Mortality Analysis of 1898-1902 Birth Cohort

December 2018

Mortality Analysis of 1898-1902 Birth Cohort

SPONSOR Reinsurance Section
Committee on Life Insurance Research
Product Development Section

AUTHORS Natalia S. Gavrilova, PhD
Leonid A. Gavrilov, PhD

The Sponsors and Authors would like to thank the following members of the Project Oversight Group:

Tom Edwalds, Chair
Mark Birdsall
Jean-Marc Fix
Tristan Fontugne
Natalie Gleed
Matt Hansen
Edward Hui
Brian Ivanovic
Bert Kestenbaum
Al Klein
Hezhong (Mark) Ma
Peretz Perl
Jeffery Rykhus
Ronora Stryker, Research Actuary
Jan Schuh, Sr. Research Administrator

CONTENTS

EXECUTIVE SUMMARY **4**

SECTION 1: BACKGROUND **6**

SECTION 2: DESCRIPTION OF DATA USED **7**
- 2.1 Main Data Resource 7
- 2.2 Supplementary Data Resources 14
- 2.3 Constructing final data set with supplementary data resources 15

SECTION 3: DATA QUALITY EVALUATION PROCEDURES **18**
- 3.1 Direct age validation 18
- 3.2 Indirect methods of data quality assessment 18
- 3.3 Results of age validation procedure for 1898–1902 birth cohorts 20
- 3.4 Mortality reconstruction based on results of age validation procedure 23

SECTION 4: ESTIMATION OF THE FORCE OF MORTALITY **27**
- 4.1 Force of mortality after age 85, by different levels of data quality 27
- 4.2 Mortality variation by the region of last residence 33
- 4.3. Mortality variation by the region of SSN application 35
- 4.4. Mortality changes at advanced ages over time 37
- 4.5 Monthly estimates of the force of mortality 38

SECTION 5: CRITIQUE OF MORTALITY ESTIMATION METHODS BY HUMAN MORTALITY DATABASE AND THE SOCIAL SECURITY ADMINISTRATION **43**
- 5.1 Social Security Administration 43
- 5.2 Human Mortality Database 48

SECTION 6: KEY OBSERVATIONS AND CONCLUSIONS **52**

SECTION 7: ACKNOWLEDGEMENTS **53**

APPENDIX — MORTALITY DATA CHARACTERISTICS FOR 1898–1902 BIRTH COHORT **54**

REFERENCES **57**

Mortality Analysis of 1898–1902 Birth Cohort

Executive Summary

Throughout the actuarial and demographic communities, colleagues debate the shape and level of mortality at the very advanced ages. The goal of this project is to address that question by identifying the old-age mortality trajectories for the five extinct (or nearly extinct) U.S. cohorts with a birth year of 1898, 1899, 1900, 1901 and 1902. Special attention was devoted to the data-cleaning procedure to identify whether the mortality deceleration at the older ages reported by some could be an artifact of poor data quality.

We assessed data quality by age group through the direct age validation of samples of records of people at ages 100, 103, 105 and 109 or over taken from the Social Security Administration Death Master File (DMF). The assessment involved individual age validation by linkage to historical resources available in the Ancestry.com database. The age of each person in the sample was evaluated by its concordance to a number of historical sources, including but not limited to decennial censuses. Depending on the result of this validation, the value for the age was rated as either good or poor quality.

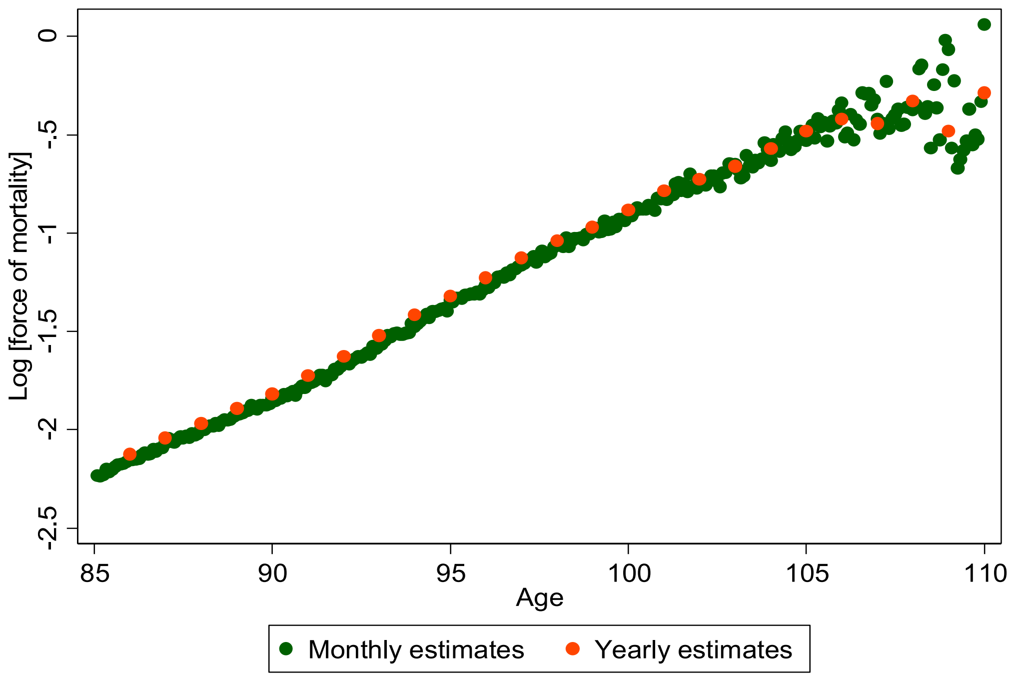
Our research found that the quality of age reporting did not differ significantly across the five studied historical birth cohorts, despite our initial expectation that more recent cohorts would have better data quality. In addition, a statistically significant increase was noted in the proportion of records with poor quality at age 109 compared to age 105, but no statistical difference was found in the proportion of poor-quality records within the ages of 100, 103 and 105.

In this project, we used actuarial estimates of the force of mortality (central death rate). Monthly (rather than traditional yearly) empirical estimates of the force of mortality are more accurate at extreme old ages. We found that monthly estimates of the force of mortality are higher after age 105 compared to traditional yearly estimates.

In addition, monthly estimates of the force of mortality produce more Gompertz-like mortality trajectories, which translates to straighter lines on a semilog scale compared to yearly estimates (up to age 108 years). An example of monthly and yearly mortality estimates for the 1898–1902 combined birth cohort are presented in Figure E1.

Figure E1

FORCE OF MORTALITY FOR 1898–1902 BIRTH COHORT (QUALITY-ADJUSTED DATA)



Although we looked at mortality difference by region, no significant differences were identified whether the regions were the region of last residence or the region where the Social Security number was obtained. Thus, regional mortality differences are negligible at extreme old ages. These results once again confirm the more general observation that many factors affecting mortality during midlife lose their importance after age 100.

Similarly, birth cohort had no effect on mortality for ages over 95 for the studied birth cohorts. That is, there was no improvement in mortality over time from the 1898 to the 1902 birth cohorts.

Mortality estimates obtained by the method of extinct generations based on DMF data are close to the corresponding cohort death rates presented in the Human Mortality Database up to age 110. The Social Security Administration estimates of cohort probabilities of dying are also in good agreement with the estimates obtained in this project up to age 105.

Our research confirms that the quality of age reporting after age 105 in the U.S. is low for the studied cohorts, which results in more apparent mortality deceleration at advanced ages. Data quality adjustments based on the results of the age validation procedure we used lead to more Gompertz-like monthly estimates of the mortality trajectories up to age 108 or older (depending on birth cohort and sex).

Finally, detailed mortality tables by age and gender can be found in Appendix.

Section 1: Background

Global population aging and rapid growth of older populations in industrialized countries underscores the need for accurate estimates of mortality at advanced ages, which are essential for population forecasts. Such estimates are also important in actuarial science because of the growing market for deferred income annuities, which are sensitive to assumptions about high age mortality (Milevsky 2014). Earlier studies suggested that the exponential growth of mortality with age, as described in Gompertz law, is followed by a period of deceleration, with slower rates of mortality increase (Greenwood and Irwin 1939; Horiuchi and Wilmoth 1998; Thatcher et al. 1998; Thatcher 1999). Most systematic studies of mortality at advanced ages have been conducted in the 1990s. Thatcher and colleagues tested several models of mortality using data on 13 countries with presumably good quality of mortality statistics (Thatcher et al. 1998; Thatcher 1999). In their report, the researchers concluded that the logistic and Kannisto models fit the observed values of mortality after age 80 years far better than the Gompertz and Weibull models (Thatcher et al. 1998).

Another approach to studying mortality deceleration after age 80 was applied by Horiuchi and Wilmoth. In this study, researchers analyzed age trajectories of the life table aging rate (LAR) for period and cohort mortality in Sweden and Japan and found that LAR has a tendency to decline after ages 75–80 years, suggesting downward deviation of mortality from the Gompertz law. These early studies as well as studies on insects (Carey et al. 1992; Curtsinger et al. 1992) convinced many researchers of the universality of the mortality deceleration phenomenon, so until recently there was no doubt among demographers that mortality slows down after the age of 80 or 85 (Robine 2007; Gampe 2010; Bebbington et al. 2014).

Researchers returned to mortality analyses at advanced ages only recently, using data for different countries. In our earlier research we found that mortality of U.S. extinct cohorts born after 1889 demonstrated the Gompertz-like trajectory of mortality growth in the age interval 85–106 years (Gavrilov and Gavrilova 2011). Due to limitations of the data source used in that study (Social Security Administration Death Master File, or DMF), hazard rates were estimated for both sexes together. In the study of old-age mortality in 15 low-mortality countries, Bebbington and coauthors found the Gompertz-like mortality growth at older ages for Australia, Canada and the United States and mortality deceleration for other countries (Bebbington et al. 2014).

Hazard rate estimation at very old ages presents difficulties because of the very small number of survivors to these ages as well as age misreporting by older persons. Age misreporting may still be a problem affecting estimates of mortality at advanced ages (Kestenbaum 1992; Coale 1996; Elo et al. 1996; Hill et al. 1997; Jdanov et al. 2008). Researchers found that even small percentages of inaccurate data can greatly distort mortality trajectories at advanced ages (Yi et al. 2007). In most cases, age misreporting at older ages results in mortality underestimation (Preston et al. 1999). Taking into account that the accuracy of age reporting is positively correlated with education (Elo et al. 2013), it is reasonable to expect improvement in age reporting over time and less prevalent mortality underestimation, or mortality deceleration at older ages for more recent birth cohorts. Indeed, we have found that mortality at advanced ages in older historical U.S. birth cohorts shows stronger mortality deceleration compared to more recent birth cohorts (Gavrilov and Gavrilova 2011). These data suggest that a spurious mortality deceleration could be caused by age misreporting at older ages when the first systematic studies of mortality trajectories were conducted (Wilmoth 1995; Horiuchi and Wilmoth 1997; Horiuchi and Wilmoth 1998; Thatcher et al. 1998; Thatcher 1999).

Previous studies of old-age mortality conducted in the 1990s avoided use of U.S. data due to concerns that the quality of old-age data in the United States is not sufficiently good. As a result, there is a lack of information about U.S. mortality trajectories at advanced ages. This project intends to fill this information gap by reconstructing the age trajectory of mortality for 1898–1902 U.S. birth cohorts. This project is focused on the study of U.S. old-age mortality taking into account that the United States has the largest number of survivors to age 100 among the advanced economies. Refining data at the tail of the survival curves gives us an opportunity to obtain more reliable estimates of mortality at advanced ages.

Section 2: Description of Data Used

2.1 Main Data Resource

2.1.1 Social Security Administration Death Master File

DMF is a publicly available data source that enables searching for deceased individuals in the United States using various search criteria: birth date, death date, first and last names, Social Security number and place of last residence (Table 1).

Table 1

SEARCHABLE VARIABLES IN THE DEATH MASTER FILE

- First, last names, Social Security number (SSN)
- Date, month, year of birth
- Month, year of death
- State of the SSN application
- Town, county, state, zip code of the last residence
- Death date verification code

Some birth cohorts covered by DMF can be studied by the method of extinct generations (Vincent 1951; Kannisto 1988; Kannisto 1994). Availability of month of birth and month of death information provides a unique opportunity to obtain hazard rate estimates for every month of age, which helps to improve accuracy of hazard rate estimation. We successfully used DMF for death date validation of centenarians in our previous studies on exceptional longevity (Gavrilov and Gavrilova 2015). This resource covers deaths that occurred after 1937 (Faig 2002) and captures about 95 percent of deaths recorded by the National Death Index (Sesso et al. 2000) and about 92–96 percent of deaths for persons older than 65 years (Hill and Rosenwaike 2001).

In this project, the DMF records are used to evaluate the quality of age reporting at extreme old ages and to estimate the force of mortality for ages 85 years and up, separately by gender, for the U.S. 1898–1902 birth cohorts. We use the last complete version of DMF officially obtained from the U.S. National Technical Information Service (NTIS). Taking into account that the latest deaths in this version were observed in September 2011, we use supplementary data sources for deaths occurring after September 2011 (see section 2.2).

There might be a question of why not to use vital statistics data for this project. Indeed, publicly available mortality files provided by the National Vital Statistics Service contain individual death records including information on deaths occurring in 2012–2016. However, these records are de-identified for confidentiality reasons and do not have information about first and last names, state of death or even year of birth. Absence of personal information makes it impossible to conduct direct validation of records at advanced ages and to make quality adjustments of mortality estimates, the main objective of this project.

After November 1, 2011, completeness of DMF versions provided by NTIS significantly declined, so the September 2011 version of DMF is the last complete version of this file used for the purpose of this project.

2.1.2 Gender Assignment Protocol for DMF

DMF does not have information about gender; therefore, we have performed a gender assignment procedure for each record using the SSA tables of the top 1,000 most common male and female first names in 1900 supplemented by our own list of male and female first names compiled after working with genealogies. This step is necessary because gender information for first names in the original SSA database appears to contain errors, as typical female names like Elizabeth appear in SSA tables of common male names and male names like John appear in the SSA list of common female names (Gavrilov and Gavrilova 2011). Our prior experience revealed that corrected SSA first-name lists allowed us to assign sex to about 90 percent of records (Gavrilov and Gavrilova 2011). Additional work with individual records can increase this percentage to approximately 91 percent, as we did for the 1900 birth cohort. The validity of this gender-assigning procedure was confirmed when mortality of men and women in DMF cohorts was compared to gender-specific U.S. death rates based on vital statistics where gender is already known. This comparison demonstrated very good agreement in gender-specific mortality between two different data sources (see Figures 1–6). Table 2 shows distribution of records by results of the gender assignment procedure for 1898–1902 birth cohorts. Note that the proportion of records with nondefined gender is approximately the same for all five birth cohorts (9–10 percent). In the case of the 1900 birth cohort, additional gender assignment measures (after age 100 years) have been undertaken using direct linkage to historical resources.

Table 2

NUMBER OF RECORDS (PERCENT) IN DMF, BY AGE AND GENDER

Birth Cohort	**Age 85+**			**Age 100+**		
	Men	Women	Not Defined	Men	Women	Not Defined
1898	131,004 (29.1)	278,112 (61.8)	40,705 (9.1)	2,497 (14.4)	13,099 (75.8)	1,686 (9.8)
1899	125,584 (28.9)	269,671 (62.0)	39,660 (9.1)	2,355 (14.0)	12,761 (76.1)	1,662 (9.9)
1900	139,067 (28.8)	298,397 (61.9)	44,826 (9.3)	2,669 (14.6)	14,030 (76.7)	1,598 (8.7)
1901	132,581 (28.4)	289,207 (62.0)	44,979 (9.6)	2,568 (14.7)	13,197 (75.5)	1,720 (9.8)
1902	145,616 (28.5)	315,211 (61.7)	50,142 (9.8)	2,736 (14.5)	14,291 (75.6)	1,880 (9.9)
Total	673,852	1,450,598	220,312	12,802	67,310	8,641

We tested the validity of this gender assignment procedure for all five birth cohorts by comparing gender-specific mortality estimates based on DMF data with U.S. age-specific cohort death rates available in the Human Mortality Database (HMD). Figures 1–5 compare gender-specific mortality based on DMF gender assignment with corresponding mortality from HMD (based on vital statistics with known information on sex).

