The Precocity-Longevity Hypothesis and Immortal Time Bias

Abstract

The precocity-longevity hypothesis, which associates an earlier success in career with a shorter lifespan, is re-examined with survival analysis techniques on a sample of 1672 U.S. governors living between 1717 and 1978. Immortal time bias was introduced to the sample through data collection, and both subsample creation and time-varying analysis are considered in order to account for the bias. Survival analysis modeling does not suggest significant correlations between age of success (age at election) and lifespan in control for the year of birth and the immortal time bias.

The Precocity-Longevity Hypothesis and Immortal Time Bias

1 Introduction

Proposed by Dr. Steward McCann in 2001, the precocity-longevity hypothesis refers to the conjecture that an individual who achieves an earlier success in their career than their peers tends to experience a shorter lifespan (McCann, 2001).

Preliminary studies in the past decade have shown controversial results on the precocity-longevity hypothesis. Dr. McCann first tested his hypothesis with 23 samples of individuals with eminent achievements such as presidency, Nobel prizes and Oscar awards. In the study, the 23 samples were divided into 5 categories: The Pearson correlation and the partial correlation between age of achievement and age of death, as well as the mean difference in longevity for the subsamples grouped by age of achievement, were calculated for each sample. The results from 22 of the 23 samples showed significant correlations between an early peak in career and a younger age of death (McCann, 2001).

A follow-up study conducted on a sample of U.S. governors also provided great support for the precocity-longevity hypothesis. Correlation and regression analyses were performed on the sample with control for year of birth, span of service, state of election and potential artifacts, and a significant positive correlation was detected between age at election and age of death in the presence of the other covariates (McCann, 2003).

More recently, a study was performed on a sample of 2971 Canadian-born National Hockey League (NHL) players who debuted between 1917 and 1986 to investigate the relationship between their career start age and length of lifespan. Kaplan-Meier and Cox regression survival analyses were used with control for player position and number of years played, and no significant correlation between career start age and length of lifespan was indicated by the data (Lemez, Wattie, Ardern, & Baker, 2014).

In 2016, the precocity-longevity hypothesis was re-examined with a sample of 1852 North American professional basketball players who debuted between 1946 and 1979. Three different measures were considered respectively as age of achievement: age of debut, age of fist All-Star game, and age of first All-League team selection. The influence of each of the three measures on age of death was studied with correlation tests, and the hazard ratio between the two subgroups with age of achievement above median and below median was calculated. The survival analyses indicated a lower risk of death for early achievers with no statistical significance, which did not support the hypothesis (Wattie, Lemez, Ardern, Rotondi, & Baker, 2016).

The goal of this research project is to apply survival analysis methods to investigate the relationship between age of achievement and longevity, and identify other factors that have significant impact on longevity.

In Section 2, we describe the data that we used to explore the precocity-longevity hypothesis. In Section 3 we provide the results of our analysis, and we discuss these results and their limitations in Section 4. In Section 5, we state the conclusions and potential future work of this project.

2 Data and Methods

The information about years of birth and death, year of first serving and span of serving for 1672 U.S. state governors was directly taken from the Biographical Directory of the Governors of the United States between 1789 and 1978 (Sobel & Raimo,1978).

In the dataset, the variable *span* refers to the span of service; *elecage* refers to the age at election and was calculated by the difference between the year of first service and the year of birth; *deathage* refers to the age at death and was calculated by the difference between the year of death and the year of birth; *lifeexpe* refers to the life expectancy in the general U.S. population corresponding to each governor at the age they were elected; *born* refers to year of birth for each governor; *statenum* refers to the different states the governors served in. The data of life expectancy is taken from the website "Life Expectancy, Whites and Non-Whites, 1900-1990" ("Historical Data from Historical Statistics of the United States; remainder from Statistical Abstract of the United States", n.d.). The life expectancy variables were recorded into the dataset with adjustments: life expectancy values on the election age were based on 1850 expectancy estimate for governors who were elected at the years up to 1870, on 1890 expectancy estimate for governors who were elected between 1871 and 1895, on 1900 expectancy estimate for governors who were elected between 1896 and 1905, on 1910 expectancy estimate for governors who were elected between 1906 and 1915, etc. For the election age that connects to the year of expectancy estimate, estimates for governors elected from age 23 to 25 were based on the estimate of age 20, estimates for governors elected from age 26 to 35 were based on the estimate of age 30, estimates for governors elected from age 36 to 40 were based on the estimate for age 40, etc. The difference in years between the actual death age of each governors and the life expectancy of the governors can be then calculated by subtraction for future reference. The units for all the variables mentioned above are years. No governors were selected from Alaska or Hawaii, thus *statenum* has only 48 levels. However, the correspondence relationship between states and levels is not clearly indicated in the dataset.

