The Longevity of Famous People from Hammurabi to Einstein*

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Abstract

We built a unique dataset of 300,000 famous people born between Hammurabi's epoch and 1879, Einstein's birth year. It includes, among other variables, the vital dates, occupations, and locations of celebrities from the *Index Bio-bibliographicus Notorum Hominum* (IBN), a very comprehensive biographical tool. Our main contribution is fourfold. First, we show, using for the first time a worldwide, long-running, consistent database, that there was no trend in mortality rates during the Malthusian era. Second, after correcting for selection and composition biases, we date the beginning of the steady improvements in longevity to the cohort born in 1640-9, clearly preceding the Industrial Revolution. Third, we find that this timing of improvements in longevity concerns most countries in Europe, as well as all types of skilled occupations. Finally, the reasons for this early increase in mean lifetime are related to age-dependent shifts in the survival law.

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1 Introduction

Having gathered estimations on adult life expectancy from various times and places, Clark (2007) (Tables 5.2 and 5.3) argues that there was no trend in adult longevity during the Malthusian stagnation era, i.e. until about the industrial revolution. Although the evidence remains scattered, the absence of a trend can hardly be contested, and is likely related to the persistent low living standards and the stagnation of medical practice (including nutritional and hygiene habits). This stagnation occurred despite the fact that the Malthusian era was characterized by technological improvements covering many fields of human activity.

There is extensive evidence showing that adult life expectancy has increased markedly and continuously since the beginning of the 19th century. The importance of the economic growth process in fostering such improvements has been stressed by Fogel (1994). Country wide statistics for Sweden, England and France show the emergence of a trend for generations born in the nineteenth century, altough little information is available for those born earlier.[1] The earliest evidence of improved adult life expectancy is provided by Wrigley et al. (1997). They reported an important reduction in adult mortality in the English population in the middle of the eighteenth century. Moreover, some authors who looked at small prominent groups of households, such as the English aristocrats (Hollingsworth 1977), identify the beginning of the change one century earlier for these groups than for the overall population. To better understand the determinants of adult life expectancy and its overall implications for human and social development, it would be useful to identify the precise time at which adult longevity started to increase in a sustained way. Moreover, understanding adult longevity in the past has implications for the prediction of future human lifespan (see Wilmoth (2007)).

The question of the timing of the rise in longevity finds a nice echo in what the contemporaries of the industrial revolution wrote about the history and prospects of life expectancy. Malthus (1798) believed that "With regard to the duration of human life, there does not appear to have existed from the earliest ages of the world to the present moment the smallest permanent symptom or indication of increasing prolongation." Writing a few years before Malthus, Condorcet (1795), instead, anticipated the emergence of large improvements in longevity: "One feels that transmissible diseases will slowly disappear with the progresses of medicine, which becomes more effective through the progress of reason and social order, ... and that a time will come where death will only be the consequence of extraordinary accidents, or of the increasingly slower destruction of vital forces."

[1] From the Human Mortality Database (HMD), cohort life expectancy at age 20 (males) started to increase in 1810-19 for Sweden, 1850-59 for France, and 1840-49 for England and Wales. For the latter, 1840-49 is the first decade of observation. An overview on the HMD is at http://www.mortality.org/Public/Overview.php.

In this paper, we aim to document the long stagnation period and identify the time at which longevity started to increase above its plateau mean. To this aim, we built a unique dataset of around 300,000 famous people born between the 24th century BCE (Hammurabi, king of Babylonia, is among the first) and 1879 CE, the year of Albert Einstein's birth. Vital dates are taken from the *Index Bio-bibliographicus Notorum Hominum* (IBN), which also contains information on multiple individual characteristics, including place of birth and death, occupation, nationality and religion, among others. This very comprehensive tool, covering 3000 biographical sources from all countries and historical periods, enables us to go beyond the current state of knowledge and to provide a global picture. Existing estimations are local, mainly European centered, and start, at best, in the 16th century.[2]

We were concerned with the fact that our results may be subject to several biases, because of the nature of our database. Consequently, when estimating the mean lifetime of human cohorts we controlled for all observed individual characteristics (including, among others, city of birth/death, occupation, nationality and religion). We also document some of these biases by comparing our results with existing data from different times and places.

The main contribution of this paper is fourfold. First, it documents, using a worldwide, long-running, consistent database, that there was no trend in adult longevity during the Malthusian era. The mean lifetime of famous people was about 60 years for four millennia. Second, it shows that permanent improvements in longevity preceded the Industrial Revolution by at least one century. The mean lifetime of famous people started to steadily increase for generations born during the first half of the 17th century, reaching a total gain of around nine years for Einstein's cohort. Third, using information about locations and occupations available in the database, we also found that the increase in longevity occurred almost everywhere in Europe, not only in the leading countries of the 17th-18th century, and for all observed occupations. Finally, we found that the reasons for this early increase in mean lifetime were mainly related to age-dependent shifts in the survival law. For this purpose, we grouped individuals into 150 cohorts of at least 1600 members and measured survival laws for these cohorts, then, following Gavrilov and Gavrilova (1991), we estimated the Gompertz-Makeham mortality law for each cohort and used the estimated coefficients to test the Compensation Effect of Mortality. We found that the changes in mortality observed since the middle of the seventieth century were mainly due to changes in the Gompertz

[2] Before the Fourth Lateran Council in 1215, which recommended parishes to hold *Status Animarum* books covering baptisms, marriages and burials, and took centuries to be adopted over Europe, no systematic register of individual life spans existed in Europe. Graunt (1661) produced the first life table using London data collected by Cromwell in 1535, and the first full-fledged life table was developed by Halley (1693) using data from Breslau (today Wroclav in Poland) for 1687-88. See Appendix D.

parameters consistent with the Compensation Effect, and showing an early tendency for the survival law to rectangularize.[3]

Famous people are those with a high level of human capital. The community of European famous people, such as scientists, artists, and entrepreneurs, is seen by Mokyr (2011) as being at the root of the Industrial Revolution. The early increase in their longevity has a specific relevance for economic growth, and may support the hypothesis that improvements in longevity were one cause of the industrial revolution. One mechanism for this effect could be through facilitating knowledge accumulation (see Lucas (2009) and Bar and Leukhina (2010)). For Lucas, "a productive idea needs to be in use by a living person to be acquired by someone else, so what one person learns is available to others only as long as he remains alive. If lives are too short or too dull, sustained growth at a positive rate is impossible." Another possible mechanism relates to the provision of incentives for investment in human capital (see Galor and Weil (1999), Boucekkine, de la Croix, and Licandro (2002), Soares (2005), Cervellati and Sunde (2007) and de la Croix and Licandro (2012)). For Galor and Weil, "Changes in mortality can serve as the basis for a unified model that describes the complete transition from the Malthusian Regime to the Modern Growth Regime. Consider the effect of an initial reduction in mortality (due to an exogenous shock to health technology or to standards of living). The effect of lower mortality in raising the expected rate of return to human capital investments will nonetheless be present, leading to more schooling and eventually to a higher rate of technological progress. This will in turn raise income and further lower mortality...".

The paper is organized as follows. In Section 2, we describe the data, study their quality, and compute the unconditional mean lifetime of famous people. In Section 3, we report a list of potential biases, define a set of control variables and provide an estimation of the conditional mean lifetime of famous people, after controlling for the reported biases. We also study whether changes in mean lifetime were general to all locations and occupations. An analytical description of the observed changes is provided in Section 4 through the lenses of the Gompertz-Makeham survival law and the Compensation Effect of Mortality. In Section 5, we compare, for some specific geographical locations and time periods, the survival probabilities of IBN famous people with existing case studies. Finally, in Section 6, we suggest a set of criteria that any good interpretation of these events should meet, advance some potential explanations and conclude.

[3]Rectangularization of the survival curves implies a decreasing variability in the distribution of ages at death. See Wilmoth and Horiuchi (1999) for various measures of rectangularization.

2 Data and Descriptive Statistics

2.1 The *Index Biobibliographicus Notorum Hominum*

Our database is built from the *Index Biobibliographicus Notorum Hominum* (IBN), which is aimed to help researchers around the world to easily access existing biographical sources. The information in the IBN was compiled from around 3000 biographical sources (dictionaries and encyclopedias) covering almost all countries and historical periods; Europeans are clearly overrepresented.

Famous People: People included in the IBN are famous in the very particular sense that they are included in a biographical dictionary or encyclopedia. For most of them, the IBN delivers name, year (and often place) of birth and death, a statement about the individual including some broad information about occupation and nationality, and the list of biographical sources in which he (rarely she) is mentioned. Data in the IBN may be coded in different languages (English, German and French are the most frequent) and basically contain the type of information reported in the two examples below (we only report one source per person, but many sources may be associated with the same person):

- Hammurapi; 1792-1750 (1728-1686) ante chr.;[4] ... ; Babylonischer könig aus der dynastie der Amoräer; Internationale Bibliographie de Zeitschriftenliteratur aus allen Gebieten des Wissens.
- Einstein, Albert; 1879-1955; Ulm (Germany) - Princeton (N.J.); German physicist, professor and scientific writer, Nobel Prize winner (1921), Swiss and American citizen; Internationale Personal Bibliographie 1800-1943.

The digital version of the IBN used in this paper contains around one million famous people whose last names begin with the letters A to L, since those from M to Z were not yet available in electronic format when we received the data. However, this criterion is not expected to introduce any selection bias in the estimation of changes in mean lifetime.

