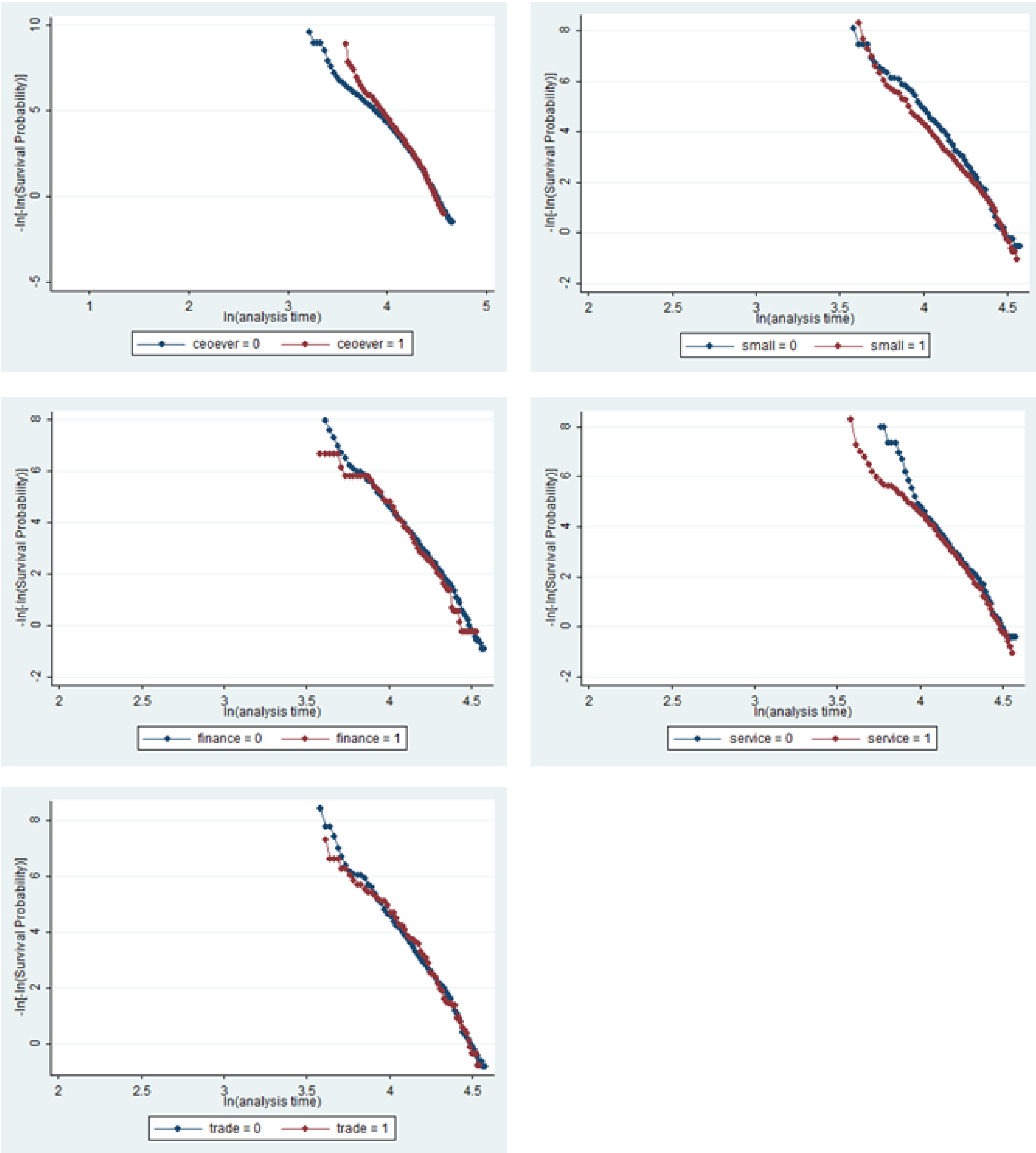

Table 8
Cox regression analysis for each study group

*, ** and *** stand for a significance level of 1%, 5% and 10%, respectively. The result from the Cox regression, which is a survival analysis model, is presented for each data set of different groups below. The variable female is specified in all models to account for gender differences. The reason for why we use the time span 1997–2005 is that we control for cohort effects and approximately 50% have died until that time for all groups. The reason for why we use the age intervals is mainly to look for robustness in a smaller dataset but also to control for cause of death effects. 40–69 are the assumed ages for dying prematurely. Ages before 40 is left out because the causes of death are hard to specify in this age group, also the death observations before the age of 40 are scarce. A hazard ratio of 0.844 means that CEOs, compared to board members, have a 16% (1-0.844) lower risk of dying at any point of time. Standard errors are reported in parentheses.