It is noteworthy that only "deceased governors with no living predecessors" (McCann, 2003) were included in the data. We interpret this assumption as a method to eliminate censored data. First, including only the deceased governors guarantees that the exact death year for every governor was recorded, and thus the exact lifespan can be calculated for each of them. In addition, the fact that all the governors in the data have no living predecessors avoids the inclusion of some governors who died of accidents or other unnatural causes at a relatively young age. Thus, in our research using survival analysis, we consider the status of all data as exact.

With the *survival* and *survminer* packages in R, we plot the Kaplan-Meier curves for the lifespan variable *deathage*, and conduct forward model selection with different parametric assumptions including weibull distribution and lognormal distribution. Likelihood ratio tests are performed, and Akaike information criterion (AIC) scores are calculated to compare the parametric regression models. We also consider the semi-parametric Cox PH model, and test the PH assumption by graphing the Schoenfeld residuals of the model.

We are mostly interested in the relationship between *deathage* and *elecage* as well as between *deathage* and *span*, as these variables are closely related to the precocity-longevity hypothesis. We have also considered the different states as a categorical variable to analyze if the geographic location can influence people's lifespan. It is also important to include the variable *lifeexpe* in our model, since the precocity-longevity hypothesis predicts an effect on the lifespan of early achievers compared to their expected lifespan, which changes over different time periods.

3 Results

3.1 Overview of the Lifespan Data

The Kaplan-Meier curve for the lifespan of all 1672 governors is plotted in Figure 1. The variable ranges from 32 to 103 years, with a mean of 70.19 years, a median of 71 years and a standard deviation of 11.63 years. A regression model assuming weibull distribution, which is chosen due to a larger log likelihood compared to exponential distribution, normal distribution and lognormal distribution, is fitted to the Kaplan-Meier curve with great consistency.

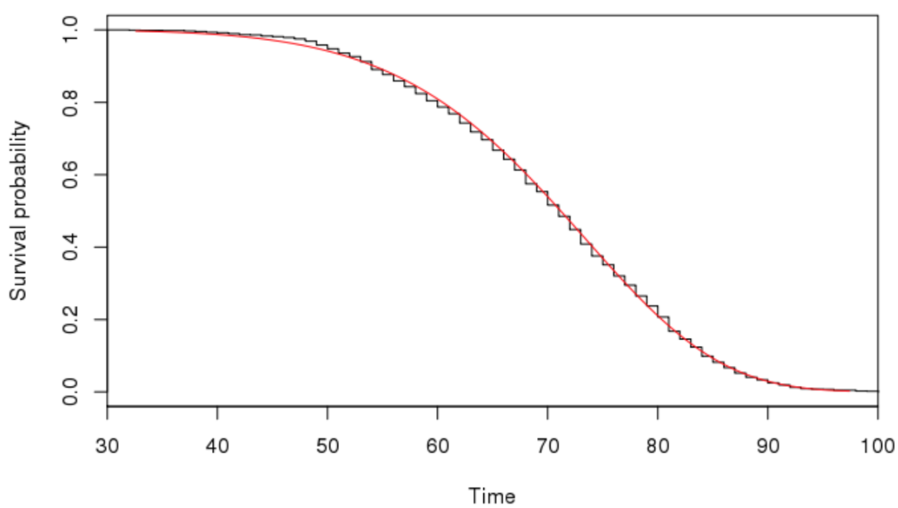


Figure 1: The Kaplan-Meier curve for the lifespan of all governors (in black) with a fitted weibull regression model (in red).

3.2 Stochastic Ordering of Lifespan grouped by Age at Election

In order to visualize the effect of age of achievement on lifespan and perform a log-rank test on it, the 1672 governors were grouped by age at election into three categories. The age at election for all governors in the dataset ranges from 23 to 82 years old. The governors in the first group were elected at the age between 20 (23) and 40; the governors in the second group were elected at the age between 40 and 60; those elected at the age older than 60 belong to the last group.