The retained database includes 297,651 individuals extracted from the IBN following three steps. First, for reasons that we will make explicit below, we restricted the sample to people born before 1880. Second, only people with known years of both birth and death were retained, allowing us to measure their lifespan. Third, individuals with lifespans less than 15 or larger than 100 years, 729 and 872 respectively, were excluded. Note that the IBN

[4] Notice that two different years of birth are reported for Hammurabi (Hammurapi in German), but a unique lifespan. The places of birth and death are not reported.

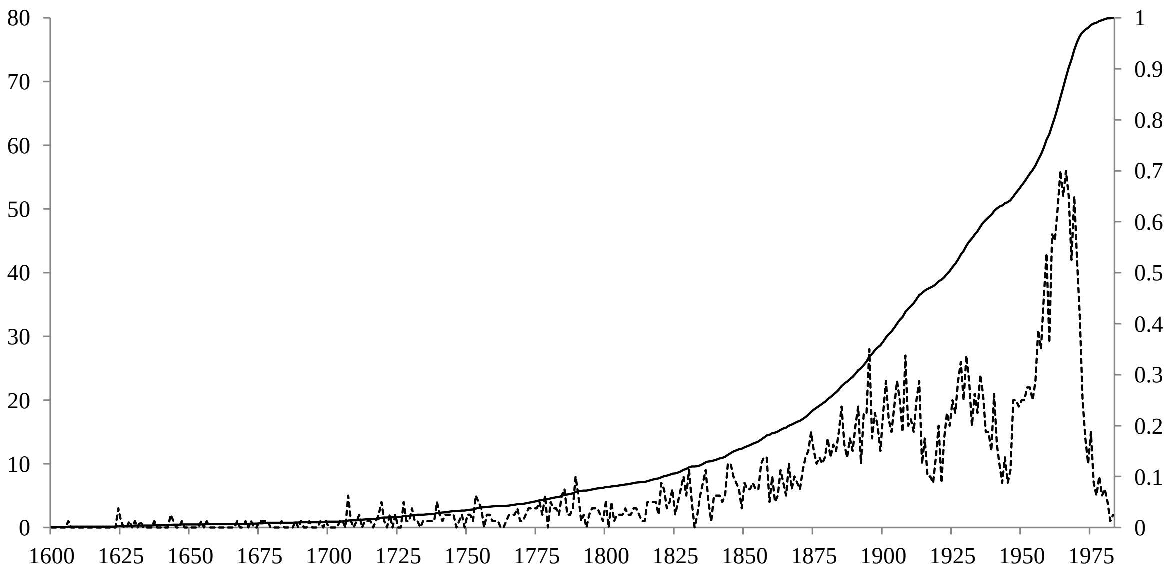

Figure 1: Time Distribution of Biographical Sources. Frequency (dashed line, left axis), cumulative (solid line, right axis)

reports information on very few people dying during childhood, and most centenarians in the database are likely to be measurement errors.

Biographical Sources: We identified 2,781 biographical sources in the IBN for which a publication year was observed. To illustrate the nature of the famous people in the database, these are four haphazard examples of sources written in the English language:

- *A Dictionary of Actors and of Other Persons Associated with the Public Representation of Plays in England before 1642.* London: Humphrey Milford / Oxford, New Haven, New York, 1929.
- *A Biographical Dictionary of Freethinkers of all Ages and Nations.* London: Progressive Publishing Company, 1889.
- *Portraits of Eminent Mathematicians with Brief Biographical Sketches.* New York: Scripta-Mathematica, 1936.
- *Who Was Who in America. Historical volume (1607-1896). A complement volume of Who's Who in American History.* Chicago: The A. N. Marquis Company, 1963.

Figure 1 plots the distribution of the years of publication (in case of multiple publication years, we retained the most recent date); they concentrate heavily in the 19th and 20th Century.

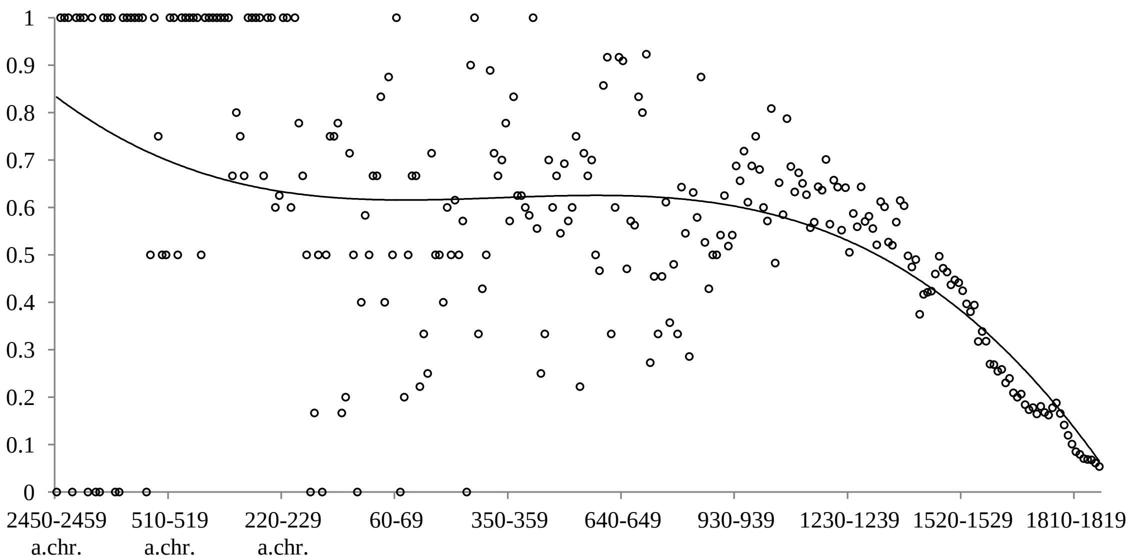

Figure 2: Frequency of Imprecise Observations

2.2 Data Precision

To assess the quality of the measured lifespans, in this section we show two different statistics: the frequency of observations with imprecise vital dates and the heaping index.

The IBN adds the indications "c.", for *circa*, or "?" to the vital dates when the years of birth or death are not known with certainty. It may also be that more than one date is reported. We retained all the imprecise observations (taking the mean if there was more than one date), but created a discrete variable called *imprecision*, allocating a value of one when the lifespan was imprecise, zero otherwise. Figure 2 shows the fraction of imprecise observations by decade. Individual lifespans measured by the IBN were highly imprecise until the end of the Middle Ages; the degree of imprecision then moves to zero as the sample reaches the 19th century.

When vital data are not known with certainty, biographers (or concerned persons themselves) often approximate them by rounding the year of death or birth to a number finishing in 0 or 5. Moreover, in the particular case of famous people, for obvious reasons, years of birth are likely to be more uncertain than years of death. The heaping index measures the frequency of observations with vital dates finishing in 0 or 5; it is commonly normalized by multiplying by 5 the ratio of such observations to the total number of observations. A heaping index close to unity shows that the vital data are very precise. Figure 3 shows birth and death

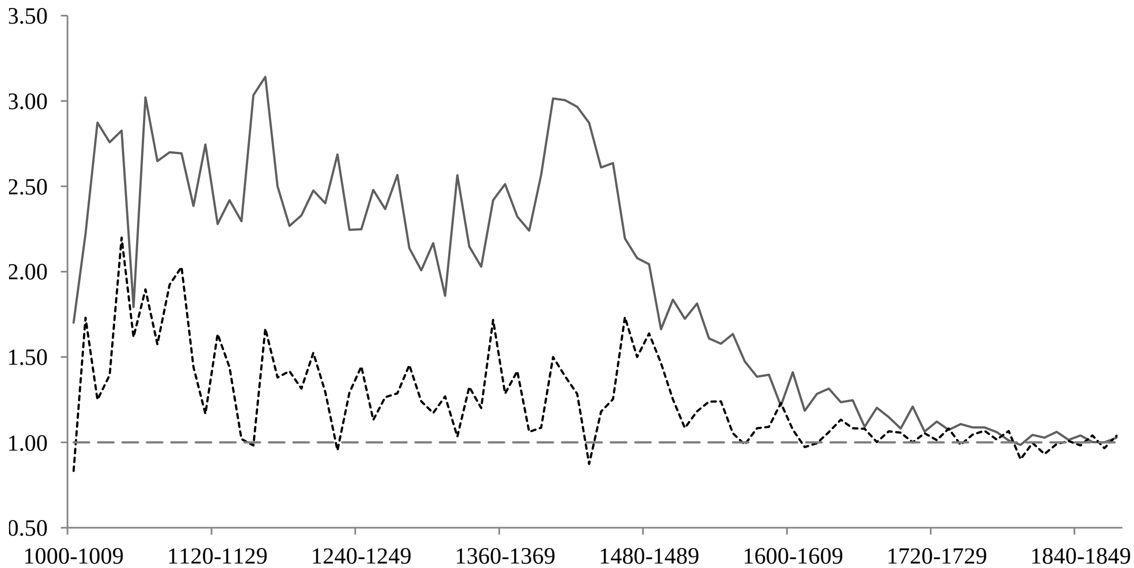

Figure 3: Heaping Index. birth year (solid line), death year (dashed line)

heaping indexes by decades up to 1879.[5] The death date heaping index is low, indicating that the dates of death of famous people were well known. Birth dates were much more uncertain, as the heaping index is about three before 1450, indicating that there are three times more dates finishing in 0 or 5 than there should be. Improvements in the birth year heaping index seem to start around 1450. This observation is consistent with the findings of De Moor and Zuijderduijn (2011) that numeracy levels among the well-to-do in the early modern period were very low (in the Netherlands). By 1700, the gap between birth and death heaping has decreased and both indexes fluctuate around one.

