SURNAME FREQUENCY AND LIFESPAN

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Abstract

Using administrative records from the Social Security Administration this article explores the relationship between surname frequency and lifespan for over 19 million people born in 1910-19 and deceased by 2011—which represent over 80% of the total population born in 1910-19. People with more frequent surnames had shorter average and median lifespans. Differences in average lifespan between the top and bottom 5% of the distribution of people according to surname frequency amount to 484 days (1.33 years). Differences in median lifespan amount to 611 days (1.67 years). This empirical finding can be explained by human capital theory, connecting well-known stylized facts on fertility, human capital and intergenerational transmission.

JEL codes: I14, I31, J1, N3, O1.

Keywords: surname, last name, human capital, fertility, lifespan, longevity, Zip's Law.

I. Introduction

The comedy film “Idiocracy” (2006) depicts a cartoonish version of the future in which the world is populated entirely by people with low IQ. The premise of the plot is that smart couples in the present do not reproduce as much as not-so-smart couples, eventually causing the extinction of smart people. In a more serious tone, evolutionary psychologist Satoshi Kanazawa makes a similar point in the book *The Intelligence Paradox*, stating that when it comes to reproductive success “intelligent people are the ultimate losers in life.” Though disputable, the argument raises questions about the role of fertility differentials across human capital levels in the long run.

Income inequality is a public-policy concern, and is at least partially due to human capital disparities (see Heckman and Krueger 2003). Effective public policies targeting income inequality require an understanding of the determinants of the distribution of human capital in a society, and fertility differentials are one of them. If human capital is transmitted from parents to children, and people with lower human capital reproduce faster, then societies could have a tendency to become more unequal.

There is evidence of a negative relationship between fertility and some proxies for human capital. On average, people with more years of schooling or higher IQ have fewer children (Castro Martin 1995, Vining 1982 and 1995). At the same time, there is evidence of intergenerational transmission of a number of traits and behaviors. Many studies have documented a positive parent-children correlation for variables ranging from years of schooling and health status to risk aversion and marital instability (Solon 1999, Black and Deveraux 2012). Finally, surnames—typically passed from parents to children—provide an indicator of a person’s ancestry (Lasker 1985, King and Jobling 2009). Data for different countries show that surnames have skewed distributions. Surnames approximately follow Zipf’s law, i.e. the number of people sharing a surname is inversely proportional to the surname’s frequency rank (Mizayima et al. 2000 present data for Japan, Kim and Park 2005 for Korea, and Zanette and Manrubia 2001 for the US and Germany). Brought together, the stylized facts above provide a hypothesis on how fertility differentials could affect the distribution of human capital. Moreover, the hypothesis can be tested using cross-sectional data on surname frequency and a measure of human capital such as lifespan.

In a society where (i) surnames are passed from parents to children, (ii) there is some degree of intergenerational transmission of traits and behaviors, including those that determine human capital and fertility, and (iii) human capital and fertility are negatively related, the surnames borne by those with lower human capital become relatively more frequent. An expected consequence, which is the hypothesis tested here, is that human capital eventually would not be independent of surname frequency: greater frequency would be associated with lower average human capital.

This article uses administrative records from the Social Security Administration for over 19 million people born in 1910-19 and deceased by 2011, and tests whether there is any relationship between surname frequency and lifespan—a measure of human capital. Although it is not the first study relating names and economic outcomes, it does contribute previously unknown results.

II. The study of names

Names constitute a fascinating tool to study behavior. They have been used in different disciplines and in a variety of ways. Studies on names can be divided into five broad groups. In the first group, names are *indicators of genetic or socioeconomic background*. For instance, Garza, Rojas, and Cerda (2000) study the prevalence of diabetes by surname origin (paraphyletic versus polyphyletic) as a proxy of ethnic origin in Mexico. In economics, given names and surnames have been used as signals of ethnic background in field experiments to measure discrimination. In those experiments fake résumés with identical descriptions except for the name are submitted to real job openings, and then response rates are compared. Perhaps the best known study is Bertrand and Mullainathan (2004), who use African-American-sounding names (e.g. Lakisha and Jamal) versus white-sounding names (e.g. Emily and Gregg) in the US. Similar experiments have been carried out in other countries.[1]

The second group of studies focuses on the effect of names on behavior by *shaping the bearer's preferences*. Several articles in the psychological and marketing literatures study the affinity of people for things whose names resemble theirs. Nuttin (1985) shows in an experimental setting that letters belonging to one's own first or last name are preferred to others. Brendl, Chattopadhyay, Pelham and Carvallo (2004) show experimental evidence on how people are more likely to choose a brand when the brand name starts with letters from their names. Jones, Pelham, Carvallo and Mirenberg (2004) show evidence of people disproportionately marrying others whose first or last name resembles their own. Nelson and Simmons (2007) find that baseball players whose names begin with K (the symbol for strikeout) strike out more, students whose names begin with C or D achieve lower GPAs and attend lower-ranked law schools than do students whose names begin with A or B.