From Figure 2, The Kaplan-Meier curves of the three age groups show significant stochastic ordering, with younger age at election corresponding to shorter lifespan. Consistently, a log-rank test indicates that there is a significant relationship between lifespan and age at election at the 0.001 level.

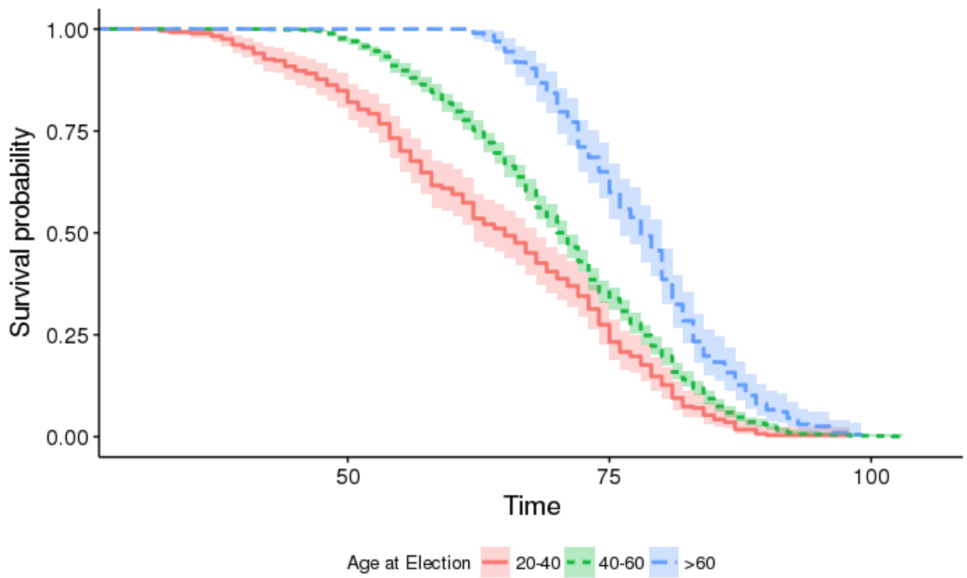


Figure 2: The Kaplan-Meier curves for the lifespan of governors grouped by age at election. The three groups are defined by the age of election between 20 and 40, between 40 and 60, and over 60. Shaded areas represent 95% confidence intervals.

3.3 Parametric Regression and Model Selection

The significance of the relationship observed from Figure 2 was further tested with an Accelerated Failure Time (AFT) model, where a weibull distribution is assumed and the age at election is treated as a continuous, quantitative variable. The model coefficient for *elecage* shows great statistical significance in the direction that is consistent with the precocity-longevity hypothesis ($p = 3.84 \times 10^{-27}$). Based on this model, we controlled for life expectancy, the span of service, and the year of birth, and the age at election remains a significant predictor for longevity in the presence of those variables. The model coefficients with standard errors and statistical significance are summarized in Table 1, with log likelihood calculated for each of the four models.

We conduct a forward selection for the most efficient model under the assumption of the weibull distribution. Within each step, we compare the two models of interest by a likelihood ratio test if they are nested, and by Akaike Information Criterion (AIC) if they are not nested. The method leads to the selection of weibull model ($deathage \sim elecage{+}span{+}born$).

Table 1: Results from Weibull AFT Models for lifespan using age at election, life expectancy, the span of service, and the year of birth. The model coefficients are summarized with standard errors in the parentheses and significance marked.

	Dependent variable:			
	deathage			
	(1)	(2)	(3)	(4)
elecage	0.004^{***}	0.004^{***}	0.004^{***}	0.004^{***}
	(0.0004)	(0.001)	(0.0004)	(0.0004)
lifeexpe		-0.001		
		(0.002)		
span			0.002^{**}	0.002^{**}
			(0.001)	(0.001)
born				0.0005^{***}
				(0.0001)
Constant	4.116^{***}	4.165^{***}	4.102^{***}	3.187^{***}
	(0.019)	(0.091)	(0.020)	(0.166)
Observations	1,672	1,672	1,672	1,672
Log Likelihood	−6,403.734	−6,403.583	−6,401.158	−6,386.028
χ^2	118.780^{***} (df = 1)	119.082^{***} (df = 2)	123.933^{***} (df = 2)	154.192^{***} (df = 3)
Note:				*p<0.1; **p<0.05; ***p<0.01

A similar forward model selection precedure is performed while assuming a lognormal distribution of longevity, and results in a model for *deathage* using the same set of explanatory variables: *elecage*, *span*, and *born*. Then the selected lognormal model ($deathage \sim elecage+span+born$) is compared with the selected weibull model ($deathage \sim elecage+span+born$) by the calculation of Cox-Snell residuals and Akaike Information Criterion (AIC). Both Cox-Snell residuals and AIC suggest that the weibull AFT model ($deathage \sim elecage+span+born$) provides a better fit for the data.