If, following A'Hearn, Baten, and Crayen (2006), we interpret the age heaping index as a measure of human capital (consistently with the robust correlation between age heaping and literacy at both the individual and aggregate level), our findings support the hypothesis that there was a major increase in human capital preceding the industrial revolution.

2.3 Unconditional Cohort Mean Lifetime

This paper focuses on the estimation of mean lifetime the of famous people, not on life expectancy at birth or at any other particular age. To be more precise, the mean lifetime of celebrities' measures life expectancy conditional on the age at which individuals become

[5]Notice that heaping has no sense before 800, when the dating system starting at the birth of Jesus of Nazareth became widely used.

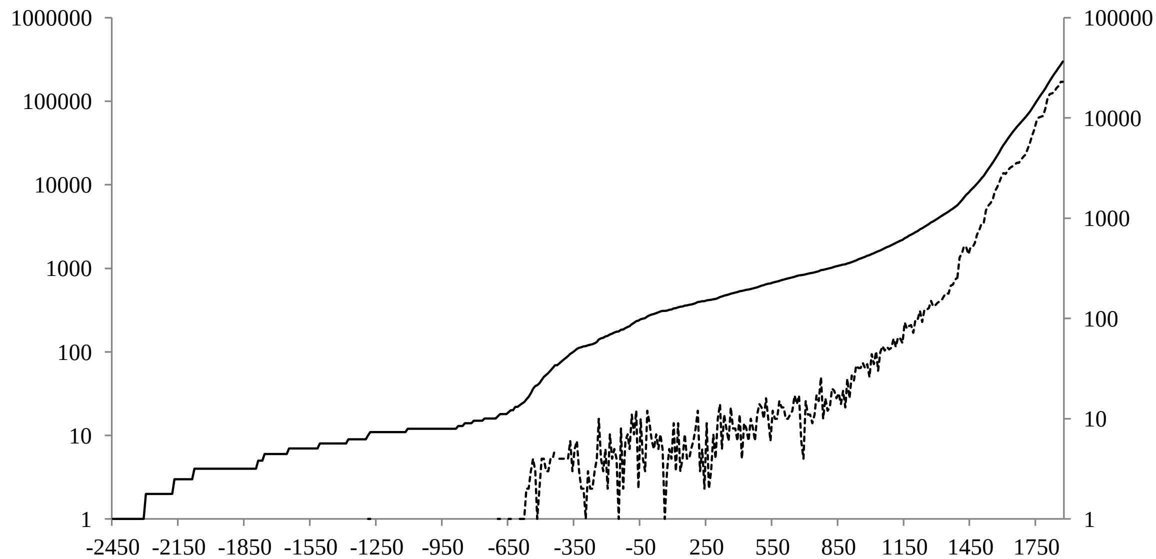

Figure 4: Number of Observations by Decade, density (dots) and cumulative (solid line)

famous. This age is a random variable following some stochastic pattern unfortunately unknown to us. For example, a book recording the life of French kings provides lifespan information conditional on the age of accession to the throne, but a book recording the members of the Royal French family provides information conditional on birth date. The latter can be used to estimate life expectancy at birth. The former, however, enables measurement of adult life expectancy at the accession age, which is a random variable.

We will concentrate on cohort mean lifetime, and not on period mean lifetime, which is subject to biases (tempo effects) when mortality changes over time (Bongaarts and Feeney 2003). Individuals in the database were grouped into cohorts by year of birth. As can be observed in Figure 4, at the beginning of the sample, the size of these cohorts is very small; there were only 274 individuals born before Christ, 400 individuals before 230 CE, and 1600 before 1040 CE.

Before estimating the conditional mean lifetime, we represented the unconditional mean lifetime from the data by grouping individuals into ten-year cohorts. To overcome the representativity problem, which is large at the beginning of the sample, when representing the data, we applied a simple adaptive rule

$$\lambda_t = \begin{cases} (n_t/x)\, l_t + (1 - n_t/x)\lambda_{t-1} & \text{if } n_t < x \\ l_t & \text{otherwise} \end{cases} \tag{1}$$

where l_t and λ_t are the actual and smoothed mean lifetimes, n_t represents the actual cohort

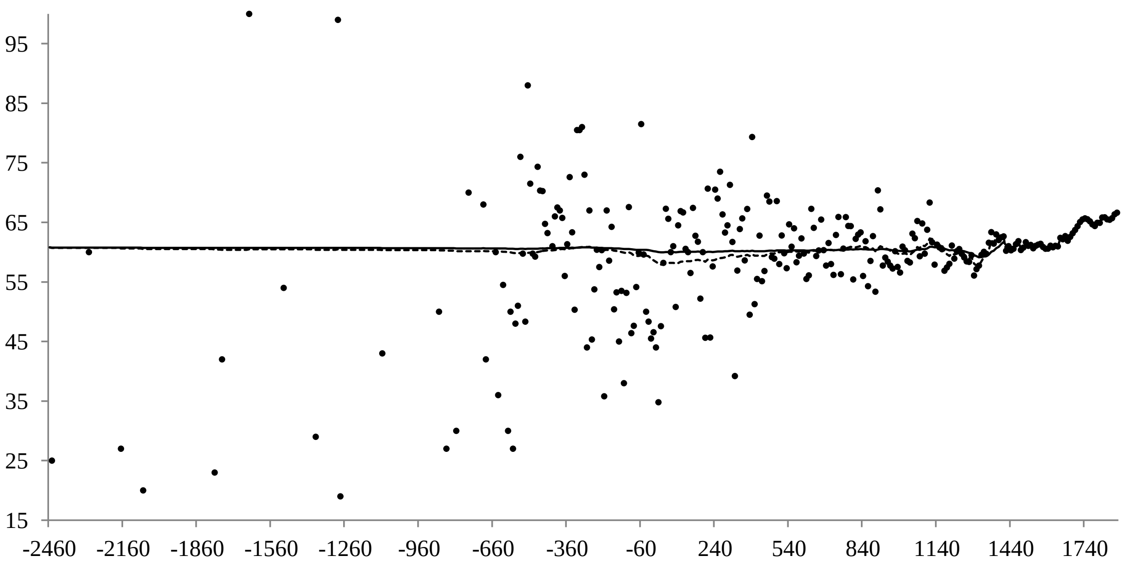

Figure 5: Unconditional Mean Lifetime. data (dots), smoothing with $x = 400$ (dotted line), smoothing with $x = 1600$ (solid line)

size, and x is an arbitrary representative size. The choice of x is based on the idea that if the lifespans of people in the sample were random draws from a Normal distribution, the standard deviation of the observed cohort mean lifetime would be $\sigma/\sqrt{x}$, where σ is the standard deviation of the population and x is the cohort size. Since $\sigma = 15$ for famous people born before 1640, we need $x = 400$ (respectively 1600) for the observed mean lifetime to be within a 95% confidence interval ± 1.5 (± 0.75).

As an initial condition we used $\lambda_{-\infty} = 60.8$, taken from Clark (2007) for the hunter-gatherers.[6] The adaptive rule adds past information λ_{t-1} when the actual size of the sample n_t is smaller than its representative size x. Current and past information, l_t and λ_{t-1}, are weighted by the relative size n_t/x, when $n_t < x$, and its complement, respectively. When the cohort size is large enough, actual and smoothed mean lifetimes are identical.

Figure 5 shows the actual mean lifetime and the corrected mean lifetime of ten-year cohorts for $x = 400$ and $x = 1600$. The actual mean lifetime fluctuates dramatically around 60.9 until the 14th Century, because of the small size of the cohorts. The corrected mean lifetime, however, moves around the mean with very small fluctuations until the Black Death (cohorts born just before 1340-1350); then, it moves around the mean until it starts to increase with the cohort born 1640-1649.

[6] This number is very close to the sample mean (60.9) for individuals born before 1640.

3 Conditional Mean Lifetime of Famous People

3.1 Possible Biases

When estimating the mean lifetime of famous people, we need to be concerned about different types of selection and composition bias. In the points below, we describe these potential biases and suggest estimation strategies to deal with them.

Notoriety Bias. An individual has to acquire some reputation or social status to be recorded in the IBN. Since the probability of obtaining such a status increases with age, mortality rates of famous people tend to be underestimated, particularly at young ages. The notoriety bias arrives because potential celebrities who die before obtaining the required reputation are excluded from the database by construction. Moreover, in some métiers, occupations are hierarchically ranked with ranks highly correlated with seniority; this is the clear case for military and clerical occupations. Since high rank occupations are more reputed, we expect to observe them more frequently in the IBN than lower rank occupations. In order to control for the notoriety bias, we include occupational dummies in the regressions. Occupations for which notoriety is expected to arrive at old (young) ages should show positive (negative) dummy coefficients.