Figure 1

FORCE OF MORTALITY FOR MEN AND WOMEN BORN IN 1898, COMPARISON OF DMF AND HMD DATA

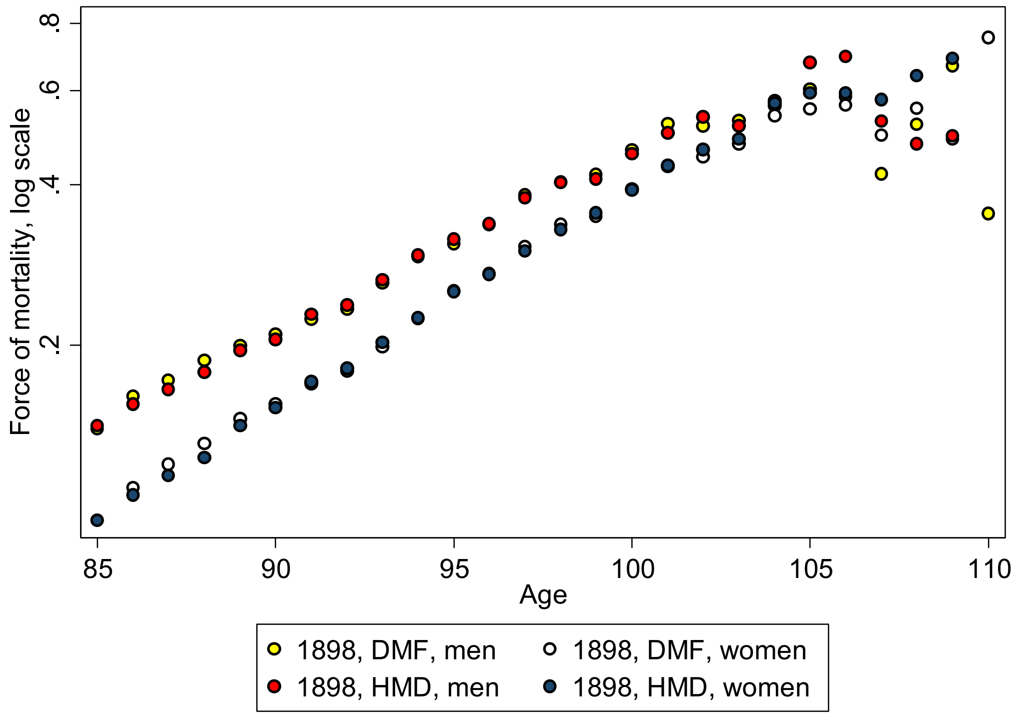


Figure 2

FORCE OF MORTALITY FOR MEN AND WOMEN BORN IN 1899, COMPARISON OF DMF AND HMD DATA

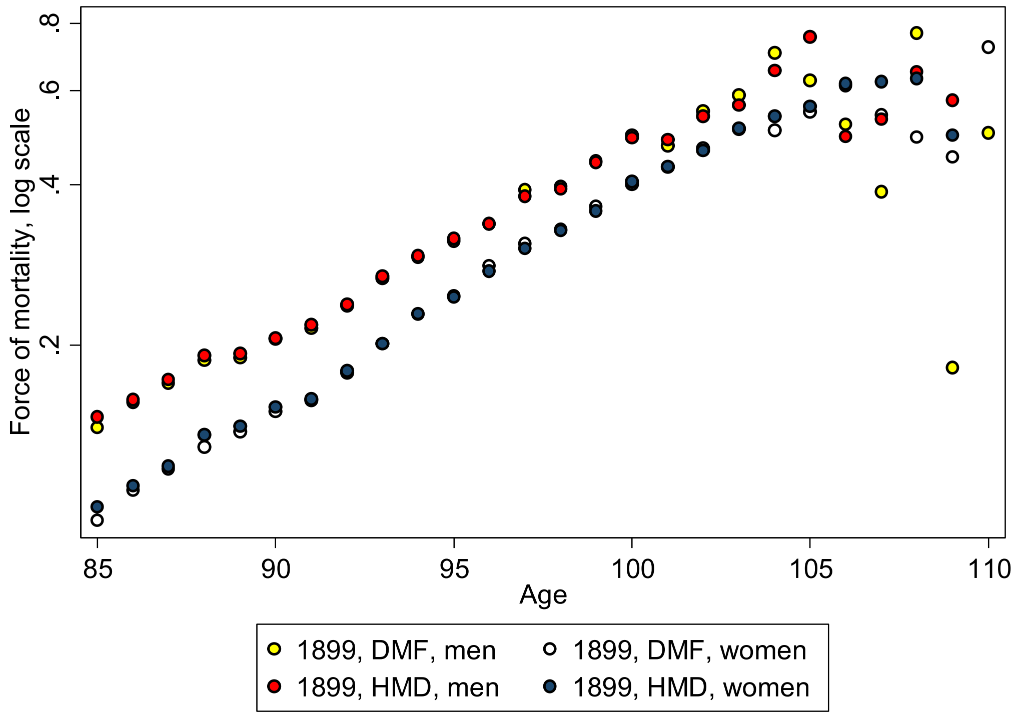


Figure 3

FORCE OF MORTALITY FOR MEN AND WOMEN BORN IN 1900, COMPARISON OF DMF AND HMD DATA

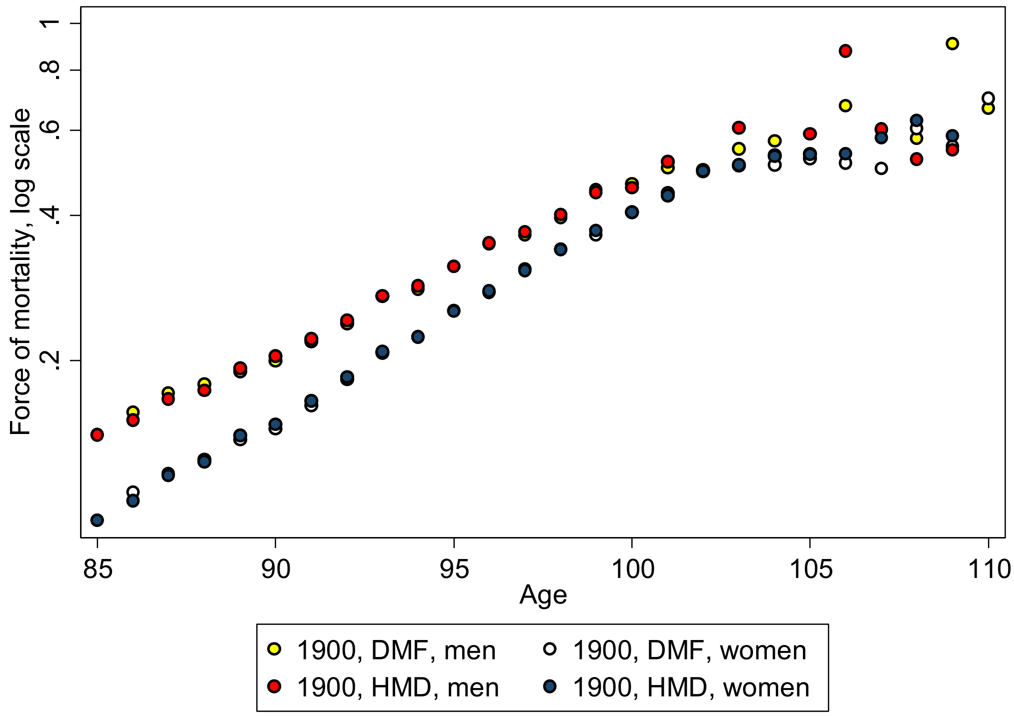


Figure 4

FORCE OF MORTALITY FOR MEN AND WOMEN BORN IN 1901, COMPARISON OF DMF AND HMD DATA

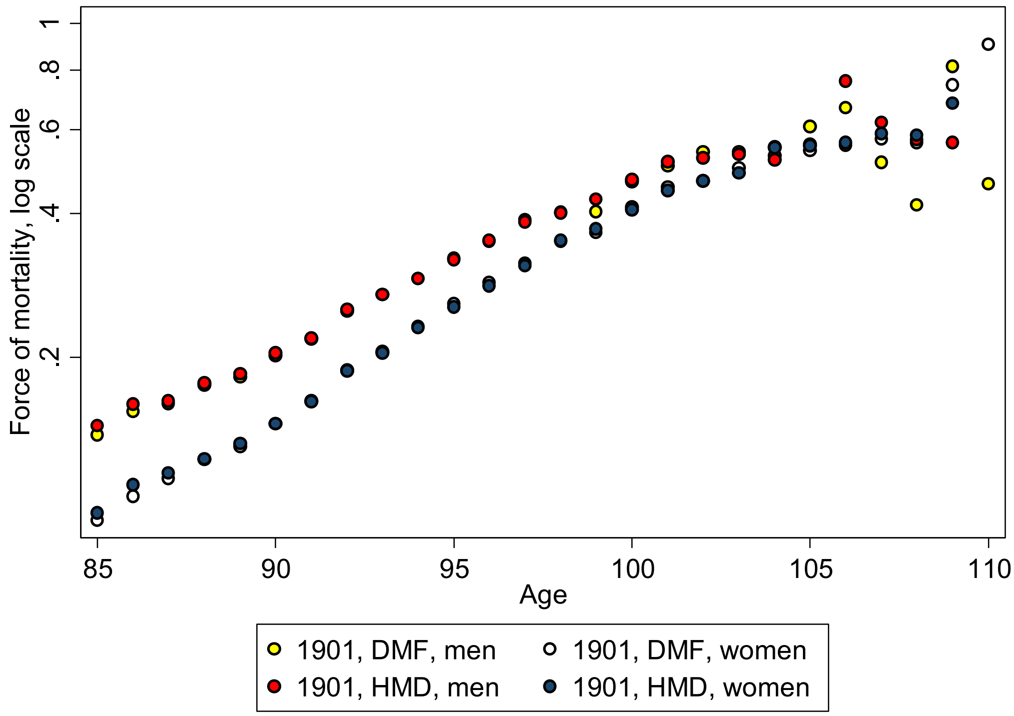
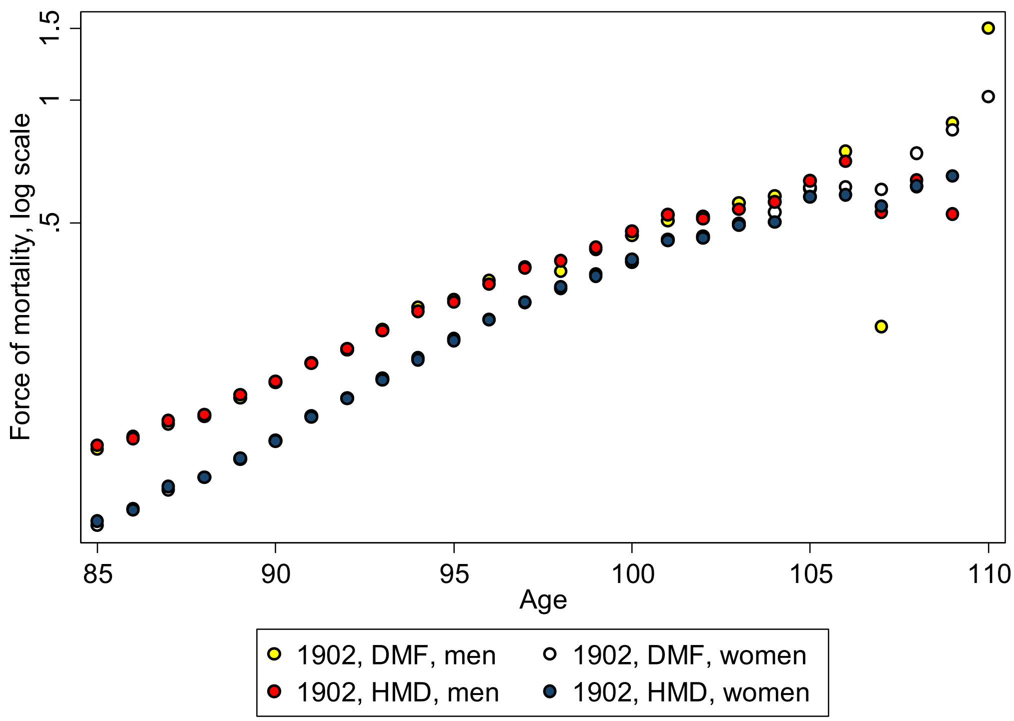


Figure 5

FORCE OF MORTALITY FOR MEN AND WOMEN BORN IN 1902, COMPARISON OF DMF AND HMD DATA

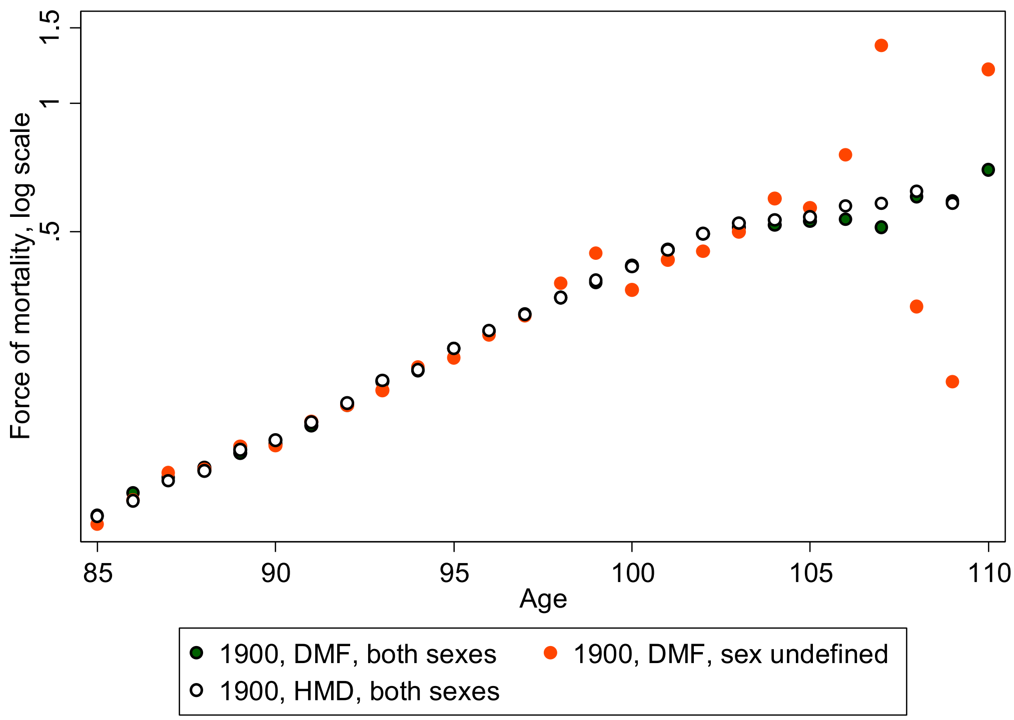


Note that for all five DMF birth cohorts, mortality demonstrates good agreement with HMD data up to ages 106–107 years, at which point mortality behavior becomes noisy. These results again confirm the validity of our suggested method of gender assignment for DMF records. These results also confirm that gender-specific mortality estimates based on DMF data in this project can be used with sufficient confidence.

Figure 6 shows that mortality of persons with unassigned gender does not differ significantly from mortality for the total population with both sexes together. Thus, elimination of this small group of records from the analyses does not significantly affect final estimates of mortality.

Figure 6

FORCE OF MORTALITY FOR PERSONS BORN IN 1900, COMPARISON OF DMF AND HMD DATA



The results presented in Figure 6 show that the gender assignment procedure does not lead to systematic biases in mortality estimation, because mortality of persons with unknown sex is approximately the same as mortality of the total population.

2.1.3 Characteristics of Data Set

In this project we use the DMF records to estimate the force of mortality by month of age for ages 85 years and up, separately by gender, for the U.S. 1898–1902 birth cohorts. We use the last complete official version of DMF obtained from the U.S. NTIS. Taking into account that the latest deaths in this version were observed in September 2011, we have used supplementary data sources for deaths occurring after September 2011, described in section 2.2). Mortality is estimated using the method of extinct generations.

2.2 Supplementary Data Resources

2.2.1 Gerontology Research Group Database on Supercentenarians

Steven Kaye, M.D., and Stephen Coles, M.D., Ph.D., cofounded the Gerontology Research Group (GRG) during the spring of 1990. One of the continuing interests of the group is to authenticate cases of the oldest humans in history, the population of the so-called supercentenarians (persons at age 110 years and above). GRG publishes the most current validated list of living and deceased supercentenarians on a regular basis in the journal *Rejuvenation Research* (Young, Muir and Adams 2015). GRG also maintains a database on supercentenarians on its website (http://www.grg.org/Adams/TableE.html). In order to be included in the GRG official database, a person needs to have at least three independent sources of documentation: a birth certificate, baptismal certificate or marriage certificate; consistent U.S. Census records dating back to 1900; and some other photo identification, such as an old driver's license. This is the most up-to-date list of supercentenarians available to the public. We used the database last updated on August 16, 2017. No deaths of U.S. supercentenarians born in 1898–1902 occurred after that date. The GRG database contains persons born in 1898–1902 and died after 2011. Currently, the GRG database does not have living individuals born in 1898–1902 and living in the United States, indicating that these birth cohorts are already extinct.

2.2.2 Human Mortality Database

The age-specific cohort death rates of males and females are available in the HMD from ages 0 to 110 or older. Data are available in one-year age and time increments denoted as M_x, where *x* indicates single year of age. Age-specific death rates from HMD are used to compare gender-specific mortality and validate the gender assignment procedure. The database is available at www.mortality.org.

2.2.3 Social Security Death Index Database at Ancestry.Com

Ancestry.com maintains the Social Security Death Index (SSDI) database, which contains records for most deaths occurring after September 2011. To date, the last deaths in the database occurred in 2014. This database allows us to complete information for the tail of the survival curve. Nevertheless, some persons belonging to 1898–1902 birth cohorts survived past 2014. In these cases, Ancestry.com SSDI data were supplemented by records from the GRG database.

2.3 Constructing the Final Data Set with Supplementary Data Resources

Sex has been assigned using existing databases of male and female first names common in 1900, supplemented by additional male and female first names typical for that time. Results of the sex assignment procedure are presented in Table 2. Overall, this procedure provided reliable assignment of sex for approximately 90–91 percent of all records.

State of Social Security number (SSN) application was assigned based on the first three digits of a person's SSN. State of the last residence was assigned using information available in DMF (state code variable and zip codes of last residence of the deceased or residence to which the lump-sum death benefit was sent.).

Table 3 shows distribution of records by the region of SSN application. The "Other" category includes undefined regions, regions belonging to nonstate territories or railroad retirees. We used the U.S. Census Bureau region definitions:

Region 1: Northeast

Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, and Pennsylvania

Region 2: Midwest

Illinois, Indiana, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota

Region 3: South

Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas

Region 4: West

Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming, Alaska, California, Hawaii, Oregon, and Washington

District of Columbia is added to the Northeast region. Puerto Rico and other US territories are not part of any census region.

Table 3

NUMBER OF RECORDS (PERCENT), BY REGION OF SSN APPLICATION AND BIRTH COHORT (AGE 85+)

Region	1898	1899	1900	1901	1902
Northeast	136,082 (30.3)	132,940 (30.6)	144,056 (29.9)	139,679 (29.9)	153,141 (30.0)
Midwest	137,160 (30.5)	133,041 (30.6)	146,213 (30.3)	142,755 (30.6)	154,767 (30.3)
South	112,677 (25.0)	106,784 (24.5)	123,787 (25.7)	117,848 (25.3)	131,101 (25.7)
West	56,302 (12.5)	54,850 (12.6)	60,342 (12.5)	58,432 (12.5)	62,922 (12.3)
Other	7,600 (1.7)	7,300 (1.7)	7,892 (1.6)	8,053 (1.7)	9,038 (1.7)
Total	449,821	434,915	482,290	466,767	510,969

Table 4 shows distribution of records by state of last residence. Overall, the state of last residence is unknown or belongs to nonstate territories for 14.6 percent of persons who died at age 85 and over, but only for 3.8 percent of persons who died after age 100 (see also Table 5). Thus, more accurate estimates of mortality by region of last residence can be made for ages 100-plus years.

Table 4

NUMBER OF RECORDS (PERCENT), BY REGION OF LAST RESIDENCE AND BIRTH COHORT (AGE 85+)

Region	1898	1899	1900	1901	1902
Northeast	101,801 (22.6)	98,344 (22.6)	108,071 (22.4)	97,563 (20.9)	104,748 (20.5)
Midwest	107,453 (23.9)	103,066 (23.7)	111,045 (23.0)	104,976 (22.5)	111,888 (21.9)
South	122,754 (27.3)	117,153 (26.9)	131,780 (27.3)	127,014 (27.2)	140,472 (27.5)
West	61,025 (13.6)	59,310 (13.7)	64,777 (13.5)	62,214 (13.3)	66,722 (13.1)
Unknown	56,788 (12.6)	57,042 (13.1)	66,617 (13.8)	75,000 (16.1)	87,139 (17.0)
Total	449,821	434,915	482,290	466,767	510,969

Table 5

NUMBER OF RECORDS (PERCENT), BY REGION OF LAST RESIDENCE AND BIRTH COHORT (AGE 100+)

Region	1898	1899	1900	1901	1902
Northeast	4,097 (23.7)	4,117 (24.5)	4,430 (24.2)	4,109 (23.5)	4,579 (24.2)
Midwest	4,652 (26.9)	4,422 (26.4)	4,797 (26.2)	4,644 (26.6)	4,835 (25.6)
South	5,080 (29.4)	4,982 (29.7)	5,460 (29.9)	5,270 (30.1)	5,811 (30.7)
West	2,716 (15.7)	2,591 (15.4)	2,913 (15.9)	2,840 (16.2)	3,020 (16.0)
Unknown	737 (4.3)	666 (4.0)	697 (3.8)	622 (3.6)	662 (3.5)
Total	17,282	16,778	18,297	17,485	18,907

Records for deaths occurring after September 2011 are taken from the SSDI provided by Ancestry.com (deaths up to year 2014) and from the GRG database (deaths up to 2017). Duplicate records from the two databases have been eliminated. Distribution of deaths added from the Ancestry.com and GRG databases is shown in Table 6.

Table 6

DISTRIBUTION (NUMBER) OF NONOVERLAPPING RECORDS ADDED TO DMF FILE FOR DEATHS OCCURRING AFTER SEPTEMBER 2011

Birth Cohort	Source*		Total
	Ancestry.com	GRG Database**	
1898	5	4	9
1899	7	14	21
1900	16	21	37
1901	34	20	54
1902	81	12	93

*Duplicate records found in both sources are counted once.

** For more details, see the Gerontology Research Group website (http://www.grg.org/SC/SCindex.html).

Section 3: Data Quality Evaluation Procedures

Our previous study demonstrated that the quality of age reporting in DMF is acceptable up to ages 106–107 years (Gavrilov and Gavrilova 2011). In this project we used two approaches for data quality control: direct age validation using linkage to historical resources and indirect methods of data quality estimation.