3.4 Immortal Time Bias

Despite the statistical significance we observe in both non-parametric and parametric models discussed in Section 3.2 and 3.3, there is potential bias in favor of the precocity-longevity hypothesis in the dataset that needs to be addressed. The immortal time bias refers to bias induced in data collection due to "a span of time in the observation or follow-up period of a cohort during which the outcome under study could not have occurred" (Suissa, 2007). In our project, the outcome under study is the death of the governors, and the "immortal time" is the time interval from the year of birth to the year at election for every governor. In other words, a governor who was elected at a particular age is guaranteed to have a lifespan at least as long as that age, as being elected at the age implies the fact that they have survived to the age. Thus, when we compare the lifespan of governors with different ages at election, we are essentially comparing the longevity of several groups with predictably different minimum survival.

Due to the immortal time bias, we are more likely to observe stochastically ordered survival curves shown in Figure.2, and small p-values of the age at election as a predictor for lifespan shown in Table 1. If the significant relationship between the age at election and the age of death is only caused by the bias, the results from the previous models could not be considered supporting evidence for the precocity-longevity hypothesis.

In order to control for the immortal time bias, we consider the subsample which include governors with a minimum deathage equal to the lower bound for age at election in the latest-elected group, which is 60 years old in our study. This method controls for the immortal time bias for the two groups of governors with younger ages at election (20-40 and 40-60), as every governor in the two groups are equally guaranteed a minimum lifespan of exactly 60 years old. On the other hand, the immortal time bias still exists when we compare the two groups with younger ages at election to the last group, as the governors in the last group have different minimum ages, or ages at election, that are at least 60 years old. As a result, we focus on the comparison between the two groups elected at ages of 20-40 and 40-60. Specifically, we further filter out governors elected after they were 60 years old and ended up with a new subsample, and perform the same survival analyses on the new subsample. The model coefficients with standard errors and statistical significance are summarized in Table 2. We observe that age at election is not a significant predictor for lifespan after we control for the bias, and the selected model is a weibull AFT model ($deathage \sim born$).

Table 2: Results from Weibull AFT Models for lifespan using age at election, life expectancy, the span of service, and the year of birth using the subsample with a minimum *deathage* of 60 and a maximum *elecage* of 60. The model coefficients are summarized with standard errors in the parentheses and significance marked.

	Dependent variable:			
	deathage			
	(1)	(2)	(3)	(4)
elecage	0.001	0.001*	0.001	0.001
	(0.0005)	(0.001)	(0.0005)	(0.0005)
lifeexpe		−0.002		
		(0.002)		
span			−0.0002	
			(0.001)	
born				0.0003***
				(0.0001)
Constant	4.320***	4.412***	4.321***	3.733***
	(0.023)	(0.088)	(0.024)	(0.160)
Observations	1,088	1,088	1,088	1,088
Log Likelihood	−3,885.213	−3,884.634	−3,885.174	−3,878.495
χ^2	2.292 (df = 1)	3.451 (df = 2)	2.370 (df = 2)	15.729*** (df = 2)
Note:				*p<0.1; **p<0.05; ***p<0.01