Source Bias. As explained above, our database only included famous people for whom the years of birth and death were reported. For this reason, celebrities in the IBN still alive at the time of publication of a biographical dictionary or encyclopedia were excluded from our database, since their year of death was not known at the time of publication. Consequently, our sample may underestimate the mean lifetime of famous people, in particular for cohorts for which the average time between birth dates and publication dates was short. We call this phenomenon the *source bias*. After dating the sources, we computed for each individual the age of her/his cohort at the date of publication of the source and created dummies for ages {15-29, 30,39,...,90-99}. We call this variable "cohort age at publication"; it is used to control for the source bias. Moreover, as most biographical sources were published during the 19th and 20th centuries (see Figure 1), we have decided to exclude people born after 1880.

Occupation Bias. The database was built on existing biographical publications reporting on people who were famous at that time. However, fame has not always been related to the same human achievements, implying that the weight of some occupations may have changed substantially over time. This effect is, for example, the case for the nobility and for religious occupations. The case of martyrs, although less frequent, is more striking, because they lived

short lives, by definition, and were concentrated in a particular period of human history. For this reason, changes in the occupational composition of the database may generate artificial changes in survival probabilities. Occupation dummies were used to control for the potential occupation bias.

Location Bias. Another form of potential composition bias is related to changes over time in the location of individuals in the sample. City dummies and nationality dummies were used to control for the location bias.

Migration Bias. Since the probability of migrating at least once is positively correlated with individual lifespan, we expect that migrants on average have a larger lifespan than non-migrants. We refer to this effect as migration bias. The IBN provides information on the city of birth and the city of death for most individuals. To control for the migration bias, we created a migration variable allocating a value of one when the place of birth and death were different, zero otherwise.[7]

3.2 Control Variables

The control variables were built using information in the IBN. For each individual, the IBN has three cells containing the places of birth and death, a statement about who the person was, and the sources citing him/her. Information may be in different languages.

In order to locate individuals in specific cities, we used the information in the *places of birth and death* cells. Among the 297,651 individuals in the database, a place of birth or death was missing for 60,637 (20% of the sample). For the remaining 237,014 individuals, we first counted words using the *Hermetic Word Frequency Counter 1089t* and identified 56,574 birth places and 35,852 death places; we took into account the fact that some cities have composed names, such as New York. We then translated city names for birth (resp. death) places with at least 30 (resp. 20) observations into 22 languages,[8] and searched again to identify all individuals who were born or died in the same city. We checked for historical names for these cities (if possible) using Wikipedia.[9] This procedure identified 584 and 603 birth and death cities, respectively. After translation, the number of observations more than doubled for some cities. We finally retained 77 cities with at least 300 observations as either birth or

[7] Mokyr (2005) measured the mobility of 1185 "creative people" in Europe over 1450-1750 and showed it was large, with 3.72 mean moves per person. Longer living people, as expected, moved somewhat more.

[8] For this, we used Nice Translator –http://nicetranslator.com/. The list of languages included were Bulgarian, Catalan, Czech, Danish, Dutch, English, Estonian, Finnish, French, German, Greek, Hungarian, Italian, Latvian, Lithuanian, Norwegian, Polish, Portuguese, Romanian, Slovak, Slovenian, Spanish, Swedish and Turkish.

[9] See http://en.wikipedia.org/wiki/Names_of_European_cities_in_different_languages.

death place (see Appendix A). For the statistical analysis below, we created a dummy for each of the 77 cities.[10] Individuals born and dying in different cities were coded as one in two different city dummies, zero in the others. We have also created a *large cities* dummy that takes value one if an individual was born or dead in at least one of the 77 selected cities, zero otherwise. Finally, for all individuals with observed birth and death places, we created a *migration* dummy that took value one only if the places of birth and death were different.

Information in the *statement* cells is more complex. Only 1,274 observations had an empty statement cell. We identified 81,078 unique words using the *Hermetic Word Frequency Counter 1089t*, and retained those words with at least 200 observations that could be associated with any type of occupation, nationality or religion. We then translated them into the same 22 languages as we used for the cities, and merged all observations corresponding to the same occupation, nationality or religion. The words collapsed into 171 occupations, 65 nationalities and 10 religions. Using these categories, 278,084 individuals had at least one occupation (94.4% of the sample) and 207,049 had more than one; 218,530 have at least one nationality (73.4%) and 11,929 have more than one. Finally, we retained all relevant words with at least 300 observations; this allowed us to identify 33 nationalities, 8 religions, and 148 occupations (see Appendix A). Occupations were then grouped into nine categories: Arts and métiers, business, clerical, educational, humanities, law and government, military, nobility, and sciences (see Appendix B). There were six other repeated words that we also used as controls.[11]

Finally, the *source* cells were used to single out for each individual the publication year of the biographical source citing her/him. We identified this year for 290,528 individuals, 99.9% of total observations. To control for the source bias explained above, ideally we should know the date of publication of the most recent source for each individual. Unfortunately, because of the way data are organized in the IBN, when an individual was cited by more than one source, we could only identify one of these sources automatically, not necessarily the most recent. In particular, for 42,600 observations, the year of publication preceded the year of death, which we take as evidence of the existence of another source published later. For all these reasons, we measured for each individual the age of her/his cohort at the

[10] It is important to notice that some cells in the IBN are empty, and when complete some contain useless information, implying that the variables here created contain missing values. Of course, by construction, this is not the case for the year of birth and the individual lifespan. When creating dummies, the missing values systematically adopt the value zero. It does imply that we tend to underestimate the dummy coefficients, since the excluded group may include individuals belonging to the control group.

[11] Chief, bengali, founder, landowner, servant and unionist. We include bengali in this group, because most were British soldiers in the Bengal war from the book "List of the officers of the Bengal army, 1758-1834. Alphabetically arranged and annotated with biographical and genealogical notices", who seem to have had particularly short lives.

publication of the source in the following way. When the individual's death year was before the publication year of the source, we took the difference between the publication year and the individual's birth year. The resulting cohort age at publication is then larger than the individual lifespan. Otherwise, we assume it is missing. Finally, we created eight "cohort age at source publication" dummies for ages {15-29, 30-39, ..., 90-99}. The dummies were allocated a value of one for individuals for whom the cohort age at publication of the source was in the age group, zero otherwise.

3.3 Estimation

The unconditional mean lifetime shown in Figure 5 may be affected by the potential biases described in Section 3.1. In this Section, we estimate conditional mean lifetimes of famous people cohorts using the following regression:

$$m_{i,t} = m + d_t + \alpha\, x_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $m_{i,t}$ is the lifespan of individual i belonging to cohort t, the constant term m measures the conditional mean lifetime of the excluded cohort dummy –for a representative individual without known city, nationality or occupation, as well as the excluded characteristic of any other control–; d_t measures the difference between the conditional mean lifetime of cohort t and the conditional mean lifetime of the excluded cohort; $x_{i,t}$ is a vector of individual controls including city, occupation and nationality dummies, precision and migration dummies, and cohort age at publication dummies, among others; α is a vector of parameters; and $\varepsilon_{i,t}$ is an error term measuring individual's i idiosyncratic lifespan circumstances. Equation (2) was estimated using Ordinary Least Squares.[12] The detailed results are in Appendix A.

Because our main objective was to identify the precise cohort after which the mean lifetime of famous people started to increase, and we had few observations per decade before the fifteen century, we created cohort dummies by decade starting in 1430-1439, the first decade with more than 300 observations. The conditional mean lifetime of all previous cohorts, consistent with the observation in Figure 5, was assumed to be constant. Figure 6 shows point estimates, and the corresponding 95% confidence intervals, for all cohort dummies. As can be observed, the mean lifetime of cohorts born before 1640 was not significantly different from the mean lifetime of celebrities born before 1430. Indeed, the mean lifetime

[12]Remember that the OLS estimators are weighted sums of random variables, the central limit theorem applies, and the OLS estimators are in any case asymptotically normal. All test statistics relying on asymptotic distribution results are typically valid with large samples such as ours.

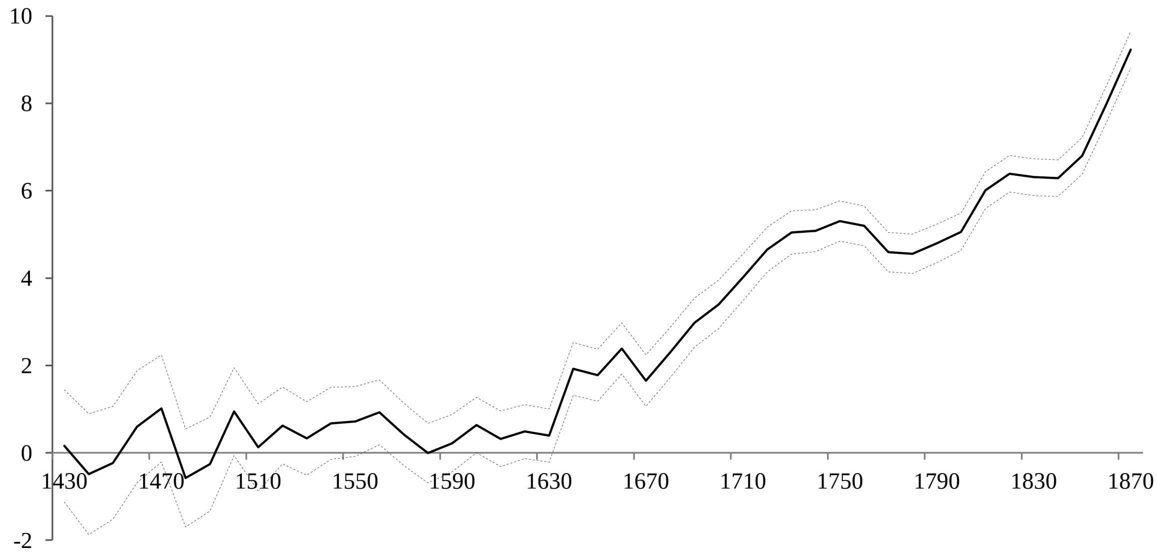

Figure 6: Conditional Mean Lifetime: Cohort dummies and 95% confidence interval

of celebrities started to increase with the cohort born in 1640-49, gaining nine years over around two and a half centuries. This figure reinforces the conclusion already stated for the unconditional mean lifetime that longevity improvements for celebrities started well before the Industrial Revolution.