3.1 Direct Age Validation

A standard way to improve data quality of records with high longevity is to link death records to historical resources, such as early U.S. censuses, military records, and birth certificates (Elo et al. 2013). We had an excellent success rate (over 97 percent) in linking individual records of centenarians to historical U.S. censuses in our study on exceptional longevity (Gavrilov and Gavrilova 2015). In that work we conducted a search of individuals in historical records using Ancestry.com, which has a powerful search engine that can find a person in multiple historical sources simultaneously, including all historical U.S. censuses that are open to the public. In this current work we select records supported by historical resources and give the highest weights to age records from earlier historical sources, for example, 1910 or 1920 U.S. censuses or World War I civil draft registration cards. Here we describe some resources, available at Ancestry.com, that were used for age validation in this project.

Early U.S. censuses. Information from the early U.S. censuses is used for age (birth date) verification. In our earlier study we developed a protocol for linking family history records to early U.S. censuses and conducted linkage to the 1900 and 1930 censuses for 2,000 records of centenarians and controls (Gavrilov and Gavrilova 2015). Currently the 1900–1940 U.S. censuses are open to the public. Linkage to early censuses was conducted using Ancestry.com services. It should be noted that the 1900 U.S. census is the only census where both birth year and age are reported while in other censuses only age of respondent and ages of household members are reported. Thus, for 1910–1940 censuses, year of birth was estimated based on age and date of census enumeration.

World War I civil draft registration cards. In 1917 and 1918, approximately 24 million men born between 1873 and 1900 completed draft registration cards. That accounts for approximately 98 percent of eligible men in the U.S. born in that time period. Our experience in linking DMF records to World War I draft registration cards showed relatively high (about 70 percent) linkage success (Gavrilov and Gavrilova 2012).

U.S. Social Security Applications and Claims Index, 1936–2007. This database contains information filed with the Social Security Administration through the application or claims process, including valuable details such as birth date, birth place, and parents' or spouse names. The main advantage of this data resource is availability of parents' names, which facilitates search for women in early U.S. censuses.

U.S. Grave Index. This resource not only provides information about death date but also often contains a detailed biography with information about parents and spouses. This information helps to search for women in early censuses.

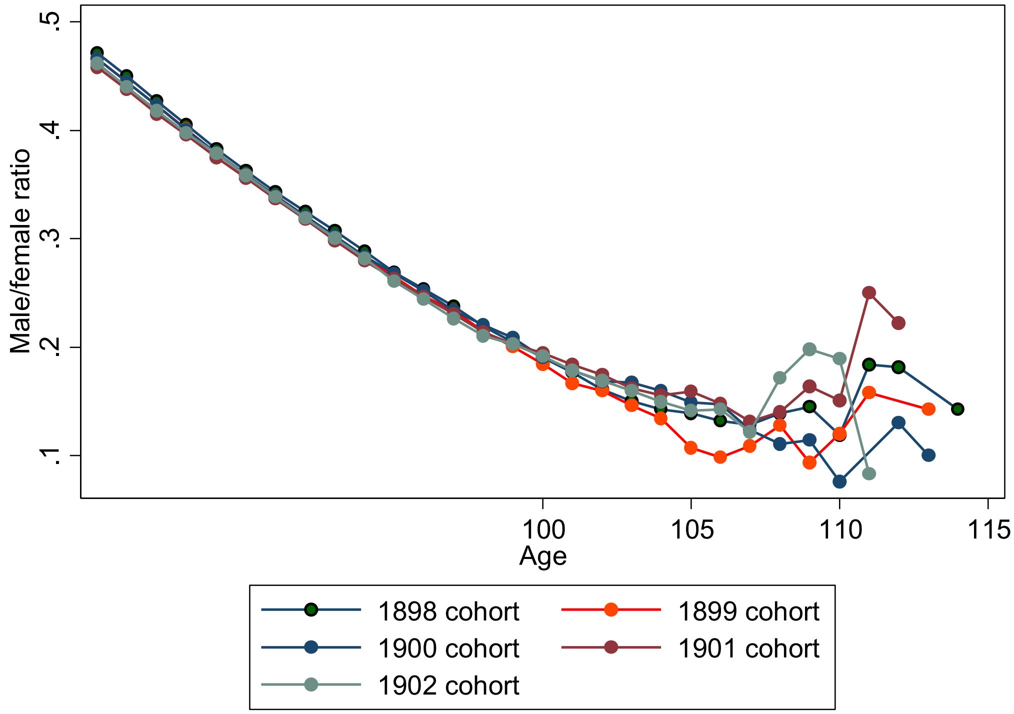
3.2 Indirect Methods of Data Quality Assessment

Demographers use several methods to evaluate quality of age reporting at older ages. One method consists of calculating the male-to-female sex ratio at different ages (Poulain 2010). Taking into account that male mortality is higher than female mortality, this ratio should decline with age (while the opposite female-to-male ratio grows with age). Our study of the U.S. 1890–1898 birth cohorts based on DMF records found that the female-to-male ratio grew with age until ages 106–107 years, indicating that age reporting is reasonably accurate up to these ages (Gavrilov and Gavrilova 2011). Records for persons who died after these ages are less reliable and contain many false claims, particularly for males. One study suggests that the percentage of false claims for persons aged 110 and older in DMF increases from 64 percent at age 110 years to 94 percent at age 115 years (Young et al. 2010). However, the method of finding false claims in this study, measured as percentage of supercentenarians in GRG database found in DMF, most likely overestimates the proportion of unreliable records in DMF.

Figure 7 shows the male-to-female ratio of survivors to specific ages for the five birth cohorts studied in this report. Note that the male-to-female ratio declines with age up to age 106–108 years, confirming results of the previous study on data quality threshold at 106–107 years (Gavrilov and Gavrilova 2011).

Figure 7

MALE-TO-FEMALE RATIO FOR SURVIVORS TO SPECIFIC AGE, BY BIRTH COHORT AND AGE



Data quality evaluation also involves calculations of various proportions and comparison of these proportions to proportions observed in countries with good quality of vital statistics, such as Sweden. For example, the ratio of persons living 105-plus years to persons living 100-plus years may be used for data quality assessment (Bourbeau and Desjardins 2006). According to DMF data, this proportion is 8.8 percent for the 1900 cohort, which is comparable to the proportion reported for Quebec, Canada, of 8.1 percent (Bourbeau and Desjardins 2006). For 1898, 1899, 1901 and 1902 birth cohorts in DMF, this ratio is 9.1, 8.8, 8.6 and 9.0 percent, respectively. These results show no improvement in the quality of age reporting for more recent birth cohorts according to this test.

Jdanov and colleagues suggested three criteria of data quality evaluation for old ages. According to the first two criteria, age heaping and Whipple's Index for centenarians, U.S. data were considered to be of good quality (Jdanov et al. 2008). The third criterion calculates the ratio of the total life table person-years lived at age 100 to the total life table person-years lived at age 80 (T100/T80). The final quality index was obtained by comparing the country-specific T100/T80 ratios to the corresponding ratios for Sweden (considered the "gold standard"). If the country-specific T100/T80 ratio was sufficiently higher than the Swedish T100/T80 ratio then the quality of old-age data on mortality is not considered to be good. The U.S. ratio compared to Sweden was 2.0, qualifying the U.S. for poor-quality data on mortality at old ages (Jdanov et al 2008).

The idea of this index is similar to that described by Bourbeau and Desjardins (2006), in that this index penalizes countries that have heavy tails of survival curves. These heavy tails correspond with more expressed mortality deceleration at older ages.

3.3 Results of Age Validation Procedure for 1898–1902 Birth Cohorts

In the first step of the age validation process, we developed and tested a scoring system based on linkage of DMF records to Ancestry.com resources. Our scoring system included the following six levels of data validity:

1 - Several early sources (before 1950) agree about exact birth year with DMF record. Higher weight is given to earlier sources (preferably 1900 and 1910 U.S. censuses or birth certificates).
2 - One earlier source agrees.
3 - Age is mentioned in at least two independent post-1950 sources, such as obituary index, grave index or state directories, for which dates of birth agree.
4 - An earlier source disagrees with DMF regarding age, or different dates of birth appear in other sources (incorrect age).
5 - Foreign-born person came to the U.S. after age 20 (unreliable age).
6 - Not available in any sources (possible unreliable record).

We conducted an age validation procedure for samples of records at ages 100, 103 and 105 years for the 1898, 1900 and 1902 birth cohorts, which were randomly selected from corresponding age and cohort group. Age validation for the oldest (109-plus) age group was conducted for all records of five 1898–1902 single-year birth cohorts. (In the case of the 1900 birth cohort, the 108-and-over age group was validated. More records for 1900 birth cohort were validated, because this cohort was initially selected to study in this project.) In total, 1,753 records were validated.

Tables 7–9 present the results of age validation for the 1898, 1900 and 1902 birth cohorts, respectively.

Table 7

RESULTS OF AGE VALIDATION SCORING PROCEDURE FOR SAMPLES OF 100 RECORDS OF 1898 BIRTH COHORT (PERCENT DISTRIBUTION OF RECORDS WITH DIFFERENT SCORES, BY AGE)

Score	100 years	103 years	105 years	109+ years*
1-Confirmed by several early sources	58	71	73	67
2-Confirmed by one early source	7	4	3	2
3-Confirmed by several post-1950 sources	22	3	7	2
Good quality (score 1–3)	**87**	**78**	**83**	**71**
4-Rejected (dates disagree)	4	9	3	8
5-Foreign-born arrived late	1	2	6	5
6-Not found in any sources	8	11	8	16
Poor quality (score 4–6)	**13**	**22**	**17**	**29**

* The 109+ age group contains 160 records.

Tables 7–9 clearly demonstrate a decrease of the percentage of records with good quality (scores 1–3) and increase of the percentage of records with poor quality of age reporting (scores 4–6) at age 109-plus years. These results are similar for all three studied birth cohorts. Note that up to age 105 years the proportion of records with unreliable age reporting is very similar across ages but increases thereafter.

Table 8

RESULTS OF AGE VALIDATION (SCORING) PROCEDURE FOR SAMPLES OF 100 RECORDS OF 1900 BIRTH COHORT (PERCENT DISTRIBUTION OF RECORDS WITH DIFFERENT SCORES, BY AGE)

Score	100 years	103 years	105 years	108+ years*
1-Confirmed by several early sources	85	73	69	59
2-Confirmed by one early source	1	1	0	2
3-Confirmed by several post-1950 sources	2	7	14	7
Good quality (score 1–3)	88	81	83	68
4-Rejected (dates disagree)	4	6	7	12
5-Foreign-born arrived late	1	4	6	8
6-Not found in any sources	7	9	4	12
Poor quality (score 4–6)	12	19	17	32

* The 108+ age group contains 298 records.

Table 9

RESULTS OF AGE VALIDATION (SCORING) PROCEDURE FOR SAMPLES OF 100 RECORDS OF 1902 BIRTH COHORT (PERCENT DISTRIBUTION OF RECORDS WITH DIFFERENT SCORES, BY AGE)

Score	100 years	103 years	105 years	109+ years*
1-Confirmed by several early sources	72	64	64	57
2-Confirmed by one early source	1	2	3	1
3-Confirmed by several post-1950 sources	6	15	8	7
Good quality (score 1–3)	79	81	75	65
4-Rejected (dates disagree)	3	5	6	5
5-Foreign-born arrived late	6	3	4	5
6-Not found in any sources	12	11	15	25
Poor quality (score 4–6)	21	19	25	35

*109+ age group contains 111 records.

Figure 8 shows the proportion of unreliable age claims (scores 4–6) in different age groups of 1898, 1900 and 1902 birth cohorts. Note the significant increase of records with poor quality after age 105 years. This difference between age groups in the proportion of records with poor quality of age reporting is highly significant ($p < 0.001$) according to Pearson's chi-squared test. Further, the proportion of records with poor quality is not sufficiently different across cohorts within each age. This result suggests that there is no improvement in the quality of age reporting for more recent birth cohorts.

Figure 8

PROPORTION OF RECORDS WITH POOR QUALITY OF AGE REPORTING (SCORES 4–6), BY AGE AT DEATH (1898, 1900 AND 1902 BIRTH COHORTS)

Table 10 shows the percentage breakdown by age validation score for the 109-plus age group for all five birth cohorts. Percent of records with poor quality of age reporting is presented with 95 percent confidence intervals. Note that the proportion of records with poor quality of age reporting for the most recent 1902 birth cohort is practically the same as for the other four birth cohorts.

Table 10

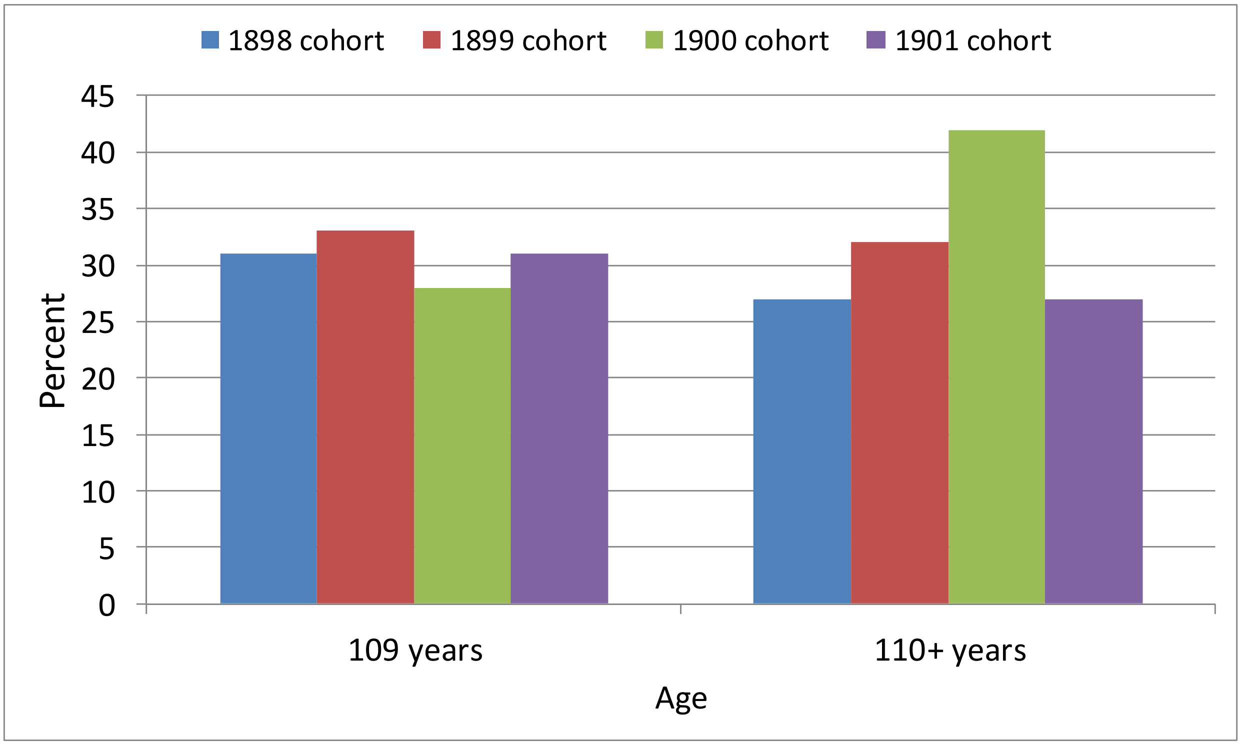
RESULTS OF AGE VALIDATION (SCORING) PROCEDURE FOR THE OLDEST AGE GROUP (109+ YEARS), BY BIRTH COHORT (PERCENT DISTRIBUTION OF RECORDS WITH DIFFERENT SCORES, WITH 95% CONFIDENCE INTERVALS)

Score	1898	1899	1900	1901	1902
1-Confirmed by several early sources	67	64	57	55	57
2-Confirmed by one early source	2	1	1	4	1
3-Confirmed by several post-1950 sources	2	2	7	5	7
Good quality (score 1–3)	71	67	65	64	65
4-Rejected (dates disagree)	8	8	14	12	5
5-Foreign-born arrived late	5	5	9	10	5
6-Not found in any sources	16	20	12	14	25
Poor quality (score 4-6) (95% CI)	29 (22.2-36.3)	33 (25.4-40.7)	35 (28.4-43.1)	36 (28.6-44.6)	35 (26.7-44.6)
Total number of records	160	144	161	138	111

Figure 9 compares proportions of records with poor quality for the five birth cohorts at ages 109 years and 110-plus years. There is no significant increase in the proportion of records with poor quality at ages 110 years and over compared to age 109 years with the exception of the 1900 birth cohort. This apparent increase in the proportion of records with poor quality at the most advanced age group may be related to rounding. Persons with poor knowledge about their exact year of birth could provide an approximate birth year of 1900. Conversely, the lack of a significant increase in the proportion of poor-quality records for the 110-plus age group may be caused by the good-quality records added from GRG database on supercentenarians that we used to complete information on deaths at extreme old ages.

Figure 9

PROPORTION OF RECORDS WITH POOR QUALITY OF AGE REPORTING (SCORES 4–6), BY AGE AT DEATH AND BIRTH COHORT



3.4 Mortality Reconstruction Based on Results of Age Validation Procedure

3.4.1 Statistical Tests to Analyze Results of Age Validation

We used Pearson's chi-squared test to study differences in the proportion of records with poor quality across groups. According to this test, there are no statistically significant differences in data quality between the studied five birth cohorts at ages 100, 103, 105 and 109-plus years. This test also did not find significant differences in data quality between men and women at all ages (up to age 108 years) with the exception of age 109 years and over. At age 109 years and over, men had a significantly higher percent of poor-quality records. Finally, the chi-squared test found statistically significant differences in data quality across age groups mainly due to a higher proportion of records with poor quality at age 109 years and over.

3.4.2 Regression Analysis of the Proportion of Records with Poor Quality by Age and Birth Cohort

Visual inspection of Tables 7–10 and Figures 9 and 10 as well as the results of the chi-squared test allow us to conclude that the proportion of data with poor quality jumps some time after age 105 years and that there are no significant changes in data quality by birth cohort. Thus, the initial hypothesis about expected improvement of data quality for 1900 and later birth cohorts is not supported by the results of this age validation procedure.

Instead of running several univariate tests, we determined it would be more convenient to run one multivariable regression analysis that simultaneously estimates effects of age and birth cohort on the proportion of records with poor quality. To this aim we have applied a multivariate regression model for the percentage of data with poor quality (continuous dependent variable named “percent”) as outcome variable, and the age at death and the birth cohort year as predictor variables. The dependent variable (“percent”) represents percent of records with poor quality (scores 4–6). To minimize assumptions about the shape of the dependencies, we treated ages at death and birth cohort years as categorical (dummy, binary) predictor variables in the regression. We used the following regression model:

$$percent = \mathrm{const} + \beta_1 AGE + \beta_2 COHORT$$

where AGE and COHORT represent sets of dummy variables (103, 105, 109 for AGE at death with 100 years used as a reference level and 1899, 1900, 1901, 1902 for COHORT birth year with 1898 used as a reference level), and β_1 and β_2 are regression coefficients.

Table 11 presents the results of the multiple regression model for the percentage of poor-quality records as a function of age at death and birth cohort year. Note that the only significant predictor variable for the percentage of poor-quality records is the age group 109 years (in bold). Thus, we have quantitative confirmation of our earlier findings that the percentage of poor-quality records does not differ across five historical birth cohorts and increases significantly for the age group 109 years. Regression coefficients show net differences in the percent of poor-quality records compared to the reference level. Note that the percentage of poor-quality records at age 109 years is about 17 percent higher compared to the reference baseline level at age 100 years (see Table 11).