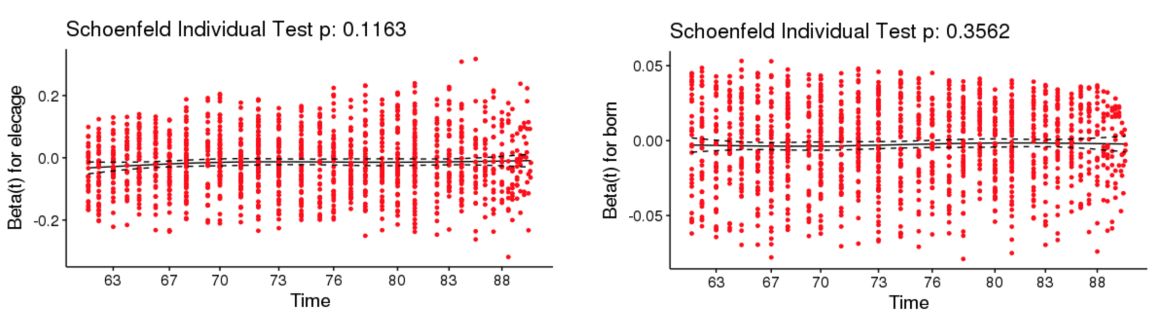
3.5 Semi-parametric Proportional Hazards Models

Given that the weibull regression model has proportional hazards, we further model lifespan with a Cox PH model, which is a semi-parametric model with proportional hazards, and perform forward model selection for the same set of predictors. The results are summarized in Table 3, which also show diminished effect of age at election in the presence of year of birth, with a Cox PH model ($deathage \sim born$) selected.

Table 3: Results from Cox PH Models for lifespan using age at election, life expectancy, the span of service, and the year of birth using the subsample with a minimum *deathage* of 60 and a maximum *elecage* of 60. The model coefficients are summarized with standard errors in the parentheses and significance marked.

	Dependent variable:			
	deathage			
	(1)	(2)	(3)	(4)
elecage	−0.006	−0.010	−0.006	−0.005
	(0.004)	(0.006)	(0.004)	(0.004)
lifeexpe		0.014		
		(0.014)		
span			0.001	
			(0.008)	
born				−0.003***
				(0.001)
Observations	1,088	1,088	1,088	1,088
R^2	0.002	0.002	0.002	0.012
Max. Possible R^2	1.000	1.000	1.000	1.000
Log Likelihood	−6,522.943	−6,522.471	−6,522.929	−6,517.214
Wald Test	1.760 (df = 1)	2.700 (df = 2)	1.780 (df = 2)	13.350*** (df = 2)
LR Test	1.746 (df = 1)	2.689 (df = 2)	1.774 (df = 2)	13.203*** (df = 2)
Score (Logrank) Test	1.757 (df = 1)	2.699 (df = 2)	1.785 (df = 2)	13.374*** (df = 2)
Note:				*p<0.1; **p<0.05; ***p<0.01

The Schoenfeld residuals for the selected model are graphed in Figure 3 in order to test the proportional hazards assumption for the Cox regression model.



(a) Schoenfeld residuals for age at election

(b) Schoenfeld residuals for year of birth

Figure 3: The Schoenfeld residuals for the Cox PH model *deathage* ∼ *elecage*+*born*.

With the subsample we create to account for immortal time bias, we group the governors by their age at election into five groups, and graphed their Kaplan-Meier curves respectively in Figure 4. The five curves overlap significantly at all time, which agrees with the results from the weibull AFT model and the Cox PH model.