The third group of studies focuses on how names affect behavior by *creating different experiences for the bearer*. Different names result in different initials, and those initials could result in different social interactions. People with initials that spell something positive like A.C.E. or V.I.P. might have better experiences than people with initials spelling something negative, like P.I.G. or D.I.E. Christenlfeld, Phillips and Glynn (1999) present evidence of males with "positive" initials living longer than males with "negative" initials.[2] Ordering according to surnames is another way in which names affect what people experience. Classroom rosters are ordered alphabetically by surname. Students with surnames close to the end of the alphabet might have a different experience than those with surnames at the beginning. Weston (1965) studied the relationship between alphabetical order of the last name and longevity for the UK and found that those with names starting with A-R live longer than those with names starting with S-Z, and he theo-

[1] Carlsson and Rooth (2007) and Rooth (2010) use Middle-Eastern/Arab-Muslim and Swedish names in Sweden. Booth, Leigh and Varganova (2012) use Anglo-saxon, Indigenous, Italian, Chinese and Middle-Eastern names in Australia. In a similar fashion, Ahmed and Hammarstedt (2008) use Internet applications for apartments for rent and Arabic/Muslim versus Swedish names in Sweden.

[2] Abel and Kruger (2007) did a similar analysis of "positive" versus "negative" initials baseball players that was later discredited by Smith (2011).

rized about an "alphabetical neurosis." Shupe (1968) did a similar study for the US and found no significant differences, although with a small sample size. Carlson and Conard (2011) find that the later in the alphabet the first letter of one's childhood surname is, the faster the person acquires items as an adult. Alphabetical ordering also takes place among coauthors of academic articles in economics. Einav and Yariv (2006) argue that perhaps such ordering favors individuals with some surnames, and find evidence on economists in academia being more successful the closer their surname initial is to the beginning of the alphabet.

In the fourth group are studies that use *uncommon surnames as identifiers of population subgroups in order to measure intergenerational mobility*. In those studies the socioeconomic status of people with uncommon names is tracked across long periods to determine if they have moved and at what rate. Among the countries studied this way are: England (Clark and Cummins 2012), Sweden, the US (Clark et al. 2012), India (Clark and Landes 2012), China (Hao and Clark 2012) and Japan (Clark and Ishii 2012).

The fifth group of studies focuses on the cross-sectional relationship between *how common a surname is and the bearers' attributes*. Collado, Ortuño-Ortín, and Romeu (2008) study data from the Yellow Pages in Spain and find that people bearing uncommon surnames tend to have a higher socioeconomic status, measured by the fraction that have certain occupations (doctors, lawyers, pharmacists, and university professors). They also study historical evidence from the 1890 census of Spain and find that surname frequency is negatively related to literacy. Peña (2013) presents evidence for Mexico of a negative relationship between surname frequency and different measures of human capital: individuals with more frequent surnames do worse in standardized tests in elementary school, have lower high school GPA, attain less postsecondary education, and self-report a worse general-health status.

The present study belongs to the last group. It analyzes the relationship between surname frequency and lifespan in the US. To the best of my knowledge, it is the first study that analyzes surname frequency and any measure of human capital for the US. At the same time, it is the first study in the world of the relationship between surname frequency and lifespan.

III. Social Security Data

With the purpose of preventing fraud, the Social Security Administration publishes the Social Security Numbers (SSN) belonging to deceased individuals in what is called the Death Master File (DMF). Besides the SSN, the file only includes last name, given name, date of birth, and date of death of the person. The file is updated periodically, and by November 2011, which is the version used here, it contained over 86 million records.[3]

SSN were issued the first time in November 1936, and by the following year over 37 million SSN were issued. Originally, only employees were issued SSN but several groups were excluded: agricultural workers, domestic servants, casual labor, maritime workers,

[3] The Death Master File is distributed by the Social Security Administration at a charge, but was made available to the author by courtesy of SSDMF.INFO.

government employees, the employees of philanthropic, educational, and similar institutions, and the self-employed. It is estimated that at the time the excluded groups comprised about 40 percent of the working population (Puckett 2009).

Coverage was later expanded and the use of SSN grew. In 1957 military personnel were covered under Social Security and were enumerated in mass. In 1962 the Internal Revenue Service began using the SSN for federal tax reporting. In 1965 Medicare enrollment required enumerating those aged 65 or older. In 1970 legislation required financial intermediaries to obtain the SSNs of all their customers. In the late 1980s people started to be enumerated at birth, in part because the SSN became a requirement to be claimed as dependent for tax purposes.