The estimated constant term was 59.04 years, which is one and a half year less than the 60.46 years of the unconditional mean before 1430 –the standard deviation is 0.19, implying that it is estimated with high precision. The difference has to be attributed to the omitted control dummies, because the constant term measures the age of the mean celebrity born before 1430 with a precise lifespan, non-migrating and without an identified city, nationality, occupation or religion. The precision dummy was estimated at -0.82 years, which is small but significantly different from zero –the standard deviation was 0.08. The negative sign is fundamentally due to the fact that imprecise observations occured more frequently before 1640. Consequently, controlling for imprecise reported lifespans, if anything, reduces the gains in mean lifetime observed after 1640.

More interestingly, the estimation also provides clear evidence that the other dummies effectively controlled for the different biases referred to in Section 3.1. From our estimation, a person living in one of the 77 retained cities had on average no survival advantage with respect to the rest of the population, since the estimated coefficient of the *large cities* dummy was small, 0.27 years, and not significantly different from zero –the standard deviation was

0.19. Figure A.1, in the appendix, shows the distribution of the 77 city dummies. The standard deviations of the estimated coefficients were in the interval $(0.21, 0.79)$, meaning that they were estimated with relatively high precision. The distribution, as expected, is concentrated around zero with few cities having mean lifetime 2.25 years larger (Frederiksberg) or smaller (Leipzig, Nuremberg, Riga) than the mean. Details for cities are in Appendix A.

The estimated coefficient for the group of *large nationalities* –a dummy grouping all individuals with at least one nationality among the 33 retained nationalities– was -0.45 with a standard deviation of 0.18. Figure A.2, in the appendix, shows the distribution of the 33 retained nationality dummies. Australians had the largest positive estimated coefficients and Brazilians, in the other extreme, have the lowest, 5.2 years and 4.7 years above and below the mean, respectively.

The estimated coefficients of the occupational group dummies are shown in Figure A.4, in the appendix, with the corresponding 95% confidence intervals. These results clearly illustrate that the regression effectively controlled for occupational composition bias, because the difference in mean lifetime between an average military occupation and an average science occupation was slightly larger than four years. The composition also changed. Nobility, for example, moved down from 28% to 22% of the observed occupations before and after 1640, whereas *business* and *sciences* jointly moved up from 7% to 15%.

The distribution of the 148 occupation dummies in the benchmark regression, after adding the corresponding occupational group dummy, are shown in Figure A.3, in the Appendix. This distribution was mainly concentrated around one-two in the interval $(-2, 4)$, although a few occupations had large negative dummies, in some cases larger than 10 years. Inequality within and between occupational groups, however, is very similar for most occupational groups. In fact, the standard deviation of the occupational dummies was 1.3 years, close to the standard deviation of occupations in most occupational groups with the exception of clerical, military and educational, which had a standard deviation of 3.7, 4.1 and 3.6, respectively. The large within-occupational-group variability basically reflects seniority, and sometimes the fact that some individuals with occupations in these groups were famous because of violent death.

Seniority is one of the main causes of the notoriety bias referred to in Section 3.1. Table 1 illustrates the extent of the notoriety bias for clerical, military and educational occupations. High ranks in both occupations had larger dummies than low ranks, since some seniority is required to climb up the rank ladder. Particularly interesting is the case of low rank military occupations and martyrs, which had a highly significant negative dummy. As noted earlier, this observation likely reflects the fact that these people became famous because they were

Clerical		Military		Educational	
archdeacon	7.08	admiral	4.77	dean	3.99
bishop	3.92	general	3.86	academician	3.47
rabbi	2.50	marshal	3.77	professor	1.44
abbot	2.41	colonel	1.48	writer	1.13
cardinal	2.00	major	-0.66	rector	0.81
archbishop	1.94	officer	-1.89	teacher	0.50
theologian	1.54	commander	-2.06	scholar	0.20
clergyman	1.29	lieutenant-colonel	-2.16	lecturer	-0.94
pastor	1.01	military	-2.47	student	-9.21
priest	0.94	captain	-2.95		
vicar	-0.24	lieutenant	-4.38		
preacher	-0.32	soldier	-5.15		
missionary	-0.55	fighter	-7.08		
deacon	-4.62	bengali	-12.85		
martyr	-14.42				

Table 1: Clerical, Military and Educational Occupations.

martyrs or heroes dying young on the battlefield.

To control for the source bias, we included in the regression eight dummies for cohort ages at source publication going from 15-29 years, 30-39 up to 90-99. All coefficients, as reported in Figure 7, were negative, sizable and statistically significant –the dotted lines correspond to the 95% confidence interval. As expected, the coefficient of the dummy decreased in absolute value with the cohort age at publication, from around 40.2 to 2.7 years. The source bias was thus high for people dying close to the publication date of the source. Note that, by construction, the lifespan of persons in the first group was between fifteen and thirty years; when added to the estimated dummy the sum was close to the mean lifetime of the representative celebrity (20+40=60).

To estimate the extent of the source bias, we ran the regression without the cohort age at publication dummies, and then measured the *source bias* as the difference between the cohort dummy coefficients of the benchmark regression and the newly estimated coefficients. The solid line in Figure 8 represents the estimated source bias, and the dotted line is twice the standard deviation of the cohort dummies in the benchmark estimation. The source bias and the precision of the benchmark estimation –the inverse of the standard deviation– both clearly increased. The source bias was close to zero until the seventeenth century, then started slowly increasing but remained small and non-significant until the cohort born in 1700; it increased to reach more than 4 years for the last cohort. Controlling for the source

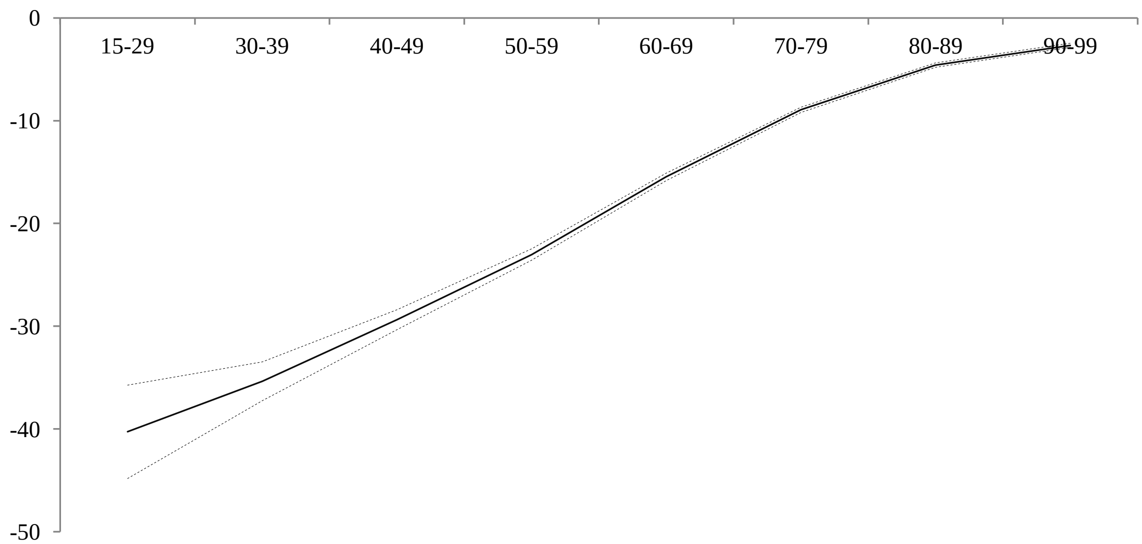

Figure 7: Cohort age at publication dummies

bias did not affect the main result that celebrities mean lifetime started increasing in 1640, as we have already observed in Figure 5. However, controlling for the source bias significantly increased the size of the improvement at the end of sample: it almost doubled the 5 year unconditional gain. Since most sources were published in the 19th and mainly 20th centuries, the number of observations included in the cohort age at publication dummies increased from around 5% of the total observations in the first half of the eighteen century to 60% in the last decade. This factor explains why controlling for the source bias had such a large impact at the end of the sample.

To further assess the validity of our approach, we looked at some characteristics of the residuals $\varepsilon_{i,t}$. First, we estimated their density function, see Figure A.5: it appears to be unimodal and negatively skewed, reflecting the known result for the lifespan distribution for adult humans (Robertson and Allison 2012).