Table 11

RESULTS OF REGRESSION MODEL FOR PERCENTAGE OF POOR-QUALITY DATA

Variable	Regression Coefficient	*P*-value	95% Confidence Intervals
1898 cohort	reference		
1899 cohort	2	0.588	-6.55–10.55
1900 cohort	-1.75	0.419	-6.69–3.19
1901 cohort	-1.56e–15	1.000	-8.55–8.55
1902 cohort	4.75	0.057	-0.19–9.69
Age 100	reference		
Age 103	4.67	0.092	-1.03–10.37
Age 105	4.33	0.112	-1.37–10.03
Age 109	**16.67**	**<0.001**	10.97–22.37
Intercept	**14.33**	**<0.001**	9.40–19.27

3.4.3 Three Variants of Data Reconstruction (Quality Adjustment)

The results of age validation for the 1898–1902 birth cohorts and the results of the regression model (Table 11) allow us to suggest several variants of data quality adjustment for DMF records. We considered three variants in order to do a sensitivity analysis and to test robustness of mortality estimates. The first two variants make different assumptions regarding scores. In short, the more inclusive variant 1 assumes that records with scores 4 and 5 have poor quality, while the stricter variant 2 assumes that records with scores 4–6 have poor quality. Both variants assume that all records between ages 100 and 105 years have similar quality (percentage of records with poor quality above the baseline mismatch level between different data sources is equal to zero). This assumption reflects the fact that we do not see deterioration of data quality between ages 100 and 105 years. In this case, our main interest is in the decline of data quality after age 105 years. In the third variant, we used the observed proportions of records with poor quality (score 4–6) for ages 100 years and over for quality adjustment.

3.4.3.1 Variant 1: Inclusive Data Quality Adjustment

In this first variant of data quality adjustment, we hypothesized that records with a score of 6 (person was not found in historical records) still may have acceptable quality of age reporting. The rationale for this approach is based on the understanding that we are not absolutely certain of the poor quality of records that we are not able to find in historical resources, for two reasons: (1) possible limitations in our age validation procedure and (2) possible incompleteness of the Ancestry.com data set. With information about the percentage of records with poor quality at age 109 years (scores 4–5), it is possible to calculate the percentages of records with poor quality for intermediate ages between 105 and 109 years using a linear interpolation procedure. We assumed that the quality of age reporting for ages 105 years and lower is reasonably good and does not require quality adjustment.

In variant 1, percentages of records with poor quality for ages 109 years and over were determined by scores of 4 and 5, when poor quality of age reporting is certain. Data were interpolated for percentages between ages 105 ("baseline level" assumed to be 0 percent) and 109 years (14 percent, observed ratio). In the case of both variant 1 and variant 2, data are interpolated for percentages between ages 105 (0 percent) and 109 years (16.67 percent). These interpolated percentages are shown in Table 12 for ages 106 and 107 years. In the case of age 108, percentages take into account directly estimated percentages for scores 4–5 (variant 1) and scores 4–6 (variant 2) of the 1900 birth cohort. Based on these percentages (obtained through interpolation), we calculated numbers of records for rejection per each age (see Table 12). Records were randomly assigned for rejections at ages 106 and 107 years (1900 cohort) and 106–108 years (other cohorts) according to these numbers. Table 12 shows the number of records rejected because of poor quality based on variant 1 of data quality adjustment (numbers obtained through interpolation are shown in italics).

Table 12

NUMBER AND PERCENTAGE OF RECORDS WITH POOR QUALITY, BY TWO VARIANTS OF DATA QUALITY ADJUSTMENT

Age	All Records	Variant 1		Variant 2		Variant 3	
		Poor-Quality Records*	%	Poor-Quality Records*	%	Poor-Quality Records*	%
100–104	80,875	0	0	0	0	14,555	18
105	3,465	0	0	0	0	629	18
106	2,010	*87*	*4.3*	*87*	*4.3*	*417*	*21.7*
107	1,046	*90*	*8.6*	*90*	*8.6*	*242*	*25.3*
108**	639	*90*	*14.1*	*105*	*16.4*	*168*	*29*
109	329	47	14.3	105	31.9	105	31.9
110	213	42	19.7	76	35.7	76	35.7
111	82	10	12.2	28	34.2	28	34.2
112	44	11	25.0	18	40.9	18	40.9
113	22	4	18.2	6	27.3	6	27.3
114	19	2	10.5	6	31.6	6	31.6
115	2	0	0	0	0	0	0
116	3	0	0	0	0	0	0
Total	7,874	383	-	521	-		

* Estimated values are shown in italics.

** Percentage of poor-quality records at age 108 years for the 1900 birth cohort was directly validated rather than estimated.

3.4.3.2 Variant 2: Strict Data Quality Adjustment

In this more strict variant of data quality adjustment we assumed that records with scores between 4 and 6 are of poor quality for age reporting. We found from the multivariate regression model on dummy (binary, "0 or 1") categorized predictor variables that the net difference in the percentage of poor records between age 100 years (reference level) and age 109 years is 16.67 percent (see Table 11). We also found that in the range of 100–105 years there is no significant increase in the percentage of poor-quality records. Table 11 shows that the effects of age 103 years (4.67 percent) and the effects of age 105 years (4.33 percent) on the percentage of poor-quality records are statistically insignificant (according to *p*-values and 95 percent confidence intervals). This allows us to justify the idea of a "baseline" level of unconfirmed age in the interval 100–105 years, with no deterioration in data quality with age. In other words, the percentage of bad records attributed to data deterioration with age is assumed to be equal to zero at ages 100–105 years. At the same time, as shown in Table 11, the percentage of poor records grows with age, from 0 percent at age 105 years to nearly 17 percent at age 109 years.

Based on these percentages, we calculated numbers of records for rejection per each age (see Table 12). Records are randomly assigned for rejection at ages 106 and 107 years (1900 cohort) and 106–108 years (other cohorts) with accordance to proportions obtained using the linear interpolation procedure. Table 12 shows numbers and percentages of records with poor quality of age reporting (both observed and estimated) for the 1898–1902 birth cohort.

3.4.3.3 Variant 3: Observed Data Quality

The third and strictest variant of data quality adjustment was based directly on the percentages of poor-quality records estimated by the age validation procedure and presented in Tables 7–10. Taking into account that there are no statistically significant differences in data quality across the five birth cohorts, we used one and the same mean percentage of poor-quality records for ages 100–105 years (18 percent, see Table 12). Percentages for ages 106 and 107 years were estimated using linear interpolation (see Table 12). This variant rejects the highest number of records and inevitably results in data discontinuity at ages 99 and 100 years.

The interpolation procedure allows us to estimate the number of records with good data quality from age 105 years upward and make new estimations of mortality at extreme old ages. Using this information, we estimated the force of mortality (see section 4).

Section 4: Estimation of the Force of Mortality

This study analyzes mortality after age 85 years for the 1898–1902 U.S. birth cohorts by applying the method of extinct generations to the SSA DMF database. Suggested by Paul Vincent (1951), the method consists of calculating the number of survivors of each generation at any given age by cumulating the deaths of the generation downward from the highest age at death. The method of extinct generations has advantages over traditional methods of mortality estimation when mortality is calculated for older ages. First, it does not suffer from the well-known denominator problem associated with traditional methods when numbers of deaths and numbers of exposed to risk are taken from different sources often leading to inflated denominator in mortality rate estimation. . Second, it does not suffer from a problem of missing individuals, a major weakness of longitudinal surveys that produces a spurious mortality deceleration and even mortality decline at advanced ages. In addition, the major assumption of the extinct generations method about lack of migration works well for populations over age 85 because of the extremely low likelihood of migration at this age. Thus, we may expect that the method of extinct generations for mortality measurement produces more accurate results compared to other approaches. The only problem of this method is a possibility of age misreporting. For this reason, additional measures of age verification have been applied to DMF records (see section 3 for details).

Force of mortality was estimated using the standard statistical package Stata (procedure *ltable* calculating life table). Procedure *ltable* calculates the force of mortality for discrete data in the following way. Let $f_j = d_j/n_j$ be within-interval failure rate, where d_j is number of deaths within interval *j* and n_j is number alive at the beginning of interval *j*. Then the maximum likelihood estimate of the force of mortality (hazard rate) for interval *j* is:

$$\mu_j = \frac{1}{\Delta x} \frac{f_j}{1 - \frac{f_j}{2}}$$

where Δx is the length of age interval *j*.

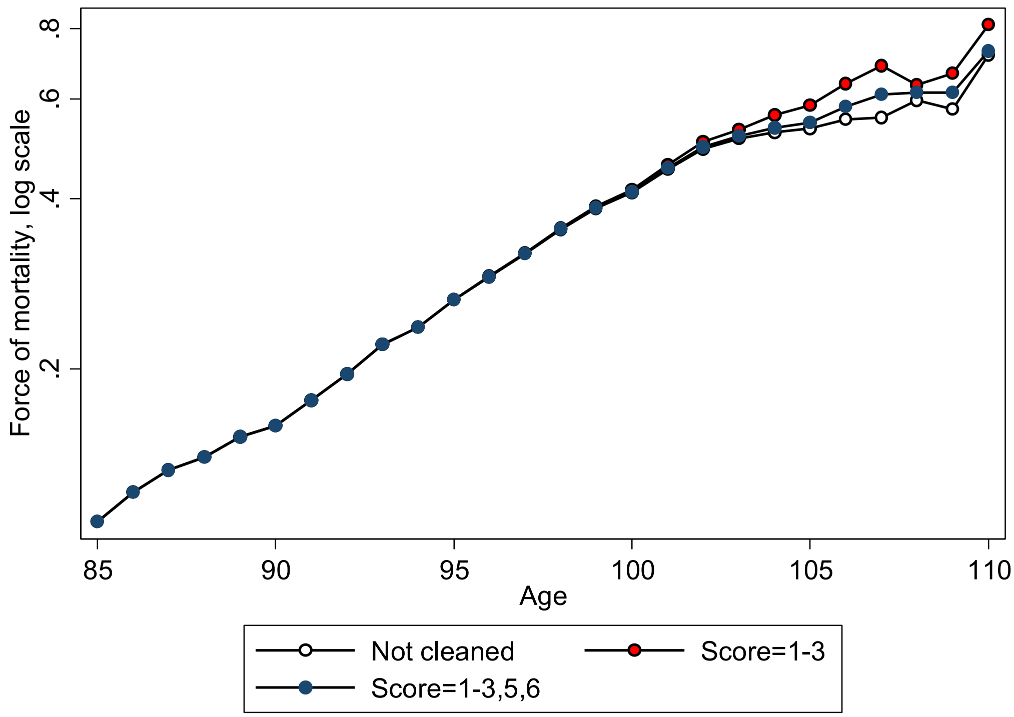
This estimate of hazard rate is also called an actuarial estimate of hazard rate (Kimball 1960). Its main assumption is uniform distribution of deaths over an age interval. This empirical estimate provides nonbiased estimates of hazard rate at old ages (up to age 110 years) in contrast to the often-used one-year probability of dying, which has a theoretical upper boundary equal to one (Gavrilov and Gavrilova 2011).

4.1 Force of Mortality after Age 85, by Different Levels of Data Quality

Estimates of the force of mortality and probability of dying, together with information on survivors and death numbers, are provided in Appendix as well as in the supplemental Excel file *DMF-Tables.xls* (available at http://health-studies.org/POG/DMF-tables.xls). The Excel file contains data for each single-year studied birth cohort (both sexes, males, females) in three versions: uncleaned data, data cleaned using variant 1, and data cleaned using variant 2 (see section 3). A separate worksheet contains data for mortality estimates of five-year (1898–1902 birth cohort). Another worksheet contains data for variant 3 of data quality adjustment for the five-year 1898–1902 birth cohort. In this section we present selected figures illustrating the results of this estimation.

After completion of our age validation procedure, we were able to estimate mortality by different levels of data quality adjustment. Figure 10 shows mortality of the 1900 birth cohort by different values of quality score based on direct age validation (for the scoring system see section 3.4). Note that mortality of the highest-quality group (score below 4, red circles) is higher at ages 105–107 years compared to mortality of the uncleaned data group. Also note that the effort of data cleaning at extreme old ages does not affect mortality for ages below 105 years. Overall, it seems that data cleaning for the tail of the survival curve affects mortality trajectory at ages 105–107 years while mortality shape at younger ages remains largely unchanged.

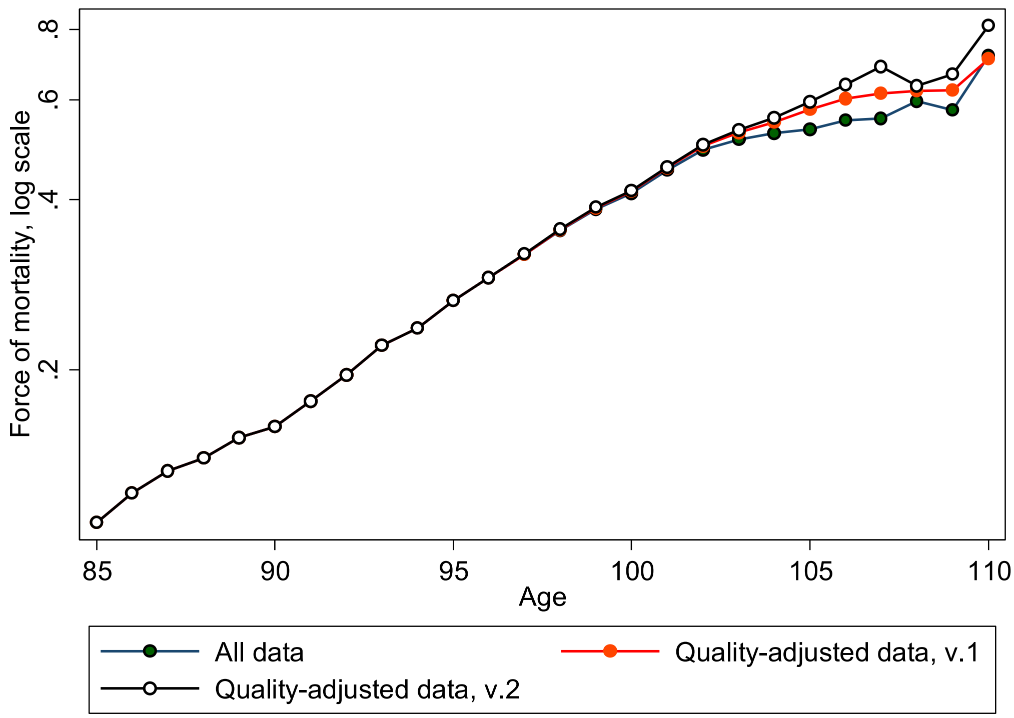
Figure 10
FORCE OF MORTALITY BY QUALITY SCORE (1900 BIRTH COHORT, BOTH SEXES)



Another way of data cleaning involves interpolation as described in the previous section (see also Table 12). Figure 11 shows mortality of the 1900 birth cohort for variants 1 and 2 of data cleaning. Applying the stricter variant 2 results in higher mortality at ages 105–107 years compared to the uncleaned variant and variant 1. Note that even after this procedure of data cleaning we still have rather heavy tails of survival curves. The indicator of data quality, the ratio of l_x at age 105 years to l_x at age 100 years (the $l_x[105]/l_x[100]$ ratio), is higher than 8 percent, which is close to the Quebec data reported by Bourbeau and Desjardins (2006).

Figure 11

FORCE OF MORTALITY BY TWO VARIANTS OF DATA CLEANING (1900 BIRTH COHORT, BOTH SEXES)



Figures 12 and 13 show mortality estimates for men and women, respectively, within the 1900 birth cohort and with variants 1 and 2 of data cleaning.

Figure 12

MORTALITY BY TWO VARIANTS OF DATA CLEANING (1900 BIRTH COHORT, MEN)

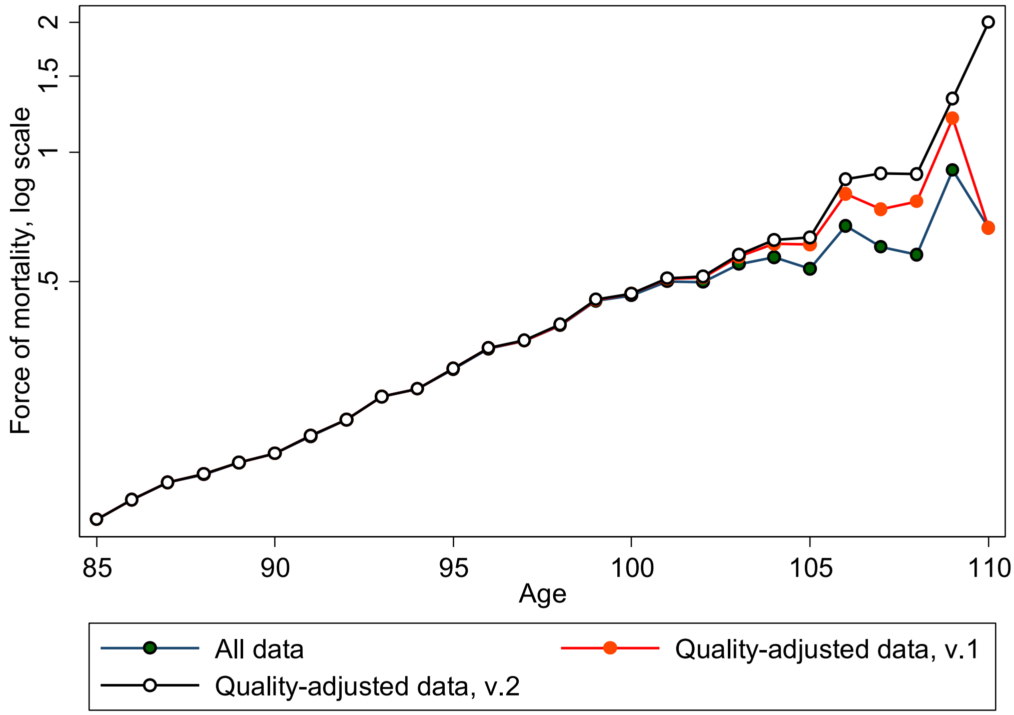
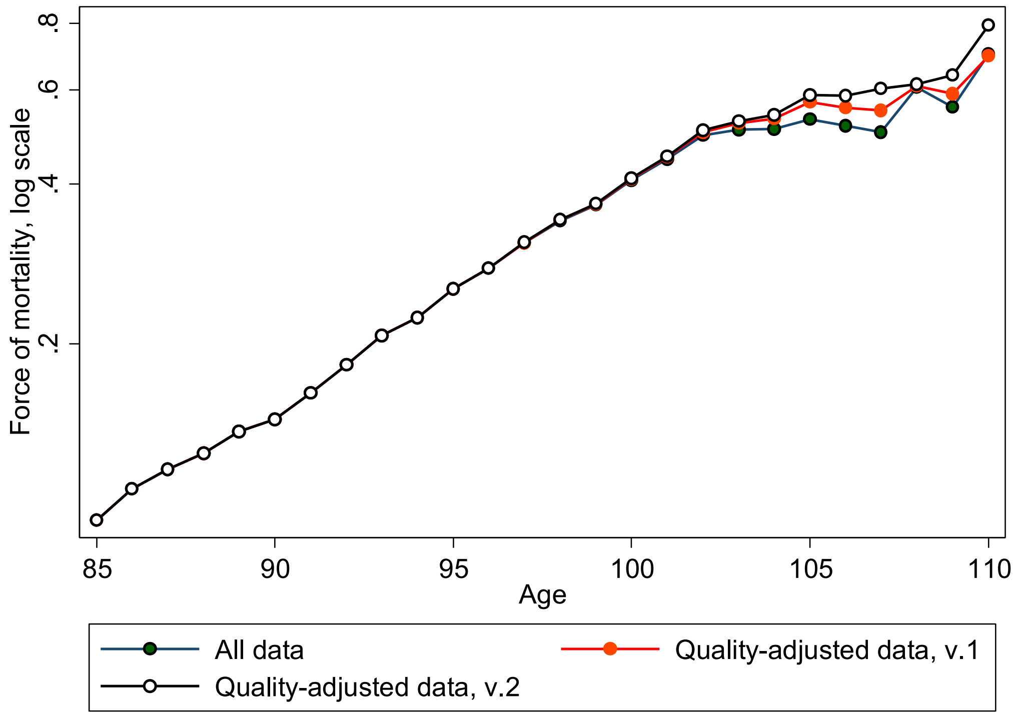


Figure 13

MORTALITY BY TWO VARIANTS OF DATA CLEANING (1900 BIRTH COHORT, WOMEN)



It follows from Figures 12 and 13 that data cleaning results in less expressed mortality deceleration compared to uncleaned data. Mortality of men does not demonstrate deceleration up to very old ages of 110 years. Mortality of women is more prone to decelerate at older age, although data cleaning leads to more Gompertz-like mortality trajectory.