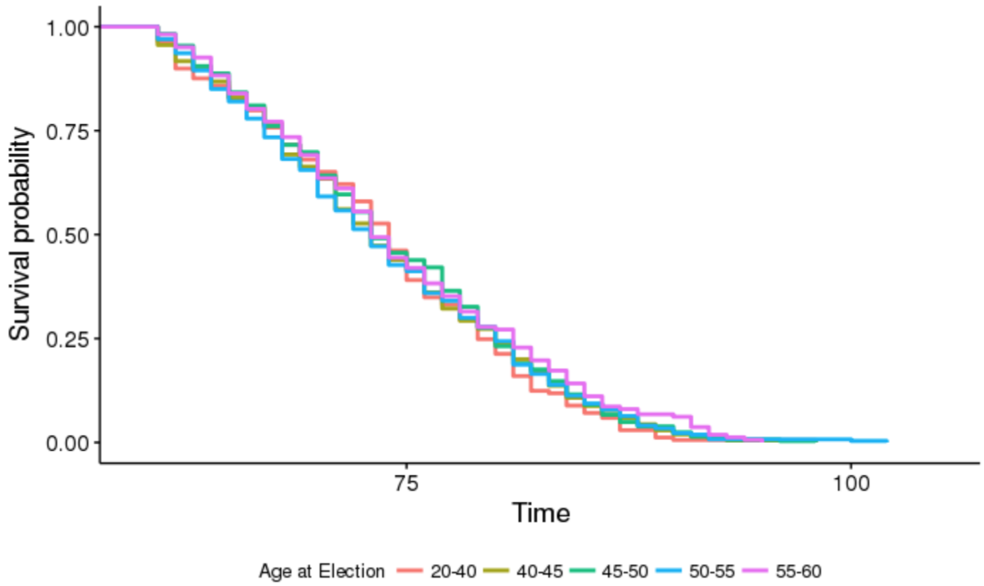
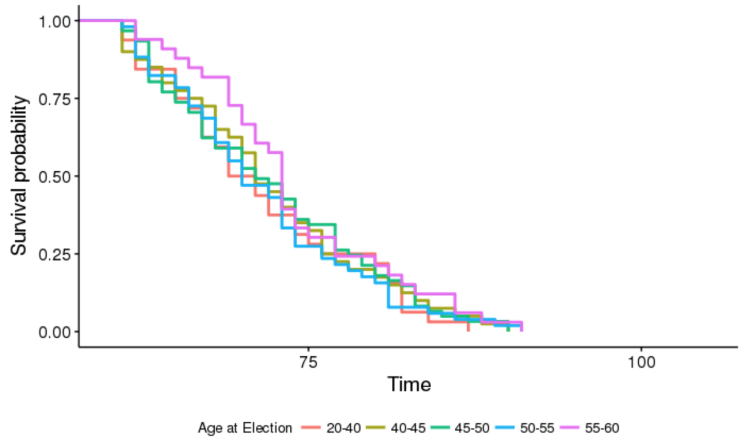
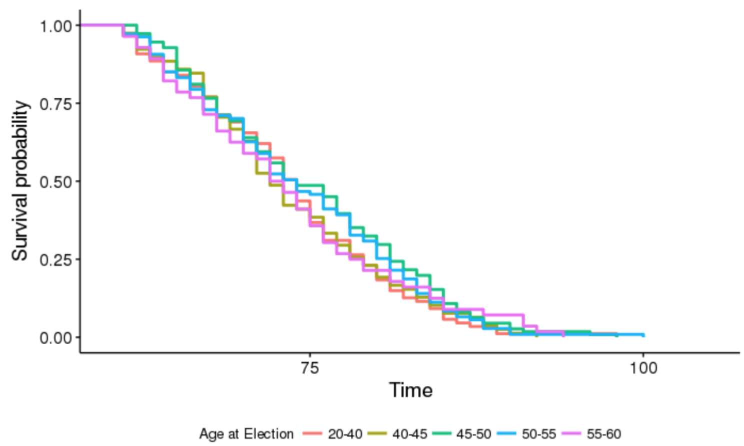


Figure 4: The Kaplan-Meier curves for the lifespan of governors grouped by age at election, with control for immortal time bias.

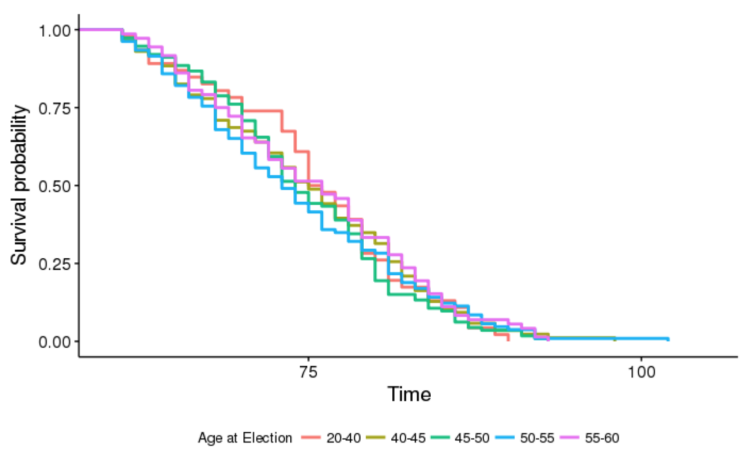
In order to better visualize the impact of year of birth on longevity, we graphed the same set of five Kaplan-Meier curves for governors who were born before 1800, between 1800 and 1850, and after 1850. The results are summarized in Figure 5. Within each interval of year of birth, we observe that Kaplan-Meier curves overlap at all time, which indicates age at election is not significantly related to lifespan after we control for year of birth. Through a comparison of the three plots, we observe an increasing trend in average lifespan as year of birth increases. This agrees with our intuition that the expected lifespan of a general person is longer if they were born more recently between 1717 and 1909.