In sum, not everyone had a SSN when they were first issued, and as time went by the coverage of SSN became almost universal. In other words, most people in cohorts born recently have an SSN, but that is not the case among older cohorts. Thus, there is a trade-off in using SSN: in order to have a more representative analysis we would like to focus in more recent cohorts (because a larger fraction is likely to have SSN), but among more recent cohorts the fraction still alive by 2011 (and therefore not in the Death Master File) is larger.

Figure 1 shows an estimate of the fraction of each decade-of-birth cohort covered by the Death Master File. The size of the cohort was estimated using the US Censuses 1920-2010 and computing the maximum population on record. There are different population totals for each cohort depending on the Census year used. The maximum was taken as the size. To estimate the fraction covered by the Death Master File, the number of SSN of individuals was divided by the total size of the cohort according to Census data. The bell shape illustrates the trade-off between using older and younger cohorts. A larger fraction of the older cohorts is likely to be dead by 2011 but a smaller fraction is likely to have had a SSN. In the case of younger cohorts, a larger fraction is likely to have a SSN but a smaller fraction is likely to be dead. The largest estimated coverage is 82% for the 1910-19 cohort. That cohort is also the most numerous in the Death Master File, with over 19 million people. For the purpose of my analysis I focus on that cohort.

Considering the 1910-19 cohort alone, the Death Master File contains 19,228,801 records and 849,524 unique surnames. Some surnames are invalid because they include digits or invalid signs such as asterisks or commas. After the elimination of those invalid names we are left with 19,228,641 records with 849,366 unique surnames.

Some surnames include suffixes (JR, SR, II, III or IV) and others have slightly different yet equivalent spellings (e.g. ONEILL, O NEILL and O-NEILL). When suffixes and spaces or hyphens are eliminated without affecting the surname, we are left with 837,782 unique surnames.[4]

In the resulting data set, 47,563 records and 21,540 unique surnames contain spaces. Some of those spaces indicate that surnames include prepositions such as DE, DELLA or VAN. Some others seem to be compositions of two surnames, which in principle could create artificially uncommon surnames. Surnames with spaces that start with common

[4] Spaces and hyphens were eliminated from surnames starting with "MC ", "MC-", "MAC ", "MAC-", "O " or "O-".

prepositions or prefixes and therefore do not seem problematic account for 28,229 records and 6,853 unique surnames.[5] Thus 19,334 records and 14,687 unique surnames are potentially problematic. However, they represent a small fraction of the records (0.1%) and surnames (1.8%) in the sample of analysis.

Once invalid surnames have been eliminated and some other surnames have been uniformed, we can compute surnames frequencies. Figure 2 shows the frequency of every surname in the cohort born in 1910-19. The vertical axis shows the number of people that share the surname and the horizontal axis shows the ranking of the surname according to frequency, both in logarithmic scale. The location of a few surnames is indicated in the graph: the top ten most frequent and those that rank 100th, 1,000th, 10,000th and 100,000th in frequency. The close-to-linear pattern is the so-called Zipf's Law: the number of people sharing a surname is inversely proportional to the surname's frequency rank.

In order to compute lifespan the exact birth and death dates are necessary. Out of the records with valid names, 269 had invalid dates of death (they predated the issuance of the SSN) and were eliminated. A large fraction of the remaining records did not report the dates with precision. In 8,249 records the day in the birth date was omitted, in 7,292,116 records the day in the death date was omitted, and 7,295,459 records had one omission or the other.[6] Thus, 38% of the records do not specify the day of birth or death, although the month and year are specified.

The omission of specific days in the date of death displays a clear pattern. For the 6,156,545 deaths that occurred before 1987, 98% do not specify the day. For the 6,018,804 deaths occurring between 1998 and 2011, virtually all specify the date (only 250 deaths do not). In the period 1987-1998, when 7,053,011 deaths occurred, the fraction not specifying the day was 18%. Figure 3 shows the fraction of deaths that occurred by year without specifying the day of the month. The sudden change in the pattern seems associated with an exogenous policy change and is probably unrelated to the people dying every year.

In order to compute the lifespan in days for the sample, the median day of the month was imputed to the dates that lacked the day. If the month of the date without a day was February, the day imputed was 14. For any other month the day imputed was 15. Figure 4 shows the distribution of the lifespan in days for the entire sample. The average lifespan is 28,096 days, which is equivalent to 76.9 years. The median is 28,638 days, or 78.4 years. The standard deviation is 4,085 days, or 11.2 years. Figure 4 also shows the distributions for the records with and without days specified. As expected, given the pattern in Figure 3, those that died earlier are more likely to not have the day specified.