Figure 14 shows mortality force estimates for the combined five-year birth cohort with variants 1 and 2 of data cleaning.

Figure 14

MORTALITY BY TWO VARIANTS OF DATA CLEANING (1898–1902 BIRTH COHORT, BOTH SEXES)

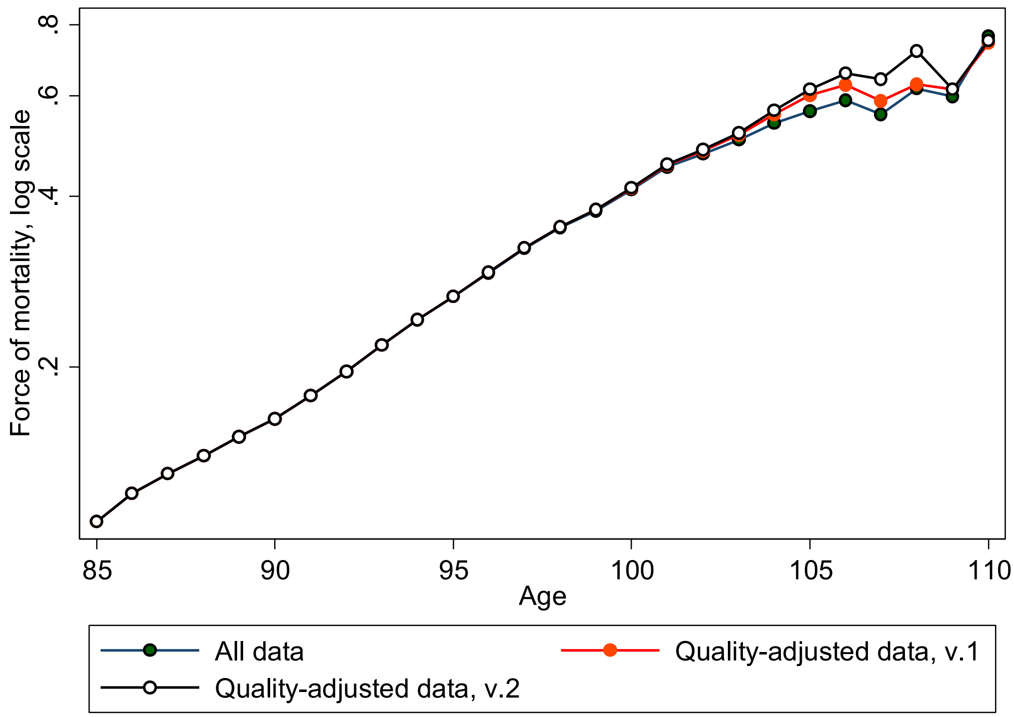


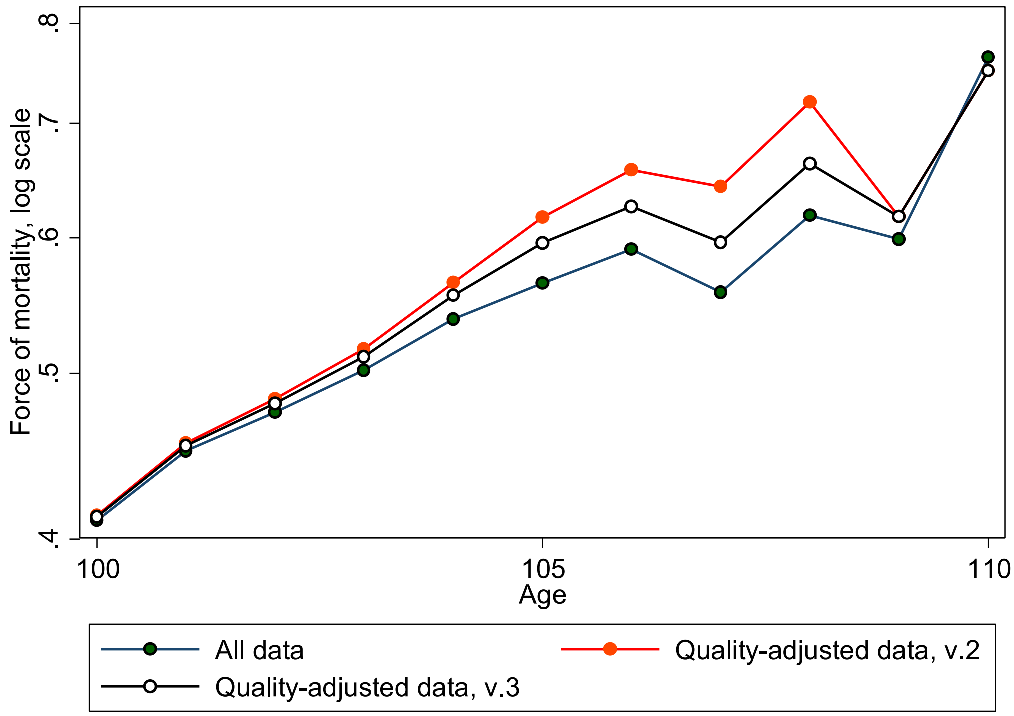
Figure 14 demonstrates that data cleaning results in straighter mortality trajectory in semilog scale, which means that mortality becomes more Gompertz-like after data quality improvement. Also, in all cases of data cleaning, the mortality of the better-quality data set is higher compared to uncleaned data. Thus, poor quality of age reporting at advanced ages leads to mortality underestimation.

Figure 15 shows mortality according to the second and third variants of data cleaning. Mortality is shown for ages 100 years and higher because of a discontinuity (jump) in mortality between ages 99 and 100 years for variant 3 data. This is caused by the rejection of a large number of records with presumably poor quality starting at age 100. However, this radical rejection rate does not result in dramatic changes in the shape of mortality.

Based on our findings, variant 2 data cleaning, with its moderate rejection level, appears to be the optimal way to clean data for U.S. death records at advanced ages.

Figure 15

MORTALITY BY VARIANTS 2 AND 3 OF DATA CLEANING (1898–1902 BIRTH COHORT, BOTH SEXES)



4.2 Mortality Variation by Region of Last Residence

Reliable estimates of mortality for separate states are difficult to obtain due to small numbers of survivors to advanced ages in single states. For this reason, data for single states were grouped into four large U.S. Census Bureau regions: Northeast, Midwest, South and West. The Northeast region includes the following states: Connecticut, Delaware, District of Columbia, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island and Vermont. The Midwest region includes Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin. The South includes Alabama, Arizona, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, New Mexico, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia and West Virginia. The West includes Alaska, California, Colorado, Hawaii, Idaho, Montana, Nevada, Oregon, Utah, Washington and Wyoming.

Mortality by region of last residence has been estimated for ages over 95 years, because data for younger ages were not very reliable (many missing records are concentrated around age 90). Figures 16 and 17 show mortality trajectories for all four regions of last residence as a function of age, for women and men, respectively. These figures demonstrate some small differences in mortality by region of last residence, but it is hard to determine a discernible pattern for these differences. The figures also show very high variations in mortality after age 106 years due to small numbers of survivors to these advanced ages.

It follows from Figures 16 and 17 that regional mortality differences at these extreme ages are small for both men and women and are rather noisy after age 105 years.

Figure 16

MORTALITY BY REGION OF LAST RESIDENCE (1898–1902 BIRTH COHORT, WOMEN)

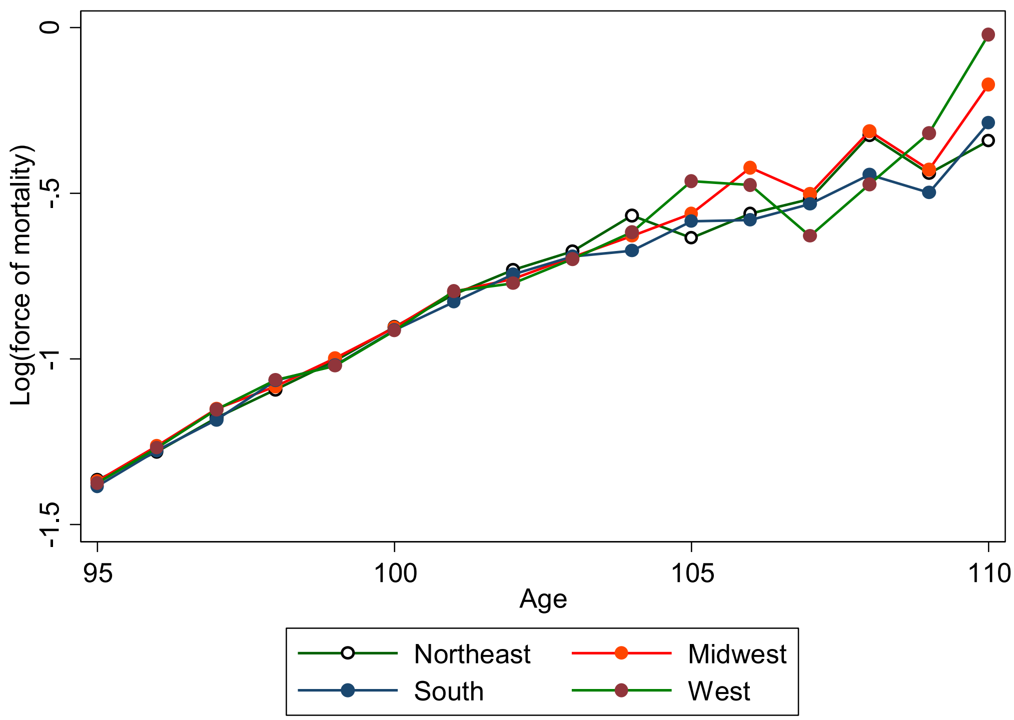
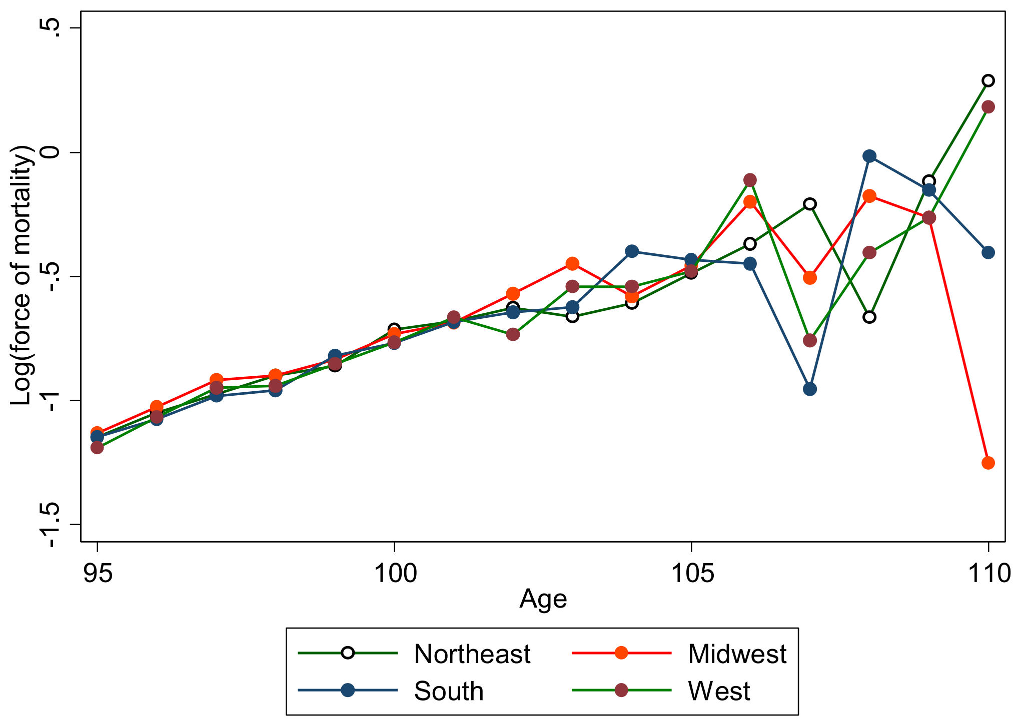


Figure 17

MORTALITY BY REGION OF LAST RESIDENCE (1898–1902 BIRTH COHORT, MEN)



4.3 Mortality Variation by Region of Social Security Number Application

It is also possible to analyze mortality by the state of SSN application. As in the case of mortality by the state of last residence, we have combined data for single states into four large regions: Northeast, Midwest, South and West (see previous section for definitions). Figures 18 and 19 present mortality of men and women, respectively, by region of SSN application. Note that mortality estimates for all four regions are very close and regional differences in mortality are relatively small at these extreme ages, with a small advantage for SSN applicants from the West (mortality is slightly lower in the age interval 85–95 years).

Figure 18

FORCE OF MORTALITY BY REGION OF SOCIAL SECURITY NUMBER APPLICATION (1898–1902 BIRTH COHORT, MEN)

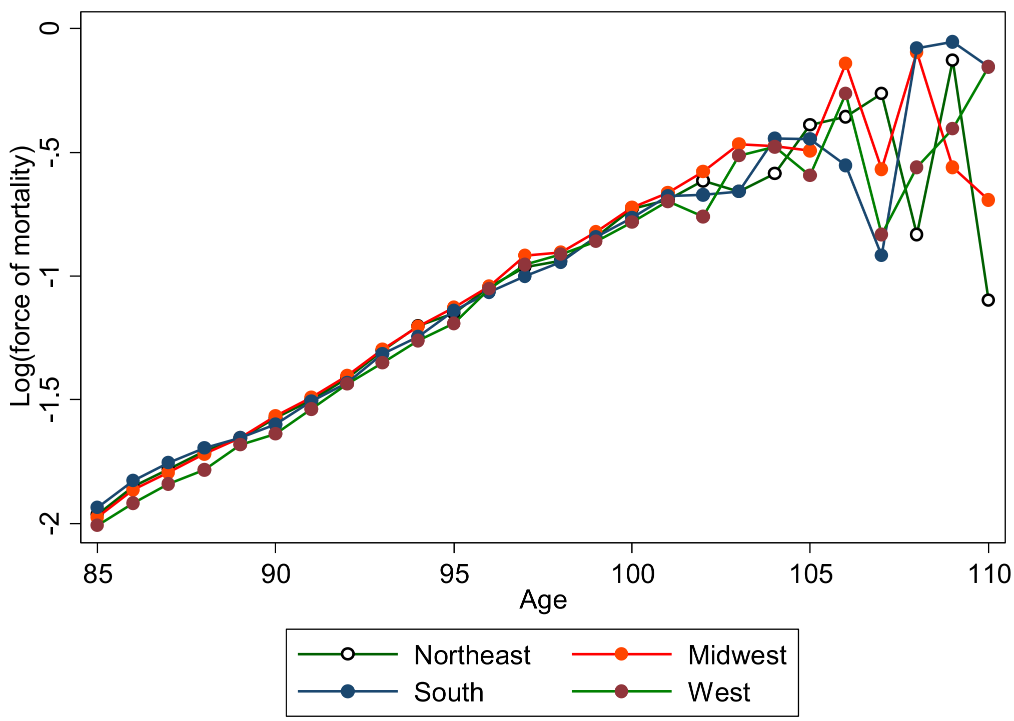
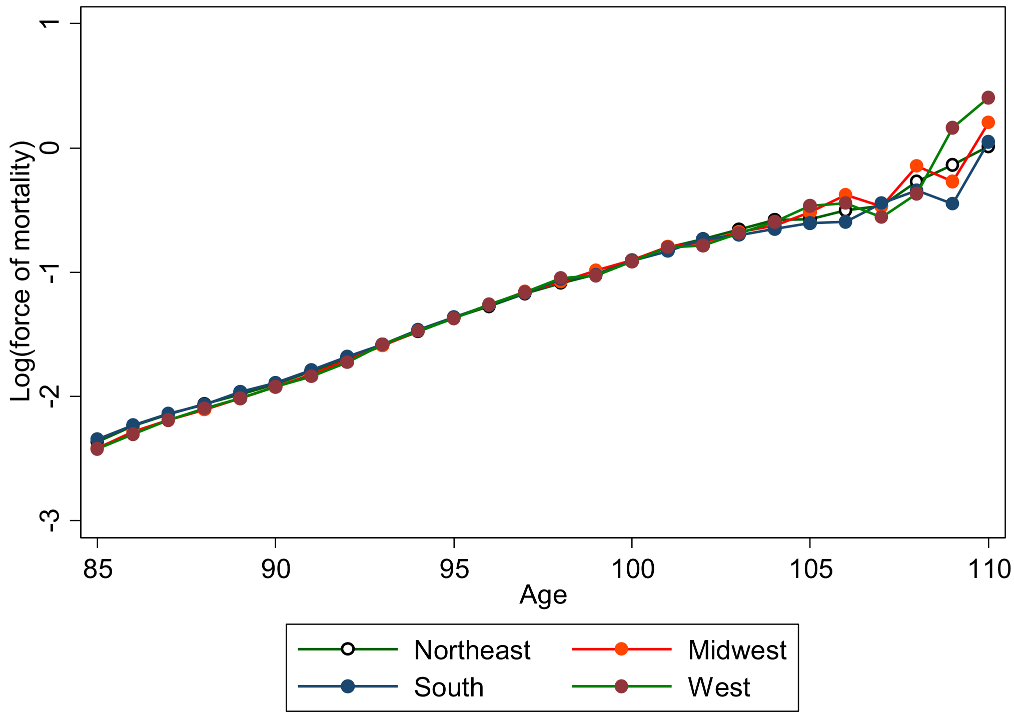


Figure 19
FORCE OF MORTALITY BY REGION OF SOCIAL SECURITY NUMBER APPLICATION (1898–1902 BIRTH COHORT, WOMEN)

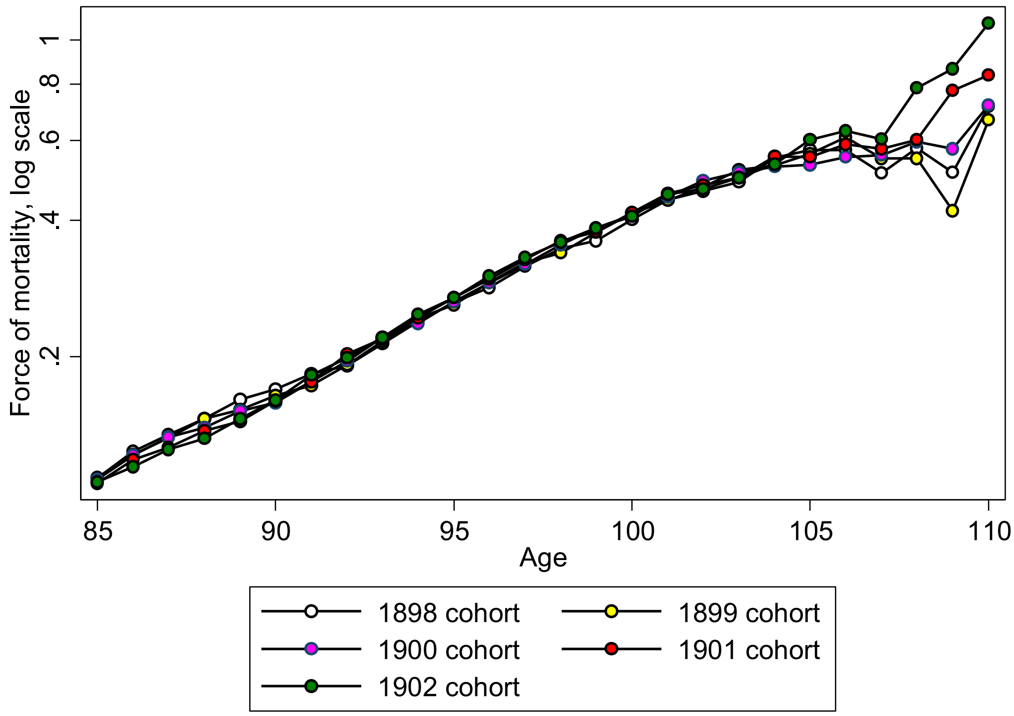


4.4 Mortality Changes at Advanced Ages over Time

With mortality estimates for the five studied birth cohorts, we were able to test whether mortality at advanced ages changes over time. Figure 20 presents mortality for both sexes in all five birth cohorts. Note that after age 90 years mortality estimates for the five birth cohorts are very close to one another, so that secular differences in mortality are relatively small at these extreme ages without a discernible pattern. Only for ages below 90 years do we observe the expected pattern, when the youngest 1902 birth cohort has slightly lower mortality.