Second, looking at Figure 6, we observed that the confidence interval got narrower as time passes. We checked whether this could be attributed to the increasing number of observations or to some heteroscedasticity in the error term. Accordingly, we computed the standard deviations of the residuals by decade, with confidence bounds around them, see Figure A.6. The only permanent large change was for the last six decades, for which the standard deviation displayed a downward trend. The reason is that, at the end of the sample, there were few people with an advanced age because of the source bias, reducing the variability in the

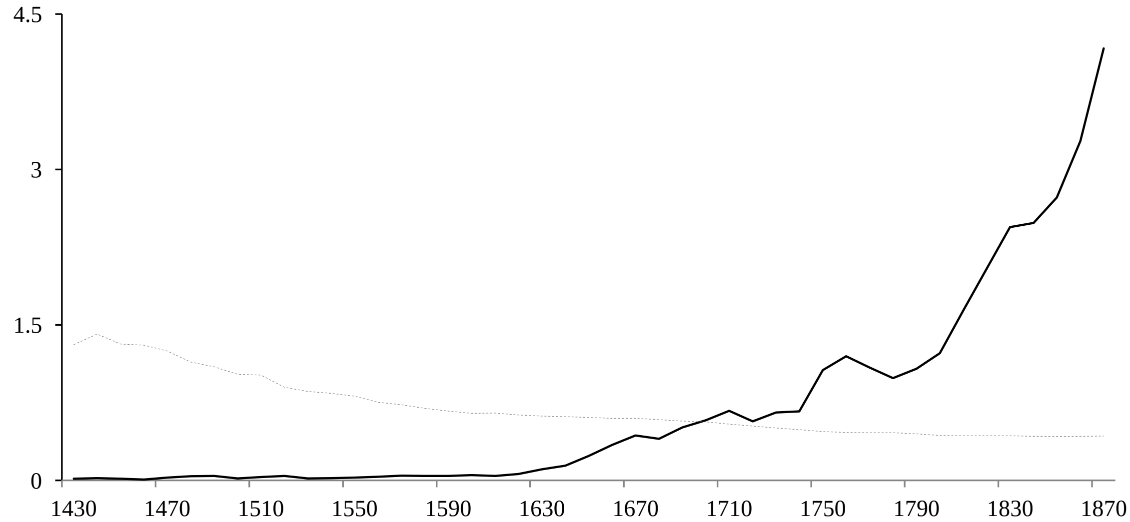

Figure 8: Source bias. Estimation (solid line), 2× std cohort dummies (dotted line)

mean lifetime. Correcting for the source bias as we did does not fully correct the problem. Such heteroscedasticity is an artificact of the selection bias, not a change in the variance of the underlying population.

Finally, we checked for the effect of exceptional events on our estimation. We computed the mean lifetime for each year of death, trying to identify particularly deadly events, See Figure A.7. By far the biggest event happened in 1794, which corresponds to the Reign of Terror during the French Revolution. Introducing a dummy variable "death in 1794" into the regression, however, did not greatly modify the estimation. The biggest change was in the coefficient for the dummy "martyr" which went from -14.65 to -12.99. The next biggest change was for decade 1730-9, with the coefficient going from 5.04 to 5.41. Coefficients, such as those for French, Bordeaux, and Toulouse, were affected, but to a very small extent. We conclude from this exercise that trying to model certain unusual events from European history would add little to our estimation.

3.4 Robustness: Is the Early Increase in Longevity General?

Model (2) states that the mean lifetime of celebrities in all occupations, cities and nationalities has moved jointly over time. Any gain in longevity is then assumed to be common. However, it may be that a particular occupational group or a particular region were behind

the observed increase from 1640, and that the mean lifetime of other occupations or regions did not improve at all or started to improve later. Perhaps income started increasing before the Industrial Revolution in the regions or for the occupations that led it, not in the others, making the mean lifetime of famous people increase only in these regions or occupations. For this propose, we identified potential characteristics for early improvement in life expectancy, created dummies and ran new regressions interacting these dummies with the cohort dummies. The model to be estimated became:

$$m_{i,t} = m + d_t + \tilde{d}_t + \alpha\, x_{i,t} + \varepsilon_{i,t} \tag{3}$$

where $\tilde{d}_t$ measured the difference between the conditional mean lifetime of the selected group and the whole cohort t.

3.4.1 Occupations

Could some occupations, because they profited from early improvements in income, or from some specific conditions, have led the reduction in mortality? To answer this question, we interacted the cohort dummies with occupational groups (arts and métiers, business, clerical, educational, humanities, law and government, military, nobility and sciences), one at a time, according to equation (3). We found that none of these groups was individually driving the main result. Figure 9 shows the coefficient of the cohort dummy d_t estimated when the interactive terms were included, i.e., after controlling for changes in the mean lifetime of each occupational group separately. In each case, the cohort dummy coefficients represent the cohort mean lifetime of famous people not belonging to each of the specified occupations. As can be observed in Figure 9, all of the coefficients were within the confidence interval of the cohort dummies in the benchmark estimation (the upper and lower dotted lines). Moreover, for each of the nine occupational groups, the interaction terms $\tilde{d}$ were always in the $(-2, 2)$ years interval, without showing any particular pattern.

3.4.2 Nationalities and Cities

Did celebrities' mean lifetime increase first in those regions that led the industrial revolution, Great Britain in particular, or was it a more general phenomenon? With this hypothesis in mind, we created three dummies. First, a *leading cities* dummy including the largest cities in the sample, i.e., those with the largest number of observations (Amsterdam, Berlin, Copenhagen, London, Paris, Rome, Stockholm, Wien). Second, a *British* dummy, including

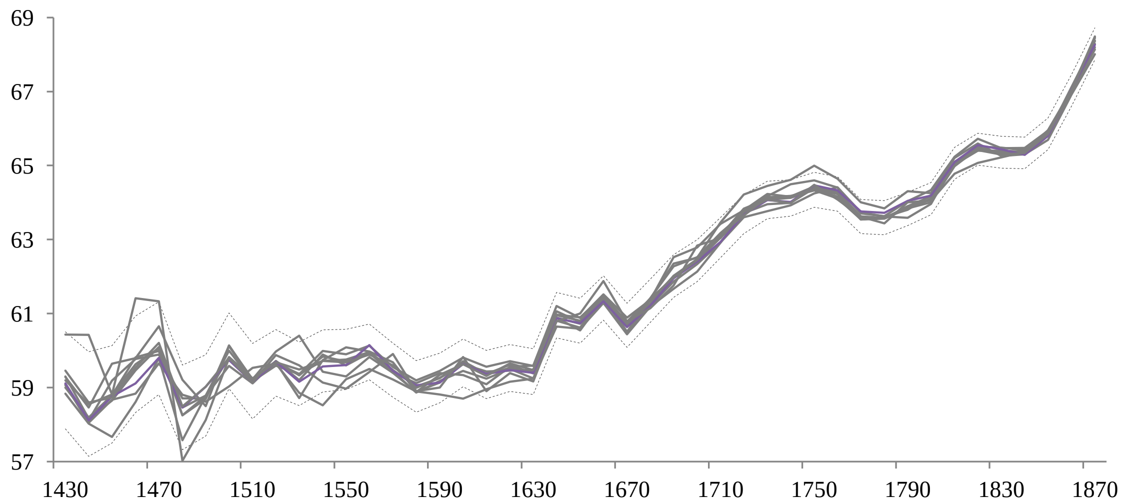

Figure 9: Robustness: Occupational groups

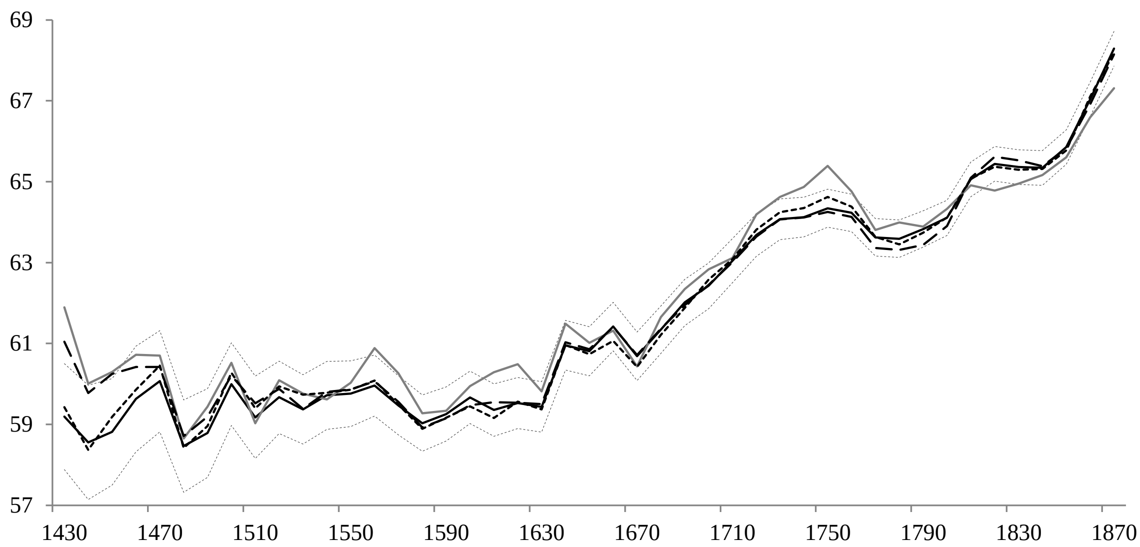

Figure 10: Robustness: British, leading nations and leading cities

English and Scottish nationalities, as well as people born or dying in London and Edinburgh, the only two British cities among the retained 77 large cities. Third, a *leading nations* dummy allocating the value of one if an individual had the nationality of a selected group of countries, or was born or died in a city, among the 77 selected cities, in the actual territory of one of the leading nations. The set of selected countries included those that, according to Maddison (2010), in 1870 had an annual GDP per capita of at least 1800 dollars (Australia, Austria, Belgium, Denmark, France, Germany, Netherlands, Switzerland, UK and US). As in the previous subsection, we added to the benchmark regression new terms interacting the cohort dummies with the three leading dummies above, one at a time. Figure 10 shows the cohort dummy coefficients estimated when the interactive terms were included (the dotted upper and lower lines correspond to the confidence intervals of the benchmark estimation). As can be observed, including the leading dummies did not significantly affect the estimation of the mean lifetime of the whole population, meaning that neither leading cities, Britain nor leading nations were behind our main result that the mean lifetime of famous people started increasing as early as in 1640 after millennia of stagnation.