IV. Hypothesis and Empirical Strategy

In its simplest form, the hypothesis to test is that surname frequency and lifespan are not independent but negatively related. First, the hypothesis relies on a negative correlation between fertility and human capital. However, it does not make a difference if there is

[5] The prepositions and prefixes considered are ST, VAN, DE, LA, DI, DU, DEL, DELLA, and VON.
[6] Days appear as 00.

causality in one direction, the other, or in both directions, or if the correlation results from a third variable causing both and human capital—e.g. ability or schooling opportunities.

Second, the hypothesis also requires that parents "pass" to their children—at least to some degree—whatever determines their human capital and fertility, so that the differences in human capital and fertility observed across families within one generation do not disappear in the next. However, it does not rely on any specific intergenerational transmission mechanism. It is inconsequential if the observed positive parent-children correlations are the result of genetics, parental investments, institutional arrangements, or other factors.[7]

If people with greater human capital on average have fewer children, and their children resemble them—to some extent—in terms of their human capital and fertility, then families with lower human capital grow faster. The descendants of those families would eventually become more numerous than the descendants of high human capital, low fertility families. Their surnames would become more popular too. As a consequence, ceteris paribus surname popularity would be negatively related to average human capital.

The empirical strategy to test the hypothesis consists of computing the frequency of every surname and calculating the lifespan in days for every person in the sample (subtracting birth and death dates), and then comparing the lifespans for different levels of surname frequency. In order to make comparisons whose results are not driven by the choice of the functional form (e.g. linear, exponential, logarithmic, or polynomial) or by observations at the tails, I use quantiles of observations according to frequency and compare mean and median lifespan across quantiles. For simplicity I computed 20 quantiles, which leave close to one million observations in each quantile.

The hypothesis to be tested is not conditional on any attributes of the person. Thus, there is no need for "controls." It should be clear that controls could attenuate the relationship between surname frequency and lifespan if such controls are proxies or are correlated with proxies for human capital. That should not be seen as a caveat. It would imply that surname frequency is also correlated to those proxies.[8]

There are several reasons why we anticipate an attenuation bias caused by measurement error. First, for many women we see their married surname and not their maiden surname—and gender is not reported. If sorting in terms of surname frequency is imperfect in the marriage market (which is most likely the case), surname frequency for those women would be measured with error. Second, misspelling causes frequency to be measured with error. What originally was the same surname derives into several surnames, making artificially uncommon some variations of the same surname. Third, it is unclear whether frequency should be measured in subsets of the country rather than nationally. It is possible that the ranking of surnames differs across states or regions (e.g. the most popular names in Alaska, Hawaii or California do not coincide with the most popular surnames in Massachusetts). Clear patterns between surname frequency and lifespan within each region could be attenuated when considering national comparisons. The

[7] See Becker and Tomes (1986) for a model that incorporates several of those elements.

[8] If the data contained information on earnings, instead of using them as a control, I would use them as another variable of analysis, comparing earnings across levels of surname frequency.

reader should bear in mind that the measured relationship between lifespan and surname frequency is most likely downward bias.

V. Results

Figures 5 and 6 present the comparisons of average and median lifespans in days across twenty quantiles of surname frequency. Both charts display the number of unique surnames and observations in each quantile. Because of ties in surname frequency, quantiles have different sizes—the maximum difference in size represents 13% of the smallest quantile. In the top quantile there are 917,742 people that share nine surnames. Their average lifespan is 27,847 days (76.24 years). In the bottom quantile there are 1,043,390 people with 584,796 surnames. Their average lifespan is 28,331 days (77.57 years). The difference in average lifespans between the top and bottom quantiles is 484 days (1.33 years). As Figure 5 shows, the relationship between average lifespan and quantile is close to linear, at an average rate of 25.6 days per quantile.

Median lifespan is less affected by the imputation of days in the dates that lacked them. The results using median lifespan are qualitatively similar and the pattern is accentuated. In the top quantile median lifespan is 28,327 days (77.56 years), whereas in the bottom quantile it is 28,938 days (79.23 years). The difference in median lifespans between the top and bottom quantiles is 611 days (1.67 years). As with average lifespan, the relationship between median lifespan and quantile is close to linear, at an average rate of 31.7 days per quantile.

The lines connecting the points in Figures 5 and 6 indicate whether the difference between the means or the medians of adjacent quantiles is significant. A solid segment indicates a significant difference, and a dashed segment indicates a not significant difference. In the case of average lifespan, a t-test was applied to determine significance. In four of the 19 tests the difference in means between adjacent quantiles is not significantly different from zero at 95% confidence (quantiles 2 and 3, 12 and 13, 15 and 16, and 19 and 20). In the other 14 cases the difference in means between adjacent quantiles is significant: on average the quantile with lower-frequency surnames has a longer average lifespan. Similar results are obtained when applying tests of equality of medians for adjacent quantiles. Since the tests were performed using adjacent quantiles and there is a (weakly) monotone relationship between means or medians across quantiles, the results are transitive. We can conclude that all differences in means or medians between non-adjacent quantiles are significant.