(a) Governors born between 1717 and 1800



(b) Governors born between 1800 and 1850



(c) Governors born between 1850 and 1909

Figure 5: The Kaplan-Meier curves for the lifespan of governors grouped by age at election, with control for immortal time bias for governors born (a) between 1717 and 1800 (b) between 1800 and 1850 (c) between 1850 and 1909.

4 Discussion

In our search for the predictors for lifespan of the governors, year of birth is the only variable that remains its statistical significance in the presence of other covariates. The other covariates, including age at election, span of service and life expectancy, do not have significant impact on lifespan when we control for year of birth and immortal time bias in both parametric regression and semi-parametric Cox proportional hazards (PH) models. The PH assumption is tested to be valid through plotting of the Schoenfeld residuals and hypothesis testing.

In other words, the results of our analyses do not support the proposed precocity-longevity hypothesis. The variance in lifespan is mostly explained by the time that the governors live in, instead of how early they were elected as governors in their lives. This agrees with the two previous studies performed on samples of sports players with survival analysis methods.

However, the approximation method used to control for the immortal time bias can potentially eliminate the effect of the precocity-longevity hypothesis. The method assumes that for most governors, the negative effect on longevity due to early success only occurs after the age of 60. If the assumption does not hold, and the true effect of the hypothesis occurs earlier than the age of 60 for the governors, the part of data supporting the hypothesis would have been filtered out as we create the subsample in order to control for immortal time bias. Therefore, the effect of precocity-longevity hypothesis needs to be further explored.

We think it is interesting that year of birth is a better predictor for lifespan than life expectancy, which is designed to be the expected lifespan based on both the time and the current age of a person. One possible explanation is that when the data were collected, life expectancy was recorded based on the 10-year intervals of time and 10-year intervals of current age that a governor falls in. The approximation leads to larger uncertainty than the original year of birth, which turns out to make life expectancy a worse predictor of lifespan than the raw data of year of birth.

5 Conclusion

In this project, we re-examined the precocity-longevity hypothesis proposed by Dr. McCann in 2001 with a dataset of 1672 U.S. governors living between 1717 and 1978. Survival analysis modeling does not indicate significant correlations between age at election and lifespan in control for the year of birth and the immortal time bias. Our results do not support the precocity-longevity hypothesis.

Besides the conclusion, there are some limitations of this project that we would like to address. First of all, the age at election of governors is better treated as a time-varying covariate, which indicates whether or not the governor has been elected in a certain year. With the expansion of the original dataset to include one year for each governor as an observation, we will be able to model the effect of being elected as a governor on lifespan. Unfortunately, it is impossible to model such effect with a Cox PH model in our dataset, as the risk of death in the not-elected observations is essentially zero due to the immortal time bias. However, if we could combine the dataset with external data of unelected individuals with similar time and social background, such as a sample of individuals who ran for governors but were not elected, we would be able to fit the combined dataset with a Cox PH model for the effect of the time-varying covariate associated with being elected.

In addition, the absence of status indicator in the dataset creates difficulties for performing survival analysis. As we discussed in Section 2, we assumed the status of all records in the dataset to be exact due to the fact that all the governors in the dataset have no living predecessors. However, these two statements are clearly not equivalent. There might be some cases when a young governor without living predecessors died of accidents, but their record was indicated as exact in the dataset. This assumption and the resulting neglect of censoring data would lead to underestimation of survival for younger governors, which also makes the observed stochastic ordering less convincing in terms of supporting the precocity-longevity hypothesis.

In future work, we would like to re-examine the hypothesis with a more comprehensive dataset which allows us to treat achievement as a time-varying covariate, so that we can model its effect with PH models. Specifically, we hope to combine the dataset with another sample of individuals living between 1700 and 1900 who ran for governors but were not elected, so that the combined dataset contain individuals with similar cultural background but were only different in whether or not they had an early achievement of being elected. There are other factors that could potentially impact longevity that we did not have access to, such as workload, pressure, exposure to public, popularity, marital status, personality, mental health, etc. Also, we are interested in looking into better alternatives to control for the immortal time bias in statistical studies.

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