Figure 20

MORTALITY BY BIRTH COHORT (BOTH SEXES)



This result is consistent with earlier findings that U.S. mortality at age 100 years does not demonstrate significant decline over time, in contrast to mortality at younger ages (Gavrilov et al. 2017). Thus, we may conclude that after age 90 years the decline of mortality over time is negligible for the studied five birth cohorts. For younger birth cohorts, mortality decline at ages 100 years and over may be possible, although cross-sectional data show very little improvement in mortality of centenarians up to calendar year 2014 (Gavrilov et al. 2017).

4.5 Monthly Estimates of the Force of Mortality

Our earlier study suggested that some empirical estimates of the force of mortality over yearly age intervals may significantly distort mortality trajectories at advanced ages, producing spurious mortality deceleration (Gavrilov and Gavrilova 2011). Further, a simulation study of various empirical estimates of the force of mortality revealed that some estimates are better than others (Gavrilova and Gavrilov 2014). For example, the so-called actuarial estimate of the force of mortality (or central death rate) can accurately estimate the force of mortality up to very high ages of 108–110 years before producing spurious mortality deceleration. An actuarial estimate of the force of mortality was used in this report for yearly age intervals. More accurate estimates of the force of mortality over monthly intervals are used here to analyze mortality trajectories after age 105 years, at which point yearly mortality estimates tend to decelerate.

Figure 21 shows monthly estimates of the force of mortality (both sexes) for the 1898 birth cohort as compared to yearly estimates. Note that yearly estimates closely follow monthly estimates up to age 105–106 years. After this age, yearly estimates are lower compared to monthly estimates and tend to show mortality deceleration. Monthly estimates, on the contrary, continue to grow according to the Gompertz law, although mortality estimates demonstrate significant fluctuations after age 107 years. Figure 22 compares monthly and yearly estimates of the force of mortality for cleaned data (variant 2) for the 1898–1902 birth cohort. The scatter of points (mortality estimates) is not symmetrical after age 105 years, with the deviations of lower estimates appearing farther from the line than the deviations of higher estimates in logarithmic scale.

Figure 1

FORCE OF MORTALITY BY MONTHLY AND YEARLY ESTIMATES (1898 BIRTH COHORT, BOTH SEXES)

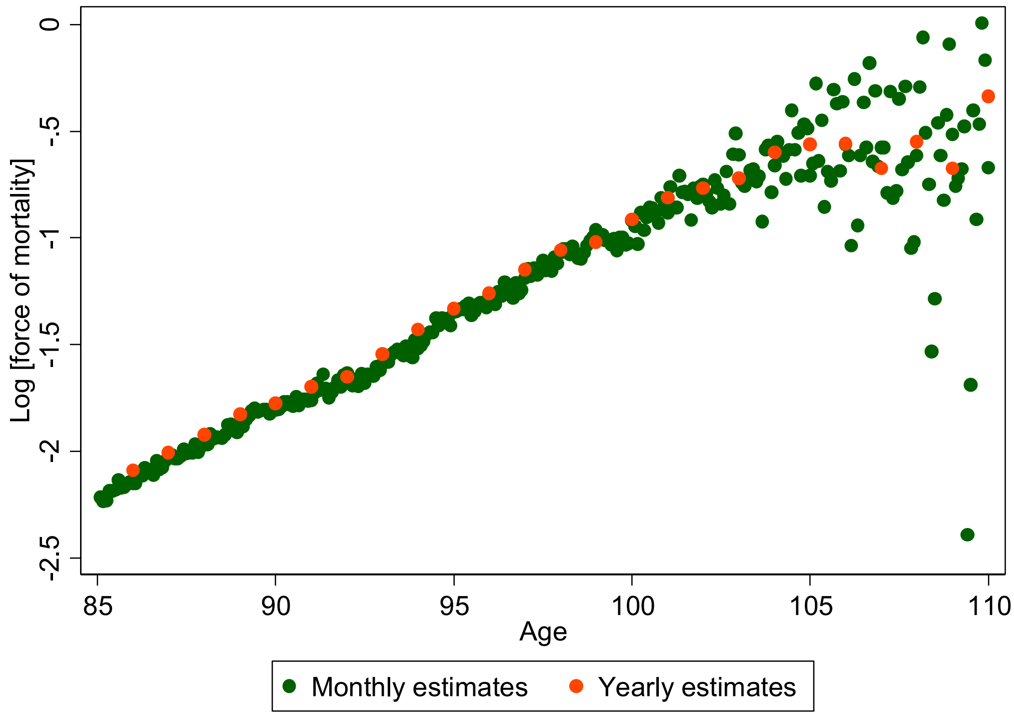
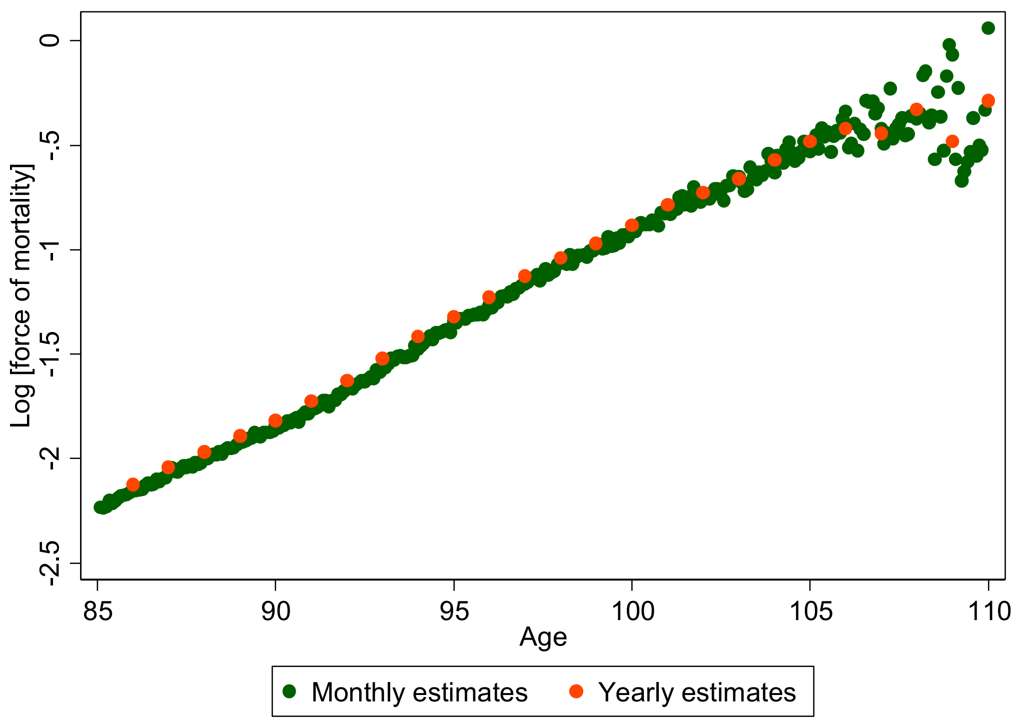


Figure 22

FORCE OF MORTALITY BY MONTHLY AND YEARLY ESTIMATES (1898–1902 BIRTH COHORT, BOTH SEXES; QUALITY-ADJUSTED DATA USING VARIANT 2)



Figures 23 and 24 present monthly and yearly estimates of mortality for men and women in the 1898–1902 birth cohort (cleaned data). As in the previous case, yearly estimates of mortality after age 105 years are somewhat lower than the monthly estimates. For men, monthly estimates of the force of mortality show growing tendency with the same pace up to age 110 years. Interestingly, the yearly estimates demonstrate declining trend of mortality after age 108 years, which is not visible in the case of monthly estimates (see Figure 23). Data for women show a tendency to decelerate after age 107 years even in the case of monthly estimates (Figure 24).

Figure 23

FORCE OF MORTALITY BY MONTHLY AND YEARLY ESTIMATES (1898–1902 BIRTH COHORT, MEN, QUALITY-ADJUSTED DATA USING VARIANT 2)

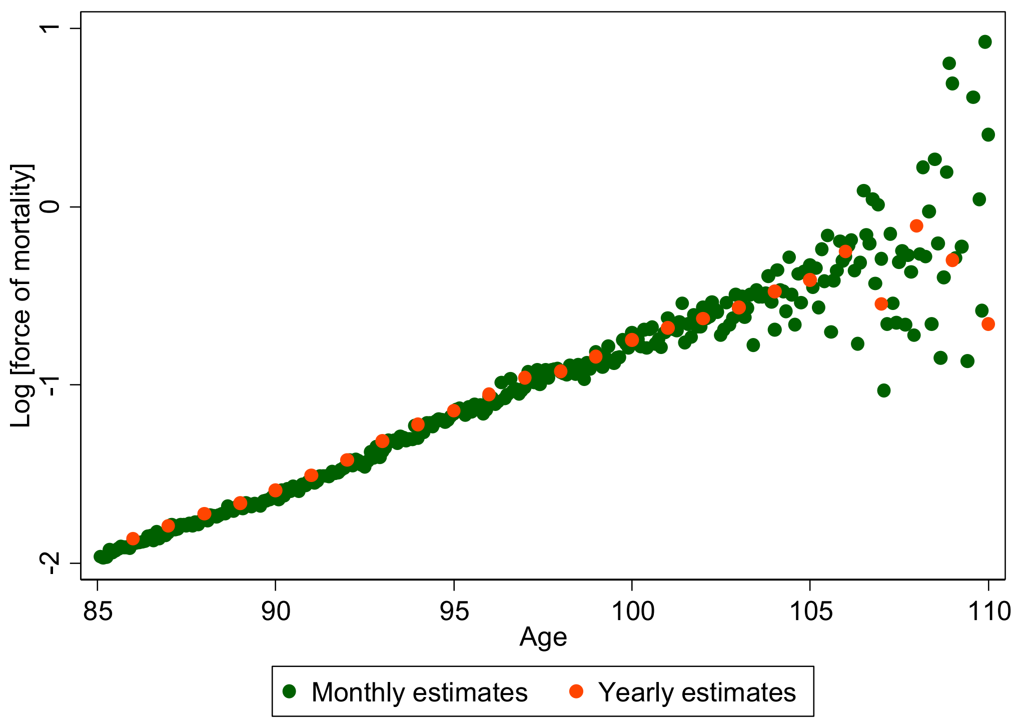


Figure 24

FORCE OF MORTALITY BY MONTHLY AND YEARLY ESTIMATES (1898–1902 BIRTH COHORT, WOMEN; QUALITY-ADJUSTED DATA USING VARIANT 2)

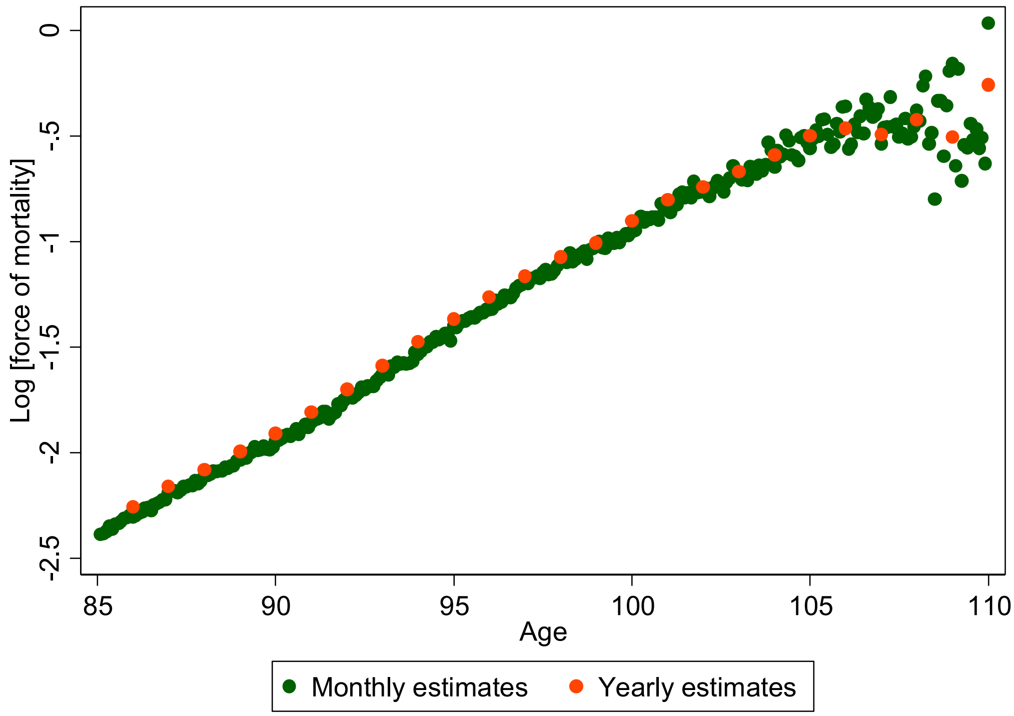


Table A3 in Appendix shows life table characteristics for the 1898–1902 birth cohort, with data quality-adjusted according to variant 2. Note that the force of mortality values (expressed in yearly units) based on monthly estimates are lower than corresponding yearly estimates. This is because the yearly estimates correspond to mortality observed in the middle of yearly age intervals while mortality based on monthly estimates corresponds to mortality at the beginning of yearly age intervals (middle of the monthly interval).

Monthly (rather than traditional yearly) empirical estimates of the force of mortality are more accurate at extreme old ages. We found that monthly estimates of the force of mortality are higher after age 105 compared to traditional yearly estimates. Monthly estimates of the force of mortality produce more Gompertz-like mortality trajectories, which translates to straighter lines on a semilog scale compared to yearly estimates (up to age 108 years).

Section 5: Comparison of Mortality Estimation Methods by Human Mortality Database and the Social Security Administration

Reliable estimates of mortality at advanced ages are difficult to obtain, so here we consider two additional sources of U.S. old-age mortality data: the Social Security Administration life tables and the Human Mortality Database cohort death rate estimates. We compare mortality estimates from these sources with mortality estimates obtained in our project. This procedure allows us first to validate mortality estimates made by the Social Security Administration (based on extrapolation) and then validate our own mortality estimates using HMD estimates based on detailed files from the National Center of Health Statistics (NCHS).

5.1 Social Security Administration

Construction of life tables for the United States Social Security Area 1900–2100 is described in a special publication from the U.S. Department of Health and Human Services (Bell and Miller 2005).

Numbers of deaths by age and sex for each calendar year were taken from the NCHS based on information supplied by states in the Death Registration Area. This information is available on the Web at www.cdc.gov/nchs/nvss.htm. Deaths were provided by five-year age groups for ages five through 84, in total for ages 85 and older, and by single-year and smaller age intervals for ages four and under. Annual estimates of the U.S. resident population by single year of age and sex were taken from the Census Bureau (Current Population Reports Series P-25). Data for older persons were taken from the Medicare database. This source of data on aged persons is not subject to errors of noncomparability (between deaths and population data) and yet does permit a very large number of observations. The Medicare database also involves fewer errors of misstatement of age, because most of the data relate to individuals who have had to prove their date of birth to receive benefits. In an additional effort of data cleaning, the Medicare-based death rates calculated for years after 1987 were limited to the records of those Medicare participants who were also eligible for Social Security or Railroad Retirement monthly income benefits. This limitation eliminated approximately 3 percent of the Medicare records.

In this section we consider various methods of calculating life table probability of dying only for older age groups (over 85 years). One method that has been used to calculate probabilities of dying for a life table that are consistent with the underlying pattern of mortality experienced in the population is to require that the life table central death rates for quinquennial age groups, $5m_x$, equal the population central death rates, $5M_x$. That is, $5m_x = 5M_x$ for x = 5, 10, 15, ... , 94. Note that the SSA method uses five-year instead of one-year central death rates in order to calculate one-year life table probabilities of dying before age 94 years.

For this project our main focus is on mortality at extreme old ages, so we consider here in more detail calculation of probabilities of dying for ages 95 years and older. The SSA approach takes into account different rates of mortality increase for men and women. An analysis of the mortality of Social Security charter Old-Age Insurance beneficiaries has shown that at the very old ages, mortality increased about 5 percent per year of age for men and about 6 percent per year for women. For period life tables, probabilities of dying for men ages 95 and older were calculated in the following way:

$$q_x = q_{x-1}\left(\frac{q_{94}}{q_{93}}\left(\frac{99-x}{5}\right) + 1.05\,\frac{x-94}{5}\right) \qquad X = 95, 96, 97, 98, 99$$

$$q_x = 1.05\, q_{x-1} \qquad X = 100, 101, 102, \ldots$$

For women, the same formulas were used, except that 1.06 was substituted for 1.05.

Note that SSA approach extrapolated the probabilities of dying for the U.S. period life tables using recursive formula. SSA researchers then arranged these graduated values of probability of dying obtained for period life tables into cohort life tables.

Our next step was to compare the probabilities of dying found in this project, which are based on DMF data, with SSA probabilities of dying at advanced ages. This comparison can be done for the 1900 birth cohort, for which a cohort life table is available from the SSA. Figures 25 and 26 compare our DMF-based estimates of probability of dying with corresponding SSA estimates for men and women, respectively. Note that the SSA estimates closely follow our DMF-based estimates up to ages 103–104 years; thereafter, SSA estimates are higher than DMF estimates. These figures also show significant statistical noise observed after age 105 years for our DMF-based data.