VI. Discussion of findings

The evidence shows important differences in average and median lifespan of people with surnames of different frequencies. Higher frequency is associated with a shorter lifespan. It is crucial to note that local differences in lifespan are significant: adjacent quantiles reproduce the big-picture pattern. This could be interpreted as a sign of robustness of the result. It is difficult to think of factors other than fertility that could affect surname frequency to create the pattern observed. Take immigration for instance.

In order to create a story of immigration that fits the pattern, one needs an ad hoc combination of human capital and surname frequency among immigrants. Highly educated immigrants with uncommon surnames alone are not enough. They could explain the pattern at the lower tail but not what happens across all levels of frequency. A mass of unskilled immigrants sharing a handful of surnames could explain the upper tail. To explain the whole picture the surnames and the human capital of immigrants would have to exhibit the same pattern we are starting with—which becomes a circular argument.

The degree to which the connection between surname frequency and lifespan is causal remains an open question. It is possible that families with greater human capital and lower fertility make greater investments in the schooling of their offspring, causing them to live longer (see Lleras-Muney 2005). Given that surnames are genetic markers (see King and Jobling 2009), it is also entirely possible that the pattern is mostly due to differences in genes.

The findings for lifespan and surname frequency in the US are consistent with previous findings for Spain and Mexico using other proxies for human capital. Although human capital theory offers an explanation, the exact mechanism through which such patterns arise is an open question. The analysis presented here and those for Spain and Mexico are cross-sectional. Although illuminating in some ways, they do not paint a dynamic picture. In order to make more robust inferences on the underlying relationship between fertility and the distribution of human capital the next step should be to analyze how surname frequency evolves.

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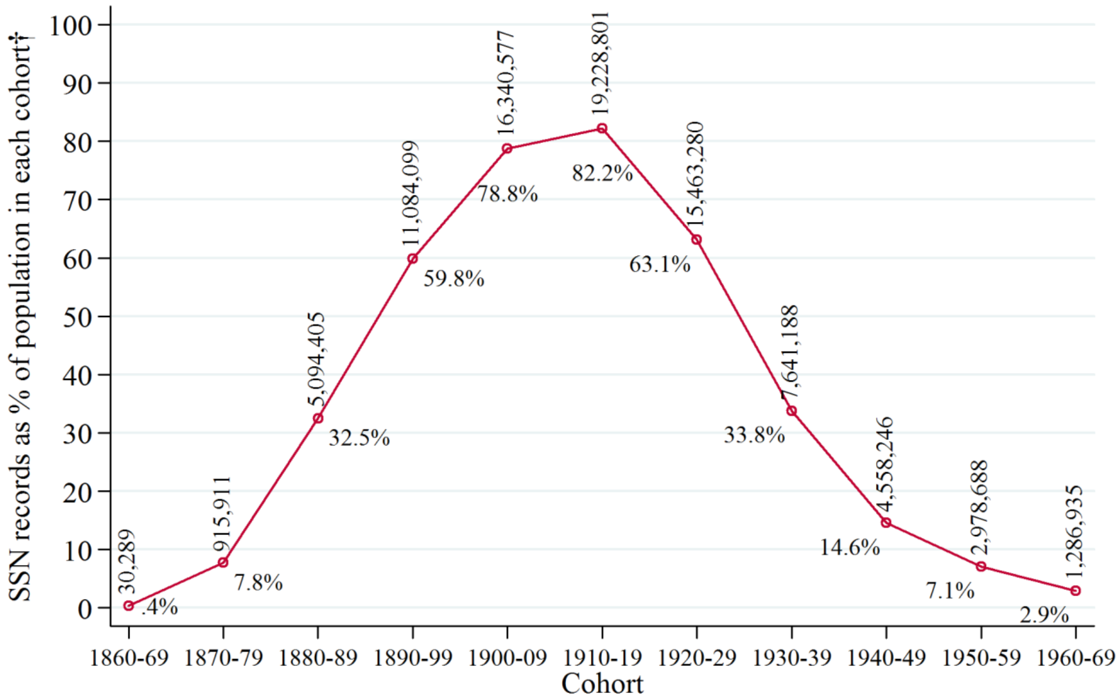
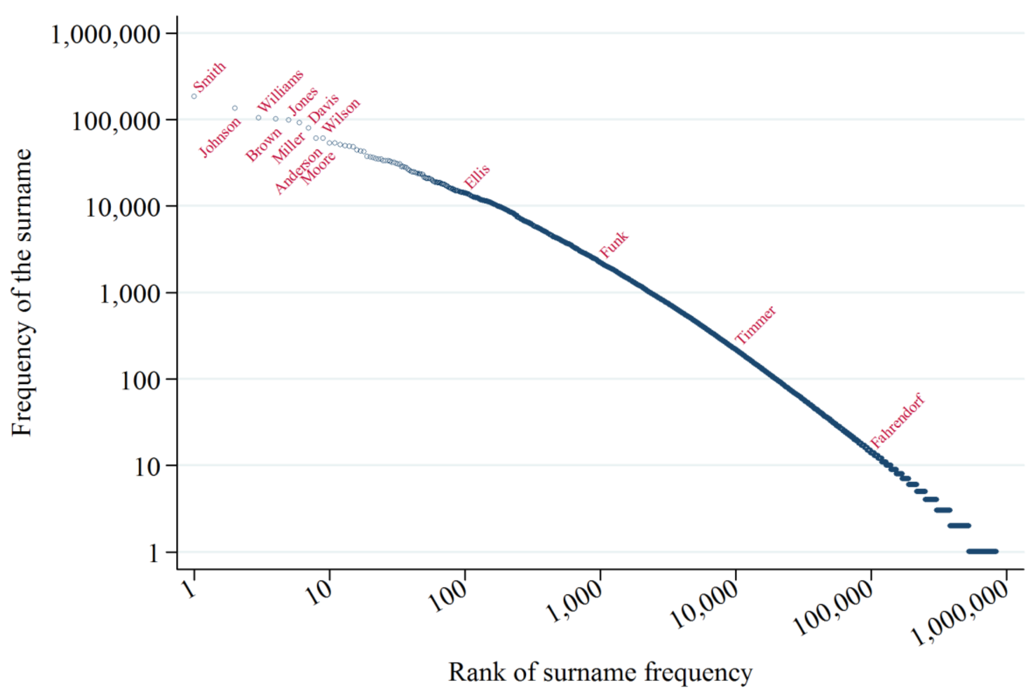
Figure 1. SSN records: total and as percentage of the population in each cohort