Cox regression estimates of mortality hazard ratios 1997–2009

	CEOs	CEOs in small companies	CEOs in the finance industry	CEOs in the service industry	CEOs in the trade industry	Females
Hazard ratio	0.844*	1.457*	1.261**	1.203**	0.949	0.606*
	(0.037)	(0.123)	(0.148)	(0.108)	(0.102)	(0.019)
Hazard ratio, ages 40–69	0.825*	1.704*	1.153	1.121	0.863	0.606*
	(0.0434)	(0.169)	(0.158)	(0.119)	(0.116)	(0.019)
Hazard ratio, ages 70–103	0.952	0.964	1.689**	1.358***	1.125	0.547*
	(0.077)	(0.156)	(0.388)	(0.234)	(0.207)	(0.026)
Hazard ratio in 1997–2005	0.869**	1.820*	1.098	1.069	0.934	0.628*
	(.0.54)	(0.226)	(0.194)	(0.137)	(0.145)	(0.028)
Hazard ratio in 2006–2009	0.811*	1.184	1.393**	1.321**	0.940	0.582*
	(0.050)	(0.138)	(0.220)	(0.169)	(0.141)	(0.026)
Number of total unique subjects studied	203 702	26 214	24 886	25 714	25 517	203 702
Number of deaths	6 662	593	534	534	534	6 662

Table 9
Gompertz regression analysis for each study group

*, ** and *** stand for a significance level of 1%, 5% and 10%, respectively. A hazard ratio of 0.857 means that CEOs, compared to board members, have a 14% (1-0.857) lower risk of dying at any point of time Standard errors are reported in parentheses.

Gompertz regression estimates of mortality hazard ratios 1997–2009

	CEOs	CEOs in small companies	CEOs in the finance industry	CEOs in the service industry	CEOs in the trade industry	Females
Hazard ratio	0.857*	1.447*	1.260**	1.200**	0.945	0.609*
	(0.037)	(0.121)	(0.147)	(0.107)	(0.101)	(0.019)
Hazard ratio, ages 40–69	0.836*	1.700*	1.154	1.127	0.863	0.668*
	(0.044)	(0.169)	(0.158)	(0.119)	(0.116)	(0.028)
Hazard ratio, ages 70–103	0.965	0.979	1.686**	1.365***	1.130	0.532*
	(0.078)	(0.154)	(0.385)	(0.233)	(0.206)	(0.026)
Hazard ratio in 1997–2005	0.886***	1.787*	1.119	1.056	0.930	0.627*
	(0.055)	(0.219)	(0.198)	(0.134)	(0.144)	(0.028)
Hazard ratio in 2006–2009	0.812*	1.200	1.386**	1.356**	0.966	0.590*
	(0.050)	(0.139)	(0.217)	(0.172)	(0.143)	(0.026)
Number of total unique subjects studied	203 702	26 214	24 886	25 714	25 517	203 702
Number of deaths	6 662	593	534	534	534	6 662

Table 10
GEE logistic model regression analysis of each study group

*, ** and *** stand for a significance level of 1%, 5% and 10%, respectively. The results of the GEE logistic regressions, a model to estimate population-average differences allowing for dependence within groups, are presented below. The variable female is specified in all models to account for gender differences. A main advantage to use a GEE logistic model is to calculate unbiased regression coefficients despite possible misspecification of correlation structure. However it does not account for censoring. Standard errors may be overestimated since age is used as a time-varying covariate. The reason why the number of total unique subjects studied differ from the size group compared to the industry groups is because some companies miss industry (SNI) codes. The reason why it differs between industries is because some CEOs have changed companies of which they are CEOs, and are therefore counted in both groups. An odds ratio of 0.839 means that CEOs, compared to board members, have a 16% (1-0.857) lower rate of death. Standard errors are reported in parentheses.

GEE logistic model regression estimates of mortality odds ratios 1997–2009

	CEOs	CEOs in small companies	CEOs in the finance industry	CEOs in the service industry	CEOs in the trade industry	Females
Odds ratio	0.839*	1.465*	1.250**	1.197**	0.949	0.606*
	(0.037)	(0.123)	(0.147)	(107)	(0.102)	(0.019)
Odds ratio, ages 40–69	0.825*	1.706*	1.152	1.119	0.862	0.662*
	(0.043)	(0.170)	(0.158)	(0.119)	(0.116)	(0.028)
Odds ratio, ages 70–103	0.945	0.970	1.698**	1.359***	1.129	0.527*
	(0.078)	(0.158)	(0.399)	(0.237)	(0.211)	(0.026)
Odds ratio in 1997–2005	0.869**	1.808*	1.106	1.047	0.931	0.625*
	(0.054)	(0.223)	(0.196)	(0.134)	(0.145)	(0.028)
Odds ratio in 2006–2009	0.792*	1.215***	1.383**	1.357**	0.972	0.585*
	(0.049)	(0.142)	(0.218)	(0.173)	(0.145)	(0.026)
Number of total unique subjects studied	203 702	26 214	24 886	25 714	25 517	203 702
Number of deaths	6 662	593	534	534	534	6 662