4 Survival Laws

To better characterize the forces responsible for the increase in the mean lifetime of famous people as early as in the seventeenth century, in this section we study the shifts in the survival law underlying the increase in longevity. In particular, we investigate whether these shifts came from a change in the process of aging, or, on the contrary, whether they were related to improvements in health conditions independently of age.

4.1 Conditional Survival and Mortality Rates

Cohort dummies and residual terms of Equation (2), as estimated in Section 3.3, were used to measure *conditional survival laws* for all individuals in the sample. For each individual i belonging to cohort t, we defined $\hat{r}_{i,t} \equiv \hat{m} + \hat{d}_t + \hat{\varepsilon}_{i,t}$, where $\hat{m}$ was the estimated constant, $\hat{d}_t$ the estimated cohort dummy parameter and $\hat{\varepsilon}_{i,t}$ the estimated residual. We denoted by $r_{i,t}$ the *conditional lifespan* of individual i belonging to cohort t, where $r_{i,t}$ was the integer part of $\hat{r}_{i,t}$.[13] This measure represents the lifespan of individual i after controlling for all observed characteristics.

[13] When the fractional part is less than 0.5, we take the largest previous integer; otherwise we take the smallest following integer.

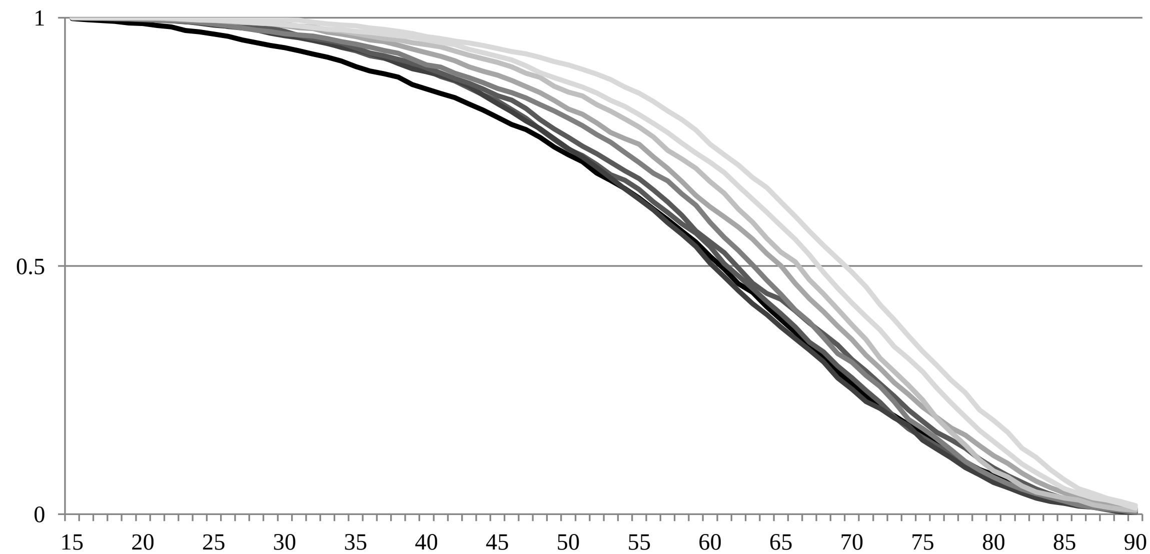

Figure 11: Conditional Survivals for some 1600-cohorts: from deep black to clear gray are cohorts 1040-1254, 1535-1546, 1623-1628, 1665-1669, 1714-1717, 1787-1788, 1807-1808, 1859, 1879.

For cohort t, let n_t be the total number of observations belonging to this cohort and, using conditional lifespans, let $s_{t,h}$ be the number of survivors at any age h. Cohort t conditional survival probabilities are then measured by computing the ratios $s_{t,h}/n_t$ for all h.[14]

In this section, following the argument developed in Section 2.3 concerning confidence intervals, we created cohorts of at least 1600 individuals; individuals born the same year always belong to the same cohort; we refer to them as the 1600-cohorts. Following this criterion, we detected 150 1600-cohorts.[15] Figure 11 shows the survival laws of some selected 1600-cohorts; they are ordered from black, the oldest, to light gray, the youngest. The first three survival laws precede 1640; they are very similar to each other. As can be observed, the survival law moves to the right from the 17th century onward in a tendency to rectangularize.

[14]Notice that conditional lifespan is not bounded between ages 15 and 100, as unconditional lifespan is by construction.

[15]Individuals in the sample are ordered by their year of birth and cohorts were created following the position of individuals in the sample; for example, the first 1600 individuals belong to the first cohort. Because individuals born the same year belong to the same cohort, cohort sizes are in general larger than 1600 individuals. Indeed, the mode was very close to 1600 and 50% of the cohorts had less than 1900 observations.

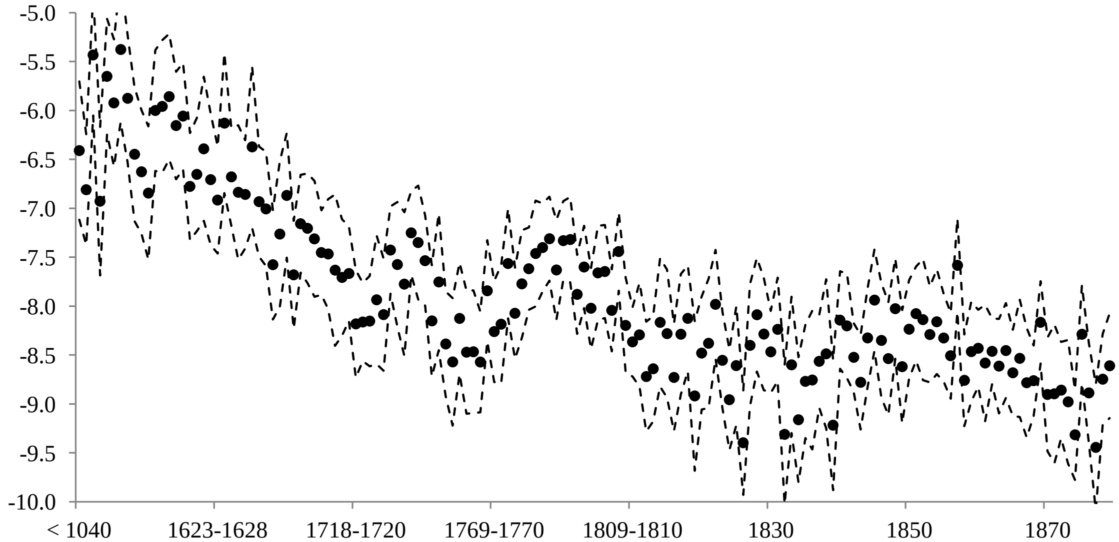

Figure 12: Estimated $\hat{\rho}$

4.2 Gompertz-Makeham Law and the Compensation Effect

We followed Gavrilov and Gavrilova (1991) to estimate and interpret the evolution of the survival law of famous people over the last millenium. The main argument was based on two observations: the Gompertz-Makeham law of mortality and the Compensation Effect.