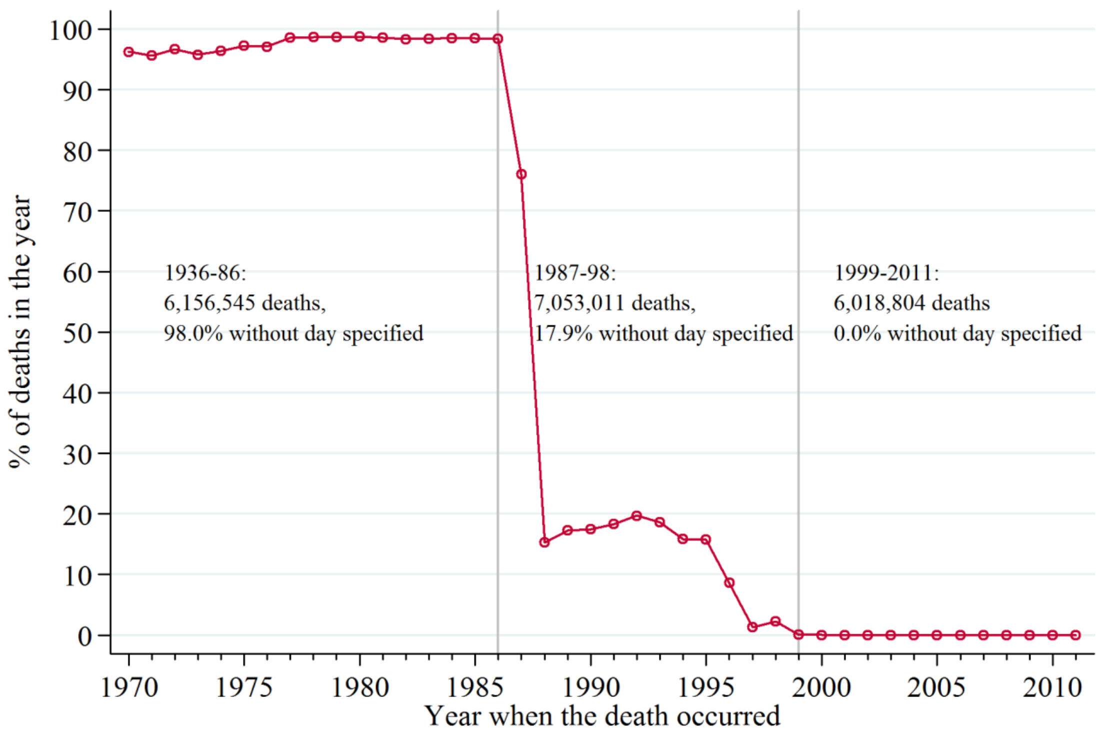
† The population in each cohort was computed as the maximum on record using Census data, 1920-2010.
The figure above the marker indicates the number of SSN records in the cohort.
Source: IPUMS-USA, and Social Security Death Master File courtesy of SSDMF.INFO.