Figure 25

PROBABILITIES OF DYING FOR MEN BORN IN 1900, BASED ON DMF AND SSA ESTIMATES

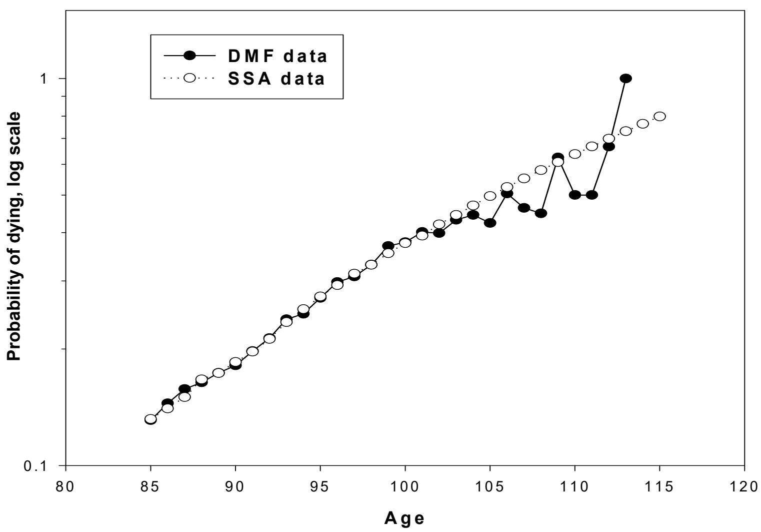


Figure 26

PROBABILITIES OF DYING FOR WOMEN BORN IN 1900, BASED ON DMF AND SSA ESTIMATES

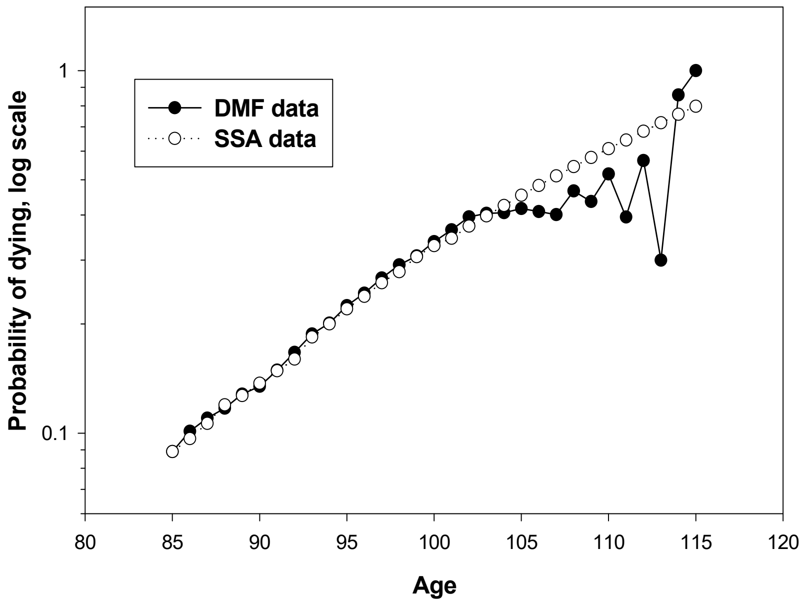
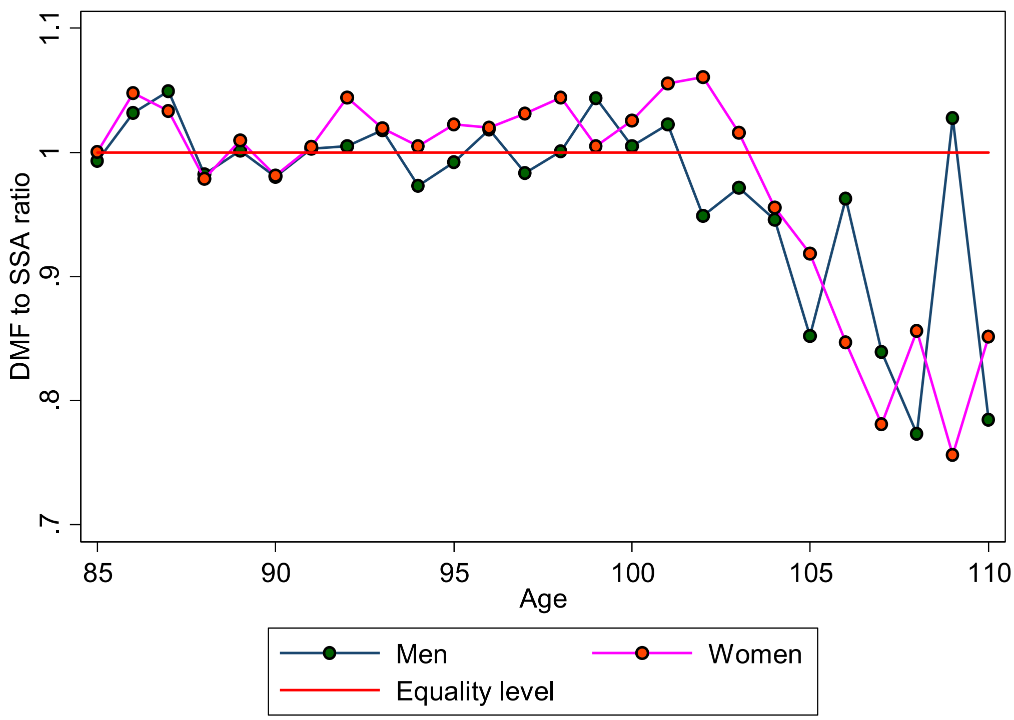


Figure 27 presents the ratio of DMF to SSA estimates of probability of dying. Note that the SSA estimates closely follow our DMF-based estimates up to age 103–104 years, at which point the SSA estimates become higher than the DMF estimates. This figure also shows significant statistical noise observed after age 105 years.

Figure 27

RATIO OF DMF TO SSA ESTIMATES OF PROBABILITY OF DYING FOR 1900 BIRTH COHORT



Figures 28 and 29 compare our DMF-based estimates of probability of dying for cleaned data (variant 2) with corresponding SSA estimates for men and women, respectively. In the case of cleaned data, the SSA estimates closely follow the DMF estimates up to age 105 years. In the case of men, the DMF estimates after age 105 years are even higher than the SSA estimates.

Figure 28

PROBABILITIES OF DYING FOR MEN BORN IN 1900, BASED ON CLEANED DMF DATA (VARIANT 2) AND SSA ESTIMATES

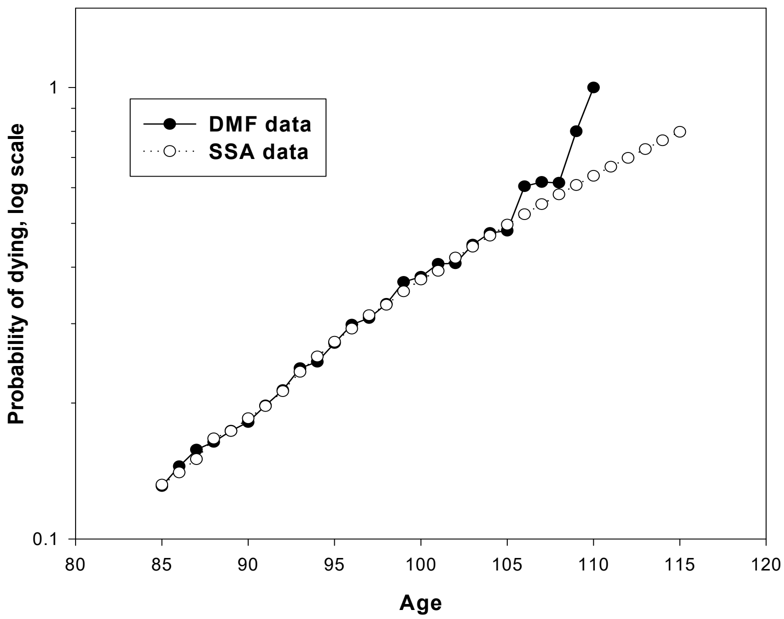
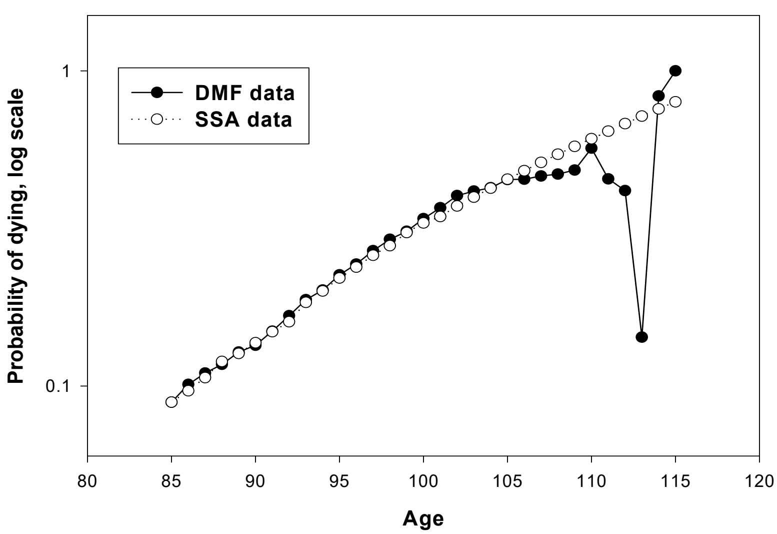


Figure 29

PROBABILITIES OF DYING FOR WOMEN BORN IN 1900, BASED ON CLEANED DMF DATA (VARIANT 2) AND SSA ESTIMATES



Overall, we can conclude that the SSA estimates are good enough for describing mortality up to age 105 years. After age 105 years, the SSA estimates probably overestimate mortality of women.

5.2 Human Mortality Database

The Human Mortality Database does not have information about cohort life tables for the United States, so instead we analyzed cohort death rates. Methods of calculating cohort death rates are presented in an online publication (Wilmoth et al. 2017) available at the Human Mortality Database website (www.mortality.org). In order to calculate cohort death rates, the HMD researchers apply the concept of the Lexis diagram.

For a single-year birth cohort, the death rate is calculated using the formula

$$M^c(x,t) = \frac{D^c(x,t)}{E^c(x,t)}$$

where *c* indicates the age-cohort Lexis shape . These quantities are estimated using death counts from the lower Lexis triangle in year *t* and the upper triangle in year *t+1*, January 1 population counts in year *t+1*, as well as information about birth distribution in year *t-x*, when available. The observed rates $M^c(x,t)$ are equated with life table rates m_x (with exception of age 0). Death counts in age-cohort Lexis shape are defined as:

$$D^c(x,t) = D_L(x,t) + D_U(x,t+1)$$

Exposure estimates are calculated as follows:

$$E^c(x,t) = P(x,t+1) + z_L D_L(x,t) - z_U D_U(x,t+1)$$

where z_L and z_U are calculated using information from the monthly birth distributions from the same cohort and are held fixed over the life of the cohort:

$$z_L = \frac{1-\bar{b}'}{2} + \frac{\sigma^2}{2(1-\bar{b}')}$$

$$z_U = \frac{\bar{b}'}{2} + \frac{\sigma^2}{\bar{b}'}$$

where $\bar{b}$ is the mean time of birth within the calendar year of birth and σ is the corresponding standard deviation. In practice it is useful to assume uniform distribution of birthdays and simplify the formula for exposure:

$$E^c(x,t) = P(x,t) + \frac{1}{3}(D_L(x,t-1) - D_u(x,t))$$

In order to calculate U.S. death rates, HMD researchers used the NCHS restricted mortality file, which has information about age, year of birth and months of birth and death. The extinct cohort method was used for ages 80 and over except for years 1933–1939 when this method was used for ages 75 and over (Wilmoth et al. 2017).

We have compared our estimates of mortality force based on the DMF data with cohort death rates from the Human Mortality Database. Figure 30 compares mortality estimates for females born in 1900 calculated using DMF data and central death rates provided by HMD. Note that HMD mortality follows closely mortality estimates obtained using the DMF data up to very high ages of 110 years. This differs from SSA data, which are compatible with DMF data up to age

104 years and then show significantly higher values of mortality. This difference is not surprising, as HMD death rates are calculated from the observed mortality data while SSA estimates are based on extrapolation. Figure 30 also demonstrates that DMF mortality estimates based on cleaned data are closer to HMD death rates at ages 104–110 years compared to the uncleaned data.

Figure 30

FORCE OF MORTALITY FOR WOMEN BORN IN 1900, BASED ON DMF AND HMD ESTIMATES

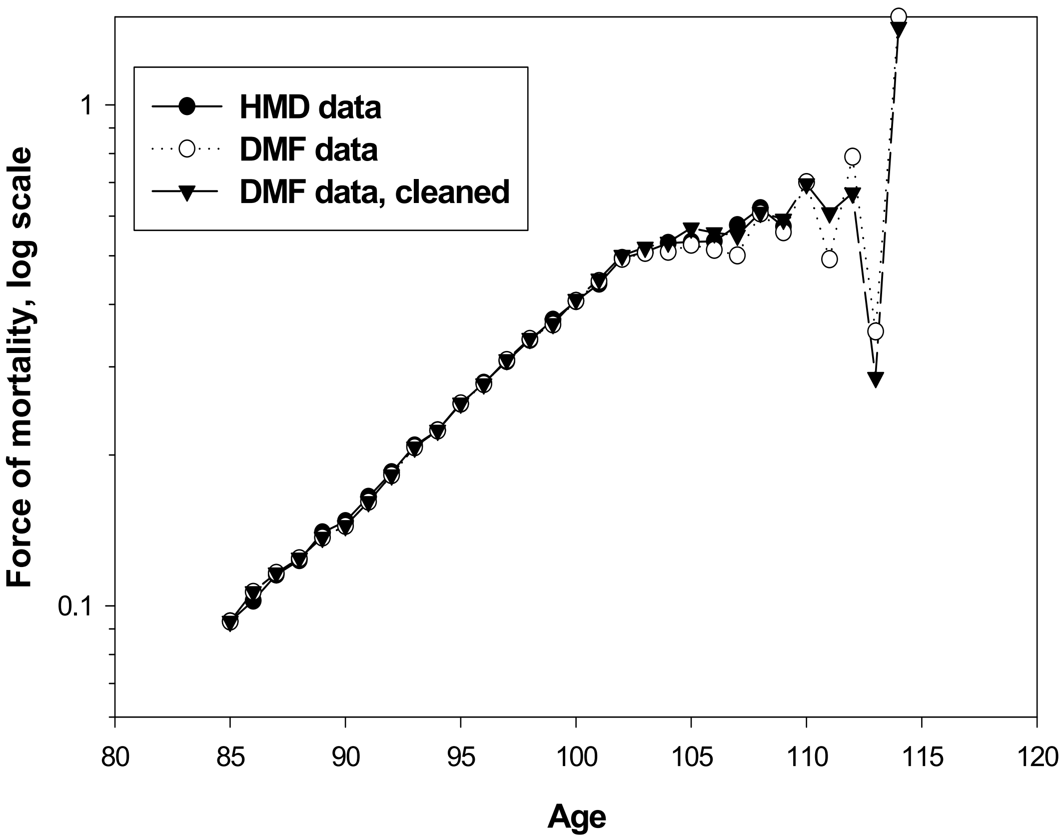


Figure 31 shows ratios of DMF to HMD estimates for both men and women born in 1900. This figure demonstrates that DMF and HMD mortality estimates are very close to each other between ages 93 and 103 years.

Figure 31

RATIO OF DMF TO HMD ESTIMATES OF THE FORCE OF MORTALITY FOR 1900 BIRTH COHORT(BOTH SEXES)

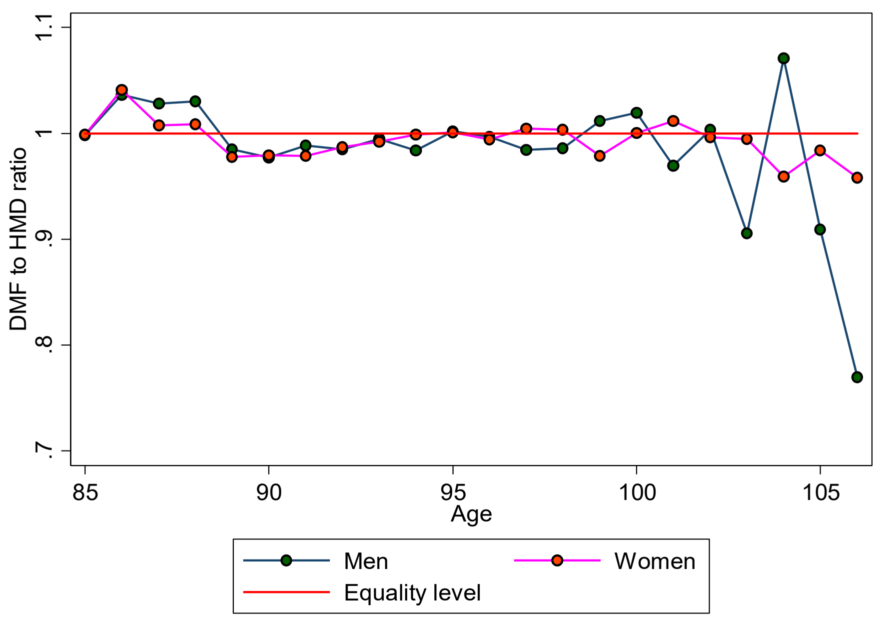
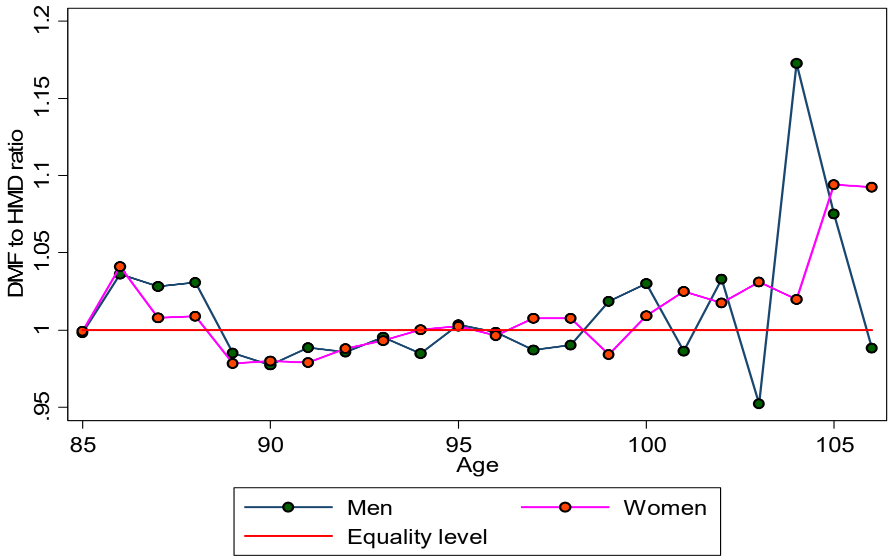


Figure 32 shows ratios of DMF (cleaned data) to HMD estimates for men and women born in 1900. Data cleaning results in greater consistency between DMF and HMD data. The reason for this is not clear. It is possible that age information on death certificates used by HMD is more accurate at extreme old ages compared to the Social Security Administration database. However, at this moment it is not possible to test this hypothesis.

Figure 32

RATIO OF DMF (CLEANED DATA) TO HMD ESTIMATES OF THE FORCE OF MORTALITY FOR 1900 BIRTH COHORT



Summarizing this comparison between HMD and SSA data we may conclude that both sources of data describe mortality with reasonable accuracy up to age 105 years. Mortality at ages higher than 105 years demonstrates significant volatility and is not regular. Thus, we conclude that both SSA and HMD mortality estimates can be used for mortality modeling until age 105 years.

Section 6: Key Observations and Conclusions

The following are key observations from the study:

- Applying age validation to DMF records does not reveal sufficient differences in data quality among the studied 1898, 1899, 1900, 1901 and 1902 birth cohorts. No improvement in data quality over time was observed, contrary to expectations.
- The age validation procedure revealed an increase in records with poor quality of age reporting after age 105 years, but not at earlier ages. Problems with data quality can be alleviated by removing observed and estimated (through the interpolation procedure) percentages of records with poor quality for ages 106 years and over.
- Data cleaning at the tail of the survival curve (based on the age validation) results in higher values of mortality estimates around ages 105–108 years compared to unclean data. This implies that the observed U.S. mortality at this age interval is underestimated and mortality most likely follows the Gompertz law up to age 108 years.
- Monthly estimates of the force of mortality are higher after age 105 years compared to yearly estimates.
- Mortality estimates by the region of SSN application reveal very small differences in old-age mortality.
- SSA estimates of cohort probabilities of dying are in good agreement with our DMF-based estimates up to age 105 years.
- HMD cohort death rates are close to our DMF-based estimates of the force of mortality up to age 110 years.

The results of this study allow us to make the following conclusions:

- Data quality adjustment based on the results of an age validation procedure leads to more Gompertz-like mortality trajectories up to age 106 years in the case of yearly estimates and up to age 110 years in the case of monthly estimates.
- Mortality for ages over 95 years does not demonstrate a decline over time in 1898–1902 birth cohorts.
- Mortality trajectories for women are more prone to decelerate after age 105 years compared to those for men.
- Mortality estimates by region of last residence reveal small, insignificant differences in old-age mortality without a discernible pattern.