Figure 2. Frequency of surnames



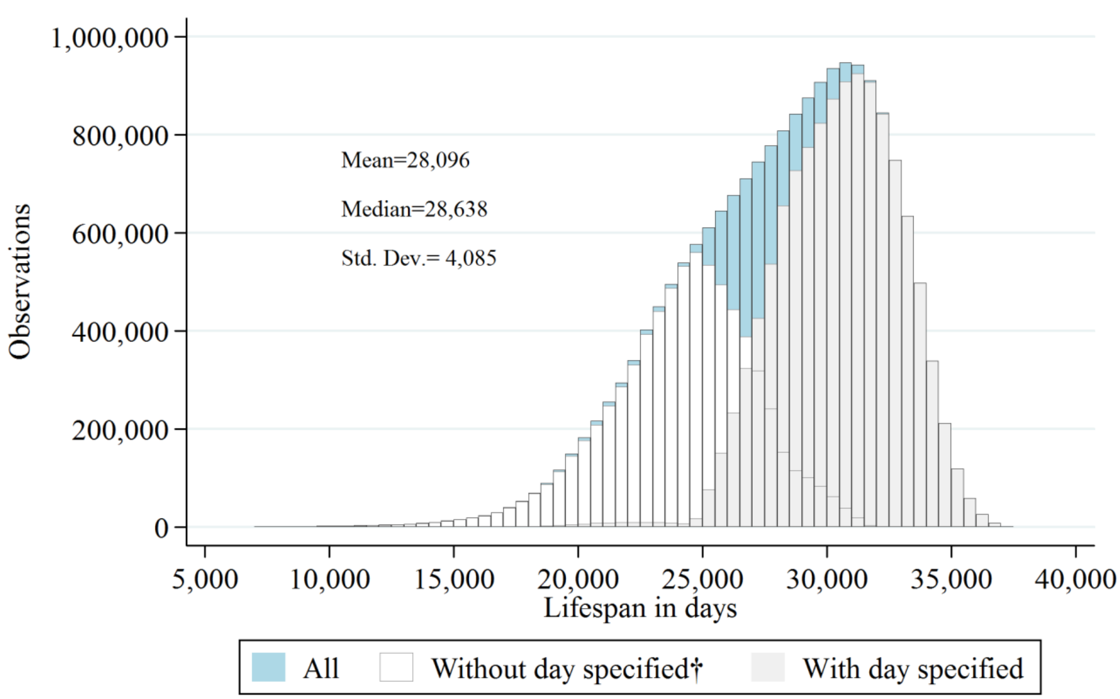
Includes 19,228,372 people born in 1910-19.
Source: Social Security Death Master File courtesy of SSDMF.INFO.

Figure 3. Percentage of deaths without a specified day, by year of occurrence



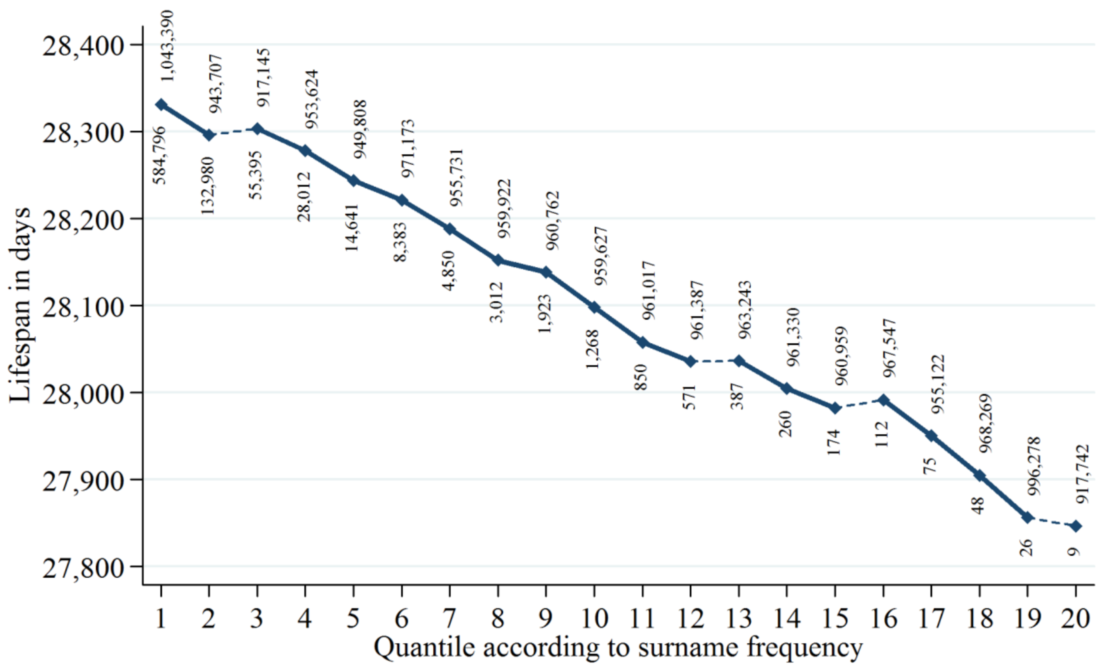
Includes 19,228,360 people born in 1910-19. All dates of death specify year and month.
Source: Social Security Death Master File courtesy of SSDMF.INFO.

Figure 4. Distribution of lifespan



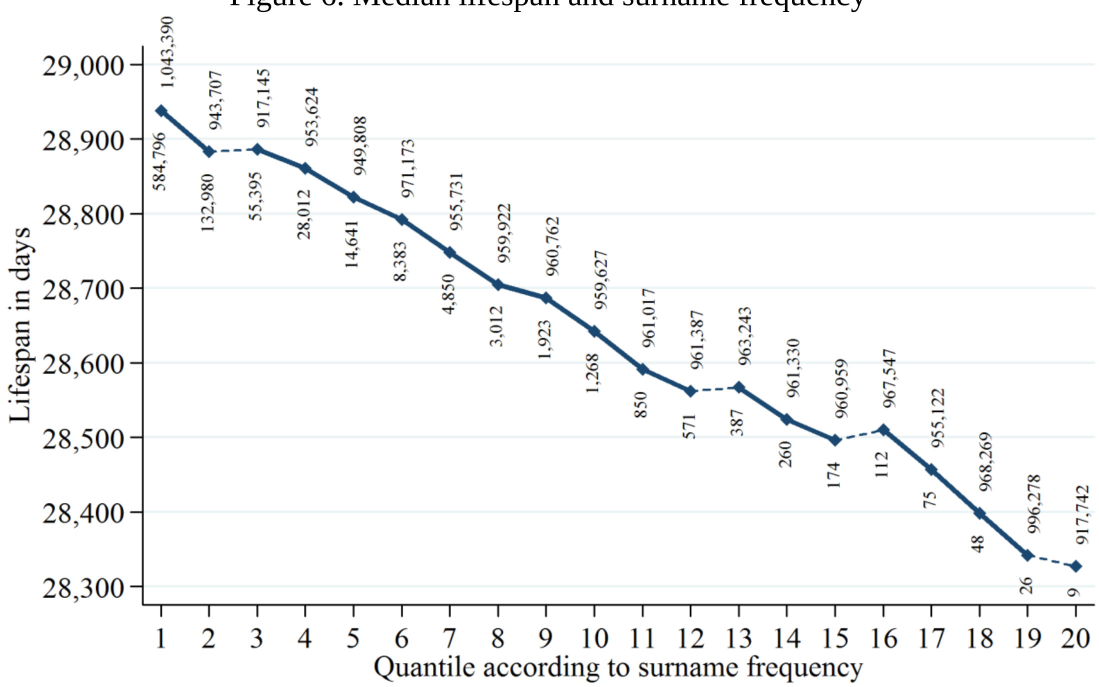
Includes 19,228,360 people born in 1910-19.
† The day of the month of birth or death was not reported. 14 was assumed for dates in February and 15 was assumed for dates in any other month.
Source: Social Security Death Master File courtesy of SSDMF.INFO.

Figure 5. Average lifespan and surname frequency



The figures above and below each marker indicate the number of observations and surnames in that quantile, respectively.
A solid line indicates a significant difference between the means of the adjacent quantiles at 95% confidence.
Quantiles were computed using all observations, regardless of the precision of the dates of birth and death reported.
Includes 19,227,783 people born in 1910-19.
If the day of the month of birth or death was not reported, 14 was assumed for February and 15 was assumed for any other month.
Source: Social Security Death Master File courtesy of SSDMF.INFO.

Figure 6. Median lifespan and surname frequency



The figures above and below each marker indicate the number of observations and surnames in that quantile, respectively.
A solid line indicates a significant difference between the medians of the adjacent quantiles at 95% confidence.
Quantiles were computed using all observations, regardless of the precision of the dates of birth and death reported.
Includes 19,227,783 people born in 1910-19.
If the day of the month of birth or death was not reported, 14 was assumed for February and 15 was assumed for any other month.
Source: Social Security Death Master File courtesy of SSDMF.INFO.