Section 7: Acknowledgments

We would like to thank the participants of the past Living to 100 international symposiums for useful comments on the topic of this report. We also would like to thank Marcelo Manzo, a student at DePaul University, for his help in age validation of the records belonging to the 1898 birth cohort. We are most grateful to the POG Chair, Tom Edwalds, for providing yearly calculations after age 109 years for men and 111 years for women and both sexes in Table A3 of the Appendix. Finally, we are most grateful to the members of the Project Oversight Group for their valuable comments and suggestions.

Appendix: Mortality Data Characteristics for 1898–1902 Birth Cohort

Note: More detailed life tables for single-year birth cohorts are available in a supplemental Excel file at the following URL: http://health-studies.org/POG/DMF-tables.xls.

Table A1

ALL DATA

	Both Sexes			Men			Women		
Age	lx	hx	qx	lx	hx	qx	lx	hx	qx
85	2344762	0.106764	0.101353	673852	0.139236	0.130174	1450598	0.092373	0.088295
86	2107113	0.119602	0.112853	586134	0.155081	0.143921	1322518	0.104462	0.099277
87	1869319	0.129893	0.121972	501777	0.166598	0.153787	1191223	0.115039	0.108781
88	1641315	0.139668	0.130551	424610	0.178465	0.163844	1061640	0.124655	0.117341
89	1427040	0.150711	0.140150	355040	0.189102	0.172766	937066	0.136142	0.127465
90	1227040	0.162160	0.149998	293701	0.203726	0.184892	817623	0.148074	0.137867
91	1042986	0.177982	0.163437	239398	0.220879	0.198911	704900	0.163737	0.151346
92	872523	0.196294	0.178751	191779	0.241018	0.215097	598216	0.182716	0.167421
93	716559	0.218322	0.196835	150528	0.268585	0.236787	498062	0.204185	0.185270
94	575515	0.242185	0.216026	114885	0.294282	0.256535	405786	0.228504	0.205074
95	451189	0.265926	0.234718	85413	0.317070	0.273682	322570	0.254753	0.225970
96	345287	0.293066	0.255611	62037	0.348085	0.296484	249679	0.281747	0.246957
97	257028	0.323496	0.278456	43644	0.382672	0.321213	188019	0.311804	0.269749
98	185457	0.351851	0.299212	29625	0.395585	0.330262	137301	0.340784	0.291171
99	129966	0.376869	0.317114	19841	0.429560	0.353611	97323	0.363614	0.307676
100	88752	0.410118	0.340330	12825	0.470979	0.381209	67379	0.402403	0.335001
101	58547	0.450409	0.367619	7936	0.500709	0.400454	44807	0.443263	0.362845
102	37024	0.474577	0.383562	4758	0.523469	0.414880	28549	0.468249	0.379418
103	22823	0.501973	0.401262	2784	0.551203	0.432112	17717	0.497727	0.398544
104	13665	0.537722	0.423783	1581	0.585446	0.452878	10656	0.527065	0.417136
105	7874	0.564194	0.440056	865	0.593703	0.457803	6211	0.556493	0.435357
106	4409	0.590482	0.455886	469	0.645980	0.488273	3507	0.570643	0.443969
107	2399	0.557569	0.436015	240	0.442748	0.362500	1950	0.539063	0.424615
108	1353	0.618287	0.472284	153	0.571429	0.444444	1122	0.586744	0.453654
109	714	0.598726	0.460784	85	0.698413	0.517647	613	0.583772	0.451876
110	385	0.764812	0.553247	41	0.603175	0.463415	336	0.788382	0.565476
111	172	0.625954	0.476744	22	0.666667	0.500000	146	0.607143	0.465753
112	90	0.647059	0.488889	11	0.933333	0.636364	78	0.600000	0.461538
113	46	0.628571	0.478261	4	1.200000	0.750000	42	0.584615	0.452381
114	24	1.310345	0.791667	1	2.000000	1	23	1.285714	0.782609
115	5	0.5	0.4				5	0.5	0.4
116	3	2	1				3	2	1

Abbreviations: lx, number of survivors; hx, force of mortality (year^{-1}); qx, probability of dying.

Table A2
QUALITY-ADJUSTED DATA ACCORDING TO VARIANT 2

	Both Sexes			Men			Women		
Age	lx	hx	qx	lx	hx	qx	lx	hx	qx
85	2344241	0.106789	0.101376	673782	0.139252	0.130188	1450187	0.0924	0.088320
86	2106592	0.119633	0.112881	586064	0.155101	0.143938	1322107	0.104496	0.099307
87	1868798	0.129932	0.122006	501707	0.166623	0.153809	1190812	0.11508	0.108819
88	1640794	0.139715	0.130592	424540	0.178497	0.163871	1061229	0.124706	0.117387
89	1426519	0.150771	0.140201	354970	0.189142	0.172801	936655	0.136205	0.127521
90	1226519	0.162235	0.150062	293631	0.203779	0.184936	817212	0.148154	0.137936
91	1042465	0.178079	0.163519	239328	0.220951	0.198970	704489	0.16384	0.151435
92	872002	0.196423	0.178857	191709	0.241116	0.215175	597805	0.182854	0.167536
93	716038	0.218498	0.196978	150458	0.268727	0.236897	497651	0.204371	0.185423
94	574994	0.242431	0.216221	114815	0.294487	0.256691	405375	0.228762	0.205282
95	450668	0.266275	0.234989	85343	0.317372	0.273906	322159	0.255119	0.226258
96	344766	0.293574	0.255997	61967	0.348547	0.296819	249268	0.282277	0.247364
97	256507	0.324259	0.279022	43574	0.383405	0.321729	187608	0.312594	0.270340
98	184936	0.353018	0.300055	29555	0.396708	0.331044	136890	0.341982	0.292045
99	129445	0.378673	0.318390	19771	0.431409	0.354863	96912	0.365438	0.308981
100	88231	0.413040	0.342340	12755	0.474177	0.383301	66968	0.405373	0.337057
101	58026	0.455373	0.370920	7866	0.506293	0.404017	44396	0.448286	0.366204
102	36503	0.482986	0.389037	4688	0.533369	0.421075	28138	0.476719	0.384960
103	22302	0.516730	0.410636	2714	0.569467	0.443257	17306	0.512577	0.408009
104	13144	0.565058	0.440581	1511	0.620989	0.473858	10245	0.554067	0.433870
105	7353	0.616493	0.471236	795	0.663317	0.498113	5800	0.607914	0.466207
106	3888	0.657099	0.494599	399	0.775652	0.558897	3096	0.630416	0.479328
107	1965	0.642905	0.486514	176	0.578755	0.448864	1612	0.611584	0.468362
108	1009	0.719677	0.529237	97	0.895522	0.618557	857	0.655306	0.493582
109	475	0.617080	0.471579	37	0.740741	0.540541	434	0.602699	0.463134
110	251	0.750685	0.545817	17	0.518519	0.411765	233	0.77381	0.557940
111	114	0.620690	0.473684	10	0.857143	0.60	103	0.591195	0.456311
112	60	0.553191	0.433333	4	1.2	0.75	56	0.516854	0.410714
113	34	0.615385	0.470588	1	2	1	33	0.588235	0.454545
114	18	1.130435	0.722222				18	1.130435	0.722222
115	5	0.5	0.4				5	0.5	0.4
116	3	2	1				3	2	1

Abbreviations: lx, number of survivors; hx, force of mortality ($year^{-1}$); qx, probability of dying.

Table A3

QUALITY-ADJUSTED DATA ACCORDING TO VARIANT 2 BASED ON MONTHLY ESTIMATES OF THE FORCE OF MORTALITY*

Note: More detailed data for each month of age are available in supplemental Excel file at the following URL: http://health-studies.org/POG/DMF-tables.xls.

	Both Sexes			Men			Women		
Age	lx	hx	qx	lx	hx	qx	lx	hx	qx
85	2344241	0.106889	0.101375	673782	0.139476	0.130186	1450187	0.092465	0.088319
86	2106592	0.119775	0.11288	586064	0.155411	0.143936	1322107	0.104591	0.099307
87	1868798	0.130114	0.122005	501707	0.167007	0.153807	1190812	0.115207	0.108818
88	1640794	0.139941	0.130591	424540	0.178970	0.163869	1061229	0.124867	0.117386
89	1426519	0.151055	0.140200	354970	0.189706	0.172797	936655	0.136415	0.127520
90	1226519	0.162589	0.150060	293631	0.204484	0.184932	817212	0.148424	0.137935
91	1042465	0.178548	0.163516	239328	0.221850	0.198965	704489	0.164206	0.151432
92	872002	0.197054	0.178854	191709	0.242286	0.215169	597805	0.183362	0.167533
93	716038	0.219368	0.196973	150458	0.270350	0.236888	497651	0.205082	0.185419
94	574994	0.243620	0.216215	114815	0.296629	0.256680	405375	0.229760	0.205276
95	450668	0.267854	0.234980	85343	0.320058	0.273893	322159	0.256507	0.226250
96	344766	0.295695	0.255986	61967	0.352116	0.296802	249268	0.284161	0.247354
97	256507	0.327126	0.279007	43574	0.388174	0.321705	187608	0.315159	0.270327
98	184936	0.356727	0.300037	29555	0.401999	0.331018	136890	0.345350	0.292028
99	129445	0.383265	0.318368	19771	0.438244	0.354831	96912	0.369559	0.308961
100	88231	0.419024	0.342312	12755	0.483307	0.383260	66968	0.411025	0.337030
101	58026	0.463439	0.370884	7866	0.517462	0.403969	44396	0.455973	0.366169
102	36503	0.492648	0.388994	4688	0.546486	0.421019	28138	0.486001	0.384919
103	22302	0.528625	0.410585	2714	0.585534	0.443192	17306	0.524179	0.407959
104	13144	0.580743	0.440518	1511	0.642025	0.473774	10245	0.568825	0.433810
105	7353	0.637063	0.471157	795	0.689184	0.498014	5800	0.627603	0.466130
106	3888	0.682215	0.494504	399	0.818132	0.558745	3096	0.652472	0.479243
107	1965	0.666357	0.486424	176	0.595618	0.448778	1612	0.631641	0.468282
108	1009	0.753133	0.529111	97	0.962865	0.618202	857	0.680191	0.493480
109	475	0.637690	0.471488	37	0.776809	0.540129	434	0.621842	0.463046
110	251	0.788918	0.545664	17	0.529858	0.411311	233	0.815935	0.557774
111	114	0.633282	0.469153	9	0.801554	0.551369	103	0.603186	0.452924
112	60	0.575968	0.437840	4	1.463492	0.768573	56	0.534499	0.414037
113	34	0.635513	0.470336				33	0.605705	0.454310
114	18	1.274475	0.720422				18	1.274475	0.720422
115	5	0.507937	0.398264				5	0.507937	0.398264

* Data are shown for whole years of age while based on monthly estimates. Annual probabilities of dying and hazard rates are calculated in the following way: (1) monthly px values calculated using monthly hx values as exp(-hx); (2) annual px calculated as the product of the monthly px's within the year of age; annual qx calculated as 1-px; annual hx calculated as –ln(px). Monthly values of probability of survival (px) and force of mortality (hx) for monthly intervals with no deaths are assumed to be equal to values in the previous monthly interval.

References

Bebbington, M., et al. 2014. Beyond the Gompertz law: exploring the late-life mortality deceleration phenomenon. *Scandinavian Actuarial Journal* 3:189–207.

Bell, F. C., and M. L. Miller. 2005. Life Tables for the United States Social Security Area 1900–2100. Actuarial Study No. 120. Baltimore, MD: U.S. Department of Health and Human Services.

Bourbeau, R., and B. Desjardins. 2006. Mortality at extreme ages and data quality: the Canadian experience. In *Human Longevity, Individual Life Duration, and the Growth of the Oldest-Old Population*, 167–185. New York: Springer.

Carey, J. R., et al. 1992. Slowing of mortality rates at older ages in large medfly cohorts. *Science* 258, no. 5081:457–461.

Coale, A. J. 1996. Age patterns and time sequence of mortality in national populations with the highest expectation of life at birth. *Population and Development Review* 22, no. 1:127–135.

Curtsinger, J. W., et al. 1992. Demography of genotypes: failure of the limited life-span paradigm in *Drosophila melanogaster*. *Science* 258, no. 5081:461–463.

Elo, I. T., et al. 2013. Age validation in the long life family study through a linkage to early-life census records. *Journals of Gerontology Series B—Psychological Sciences and Social Sciences* 68, no. 4:580–585.

Elo, I. T., et al. 1996. Consistency of age reporting on death certificates and Social Security records among elderly African Americans. *Social Science Research* 25, no. 3:292–307.

Faig, K. Reported Deaths of Centenarians and Near-centenarians in the U.S. Social Security Administration's Death Master File. Paper presented at Living to 100 and Beyond International Symposium, The Society of Actuaries, January 17-18, 2002, Orlando, Florida.

Gampe, J. 2010. Human mortality beyond age 110. In *Supercentenarians*, 219–230. New York: Springer.

Gavrilov, L. A., and N. S. Gavrilova. 2011. Mortality measurement at advanced ages: a study of the Social Security Administration Death Master File. *North American Actuarial Journal* 15, no. 3:432–447.

Gavrilov, L. A., and N. S. Gavrilova. 2012. Biodemography of exceptional longevity: early-life and mid-life predictors of human longevity. *Biodemography and Social Biology* 58, no. 1:14–39.

Gavrilov, L. A., and N. S. Gavrilova. 2015. Predictors of exceptional longevity: effects of early-life and midlife conditions, and familial longevity. *North American Actuarial Journal* 19, no. 3:174–186.

Gavrilov, L. A., et al. 2017. The future of human longevity. *Gerontology* 63, no. 6:524–526.

Gavrilova, N. S., and L. A. Gavrilov. 2014. Mortality trajectories at extreme old ages: a comparative study of different data sources on U.S. old-age mortality. In *2014 Living to 100 Monograph*. Schaumburg, IL: The Society of Actuaries.

Gavrilova, N. S., and L. A. Gavrilov. 2015. Biodemography of old-age mortality in humans and rodents. *Journals of Gerontology Series A—Biological Sciences and Medical Sciences* 70, no. 1:1–9.

Greenwood, M., and J. O. Irwin. 1939. The biostatistics of senility. *Human Biology* 11:1–23.

Hill, M. E., et al. 1997. Age-linked institutions and age reporting among older African Americans. *Social Forces* 75, no. 3:1007–1030.

Hill, M. E., and I. Rosenwaike. 2001. The Social Security Administration's Death Master File: the completeness of death reporting at older ages. *Social Security Bulletin* 64, no. 1:45–51.

Horiuchi, S., and J. R. Wilmoth. 1997. Age patterns of the life table aging rate for major causes of death in Japan, 1951–1990. *Journals of Gerontology Series A—Biological Sciences and Medical Sciences* 52, no. 1:B67–B77.

Horiuchi, S., and J. R. Wilmoth. 1998. Deceleration in the age pattern of mortality at older ages. *Demography* 35:391–412.

Jdanov, D. A., et al. 2008. Beyond the Kannisto-Thatcher Database on Old Age Mortality: An Assessment of Data Quality at Advanced Ages. Max Planck Institute for Demographic Research working paper WP 2008-013. Rostock, Germany: Max Planck Institute for Demographic Research.

Kannisto, V. 1988. On the survival of centenarians and the span of life. *Population Studies: A Journal of Demography* 42:389–406.

Kannisto, V. 1994. *Development of Oldest-Old Mortality, 1950–1990: Evidence from 28 Developed Countries*. Odense, Denmark: Odense University Press.

Kestenbaum, B. 1992. A description of the extreme aged population based on improved Medicare enrollment data. *Demography* 29, no. 4:565–580.

Milevsky, M. A. 2014. Mortality plateaus and the pricing of longevity insurance. *Journal of Retirement* 2, no. 2:99–107.

Poulain, M. 2010. On the age validation of supercentenarians. In *Supercentenarians*, 3–30. New York: Springer.

Preston, S. H., et al. 1999. Effects of age misreporting on mortality estimates at older ages. *Population Studies: A Journal of Demography* 53, no. 2:165–177.

Robine, J.-M. 2007. Research issues on human longevity. In *Individual Life Duration and the Growth of the Oldest-Old Population,* 7–42. New York: Springer.

Rosenwaike, I., and L. F. Stone. 2003. Verification of the ages of supercentenarians in the United States: results of a matching study. *Demography* 40, no. 4:727–739.

Sesso, H. D., et al. 2000. Comparison of National Death Index and World Wide Web death searches. *American Journal of Epidemiology* 152, no. 2:107–111.

Thatcher, A. R. 1999. The long-term pattern of adult mortality and the highest attained age. *Journal of the Royal Statistical Society Series A—Statistics in Society* 162:5–30.

Thatcher, A. R., et al. 1998. *The Force of Mortality at Ages 80 to 120*. Odense, Denmark: Odense University Press.

Vincent, P. 1951. La mortalite des Viellards. *Population* 6:181–204.

Wilmoth, J. R. 1995. Are mortality rates falling at extremely high ages: an investigation based on a model proposed by Coale and Kisker. *Population Studies: A Journal of Demography* 49, no. 2:281–295.

Wilmoth, J. R., et al. 2007. *Methods Protocol for the Human Mortality Database*. Version 5. Rostock, Germany.

Wilmoth, J. R., et al. 2017. *Methods Protocol for the Human Mortality Database*. Version 6. Rostock, Germany.

Yi, Z., et al. 2007. The association of childhood socioeconomic conditions with healthy longevity at the oldest-old ages in China. *Demography* 44, no. 3:497–518.

Young, R. D., et al. 2010. Typologies of extreme longevity myths. *Current Gerontology and Geriatrics Research* 2012: 423087.

About The Society of Actuaries

The Society of Actuaries (SOA), formed in 1949, is one of the largest actuarial professional organizations in the world dedicated to serving 32,000 actuarial members and the public in the United States, Canada and worldwide. In line with the SOA Vision Statement, actuaries act as business leaders who develop and use mathematical models to measure and manage risk in support of financial security for individuals, organizations and the public.

The SOA supports actuaries and advances knowledge through research and education. As part of its work, the SOA seeks to inform public policy development and public understanding through research. The SOA aspires to be a trusted source of objective, data-driven research and analysis with an actuarial perspective for its members, industry, policymakers and the public. This distinct perspective comes from the SOA as an association of actuaries, who have a rigorous formal education and direct experience as practitioners as they perform applied research. The SOA also welcomes the opportunity to partner with other organizations in our work where appropriate.

The SOA has a history of working with public policymakers and regulators in developing historical experience studies and projection techniques as well as individual reports on health care, retirement and other topics. The SOA's research is intended to aid the work of policymakers and regulators and follow certain core principles:

Objectivity: The SOA's research informs and provides analysis that can be relied upon by other individuals or organizations involved in public policy discussions. The SOA does not take advocacy positions or lobby specific policy proposals.

Quality: The SOA aspires to the highest ethical and quality standards in all of its research and analysis. Our research process is overseen by experienced actuaries and nonactuaries from a range of industry sectors and organizations. A rigorous peer-review process ensures the quality and integrity of our work.

Relevance: The SOA provides timely research on public policy issues. Our research advances actuarial knowledge while providing critical insights on key policy issues, and thereby provides value to stakeholders and decision makers.

Quantification: The SOA leverages the diverse skill sets of actuaries to provide research and findings that are driven by the best available data and methods. Actuaries use detailed modeling to analyze financial risk and provide distinct insight and quantification. Further, actuarial standards require transparency and the disclosure of the assumptions and analytic approach underlying the work.

Society of Actuaries
475 N. Martingale Road, Suite 600
Schaumburg, Illinois 60173
www.SOA.org