Gompertz-Makeham Mortality Law: Let death rates be denoted by $\delta(a)$, an age dependent function, where a denotes individuals' age. The Gompertz-Makeham law of mortality, as suggested by Gompertz (1825) and Makeham (1860), asserts that death rates follow

$$\delta(a) = A + e^{\rho+\alpha a}. \tag{4}$$

Death rates depend on an age-dependent component, the Gompertz function $e^{\rho+\alpha a}$, and an age-independent component, the Makeham constant A, $A > 0$. In the Gompertz function, parameter ρ measures the mortality of young generations while parameter α, $\alpha > 0$, represents the rate at which mortality increases with age. The corresponding survival law is

$$S(a) = \exp\{-Aa - (e^{\rho+\alpha a} - 1)/\alpha\}. \tag{5}$$

To assess whether the observed shifts in the survival law were related to age-dependent or age-independent factors, we estimated, by non-linear least squares, the Gompertz-Makeham

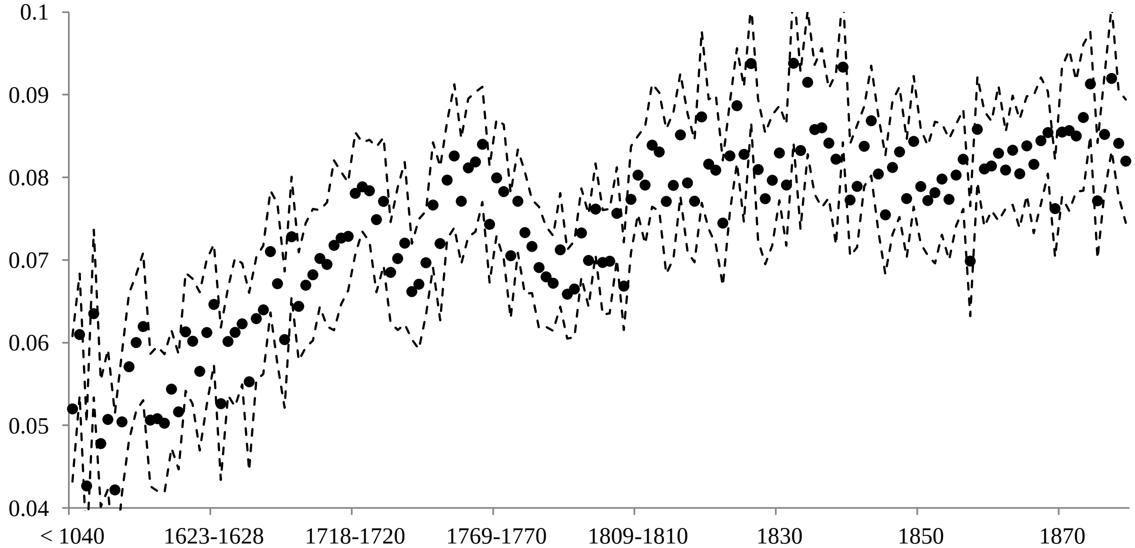

Figure 13: Estimated $\hat{\alpha}$

law (4) (in logs) for each of the 1600-cohorts. As usual in this literature, the estimation only considered the observed mortality rates between 30 and 90 years, because the Gomperz-Makeham law mainly applies to this age bracket.

Consistent with the main findings in Gavrilov and Gavrilova (1991), the estimated Gompertz parameter ρ decreased over time whereas the estimated Gompertz parameter α increased, as can be observed in Figures 12 and 13 –the dotted lines correspond to the 95% confidence intervals. These parameter changes took place as early as for the cohort born in 1640, i.e., earlier than in Gavrilov and Gavrilova (1991). Contrary to the estimations in Gavrilov and Gavrilova (1991), the age-independent parameter A was systematically non-significantly different from zero. This last observation is because the mortality rates of famous people mortality rates were close to zero for ages below 40. We develop this argument in Section 4.3 below.

Compensation Effect of Mortality: The Compensation Effect of Mortality states that any observed reduction in the mortality of the young, ρ, has to be compensated by an increase in the mortality of the old, α, following the relation

$$\rho = M - T\alpha, \tag{6}$$

where M and T, $T > 0$, are constant parameters, the same for all human populations. For $A = 0$, it is easy to see that under the Compensation Effect, survival tends to rectangularize

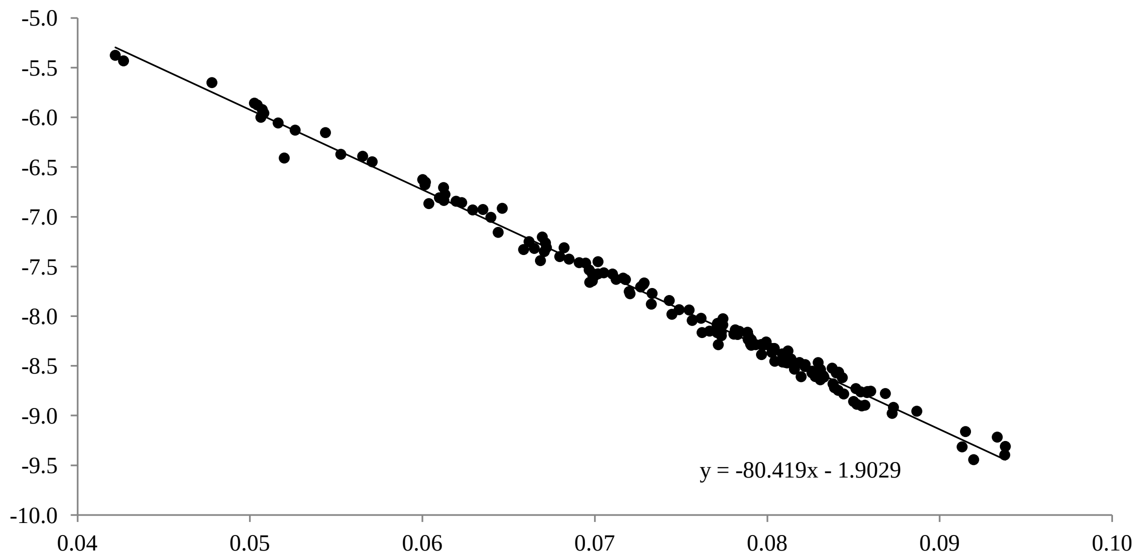

Figure 14: The Compensation Effect of Mortality: ρ (Y-axis), α (X-axis)

when α goes to infinity; in this case, the maximum life span of humanity is T.[16] Following (6), any reduction in ρ compensated by an increase in α rectangularizes the survival and increases the mean lifetime. However, such an improvement in the mean lifetime is bounded by the maximum lifespan T.

Figure 14 represents the point estimates $\{\rho, \alpha\}$ for the 150 1600-cohorts retained in this section. They clearly move around a straight line. Indeed, the Compensation Effect of Mortality holds for famous people in the IBN during the sample period. This finding is also in line with Gavrilov and Gavrilova (1991).[17] Since ρ decreased and α increased consistently with the Compensation Effect, the survival law of famous people tends to rectangularize as observed in Section 4.1. The Compensation Effect equation (6) was estimated by OLS on the 150 pairs $\{\rho, \alpha\}$ previously estimated. The life span parameter T was estimated at 80.4 years –with a standard deviation of 0.57 years.

[16]For this purpose, take ρ in (6) and substitute it in (4). Then, let α go to infinity, which implies that the death rates tend to zero for $a < T$ and to infinity when $a > T$.

[17]Strulik and Vollmer (2011) found changes in the Compensation Law in the last half of the 20th Century, with a corresponding increase in human lifespan T.

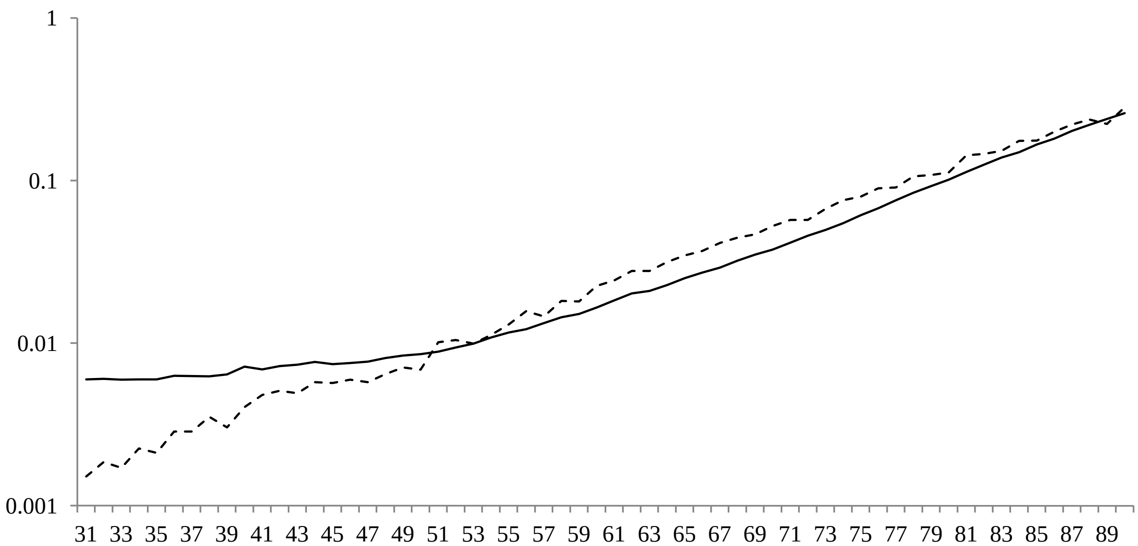

Figure 15: Mortality Rates 1871-79: Ages 30 to 90 (X-axis) and death probabilities in log scale (Y-axis). Swedish from Human Mortality Database (solid line), IBN (dashed line)

4.3 Mortality of Potentially Famous People

As explained in Section 3.1, the IBN suffers from the *notoriety bias*, such that some potentially famous people are excluded from the IBN because they died before becoming famous, which tends to underestimate mortality rates particularly at young ages. Figure 15 illustrates this point by comparing, for the cohorts 1871-1879, the mortality rates of the Swedish population, as reported in the Human Mortality Database, with the conditional mortality rates of the IBN famous people.[18] Even though the IBN tends to slightly overestimate Swedish mortality rates for ages larger than 50, the main difference is at young ages, with a clear underestimation for ages lower than 40. Moreover, the death rates of famous people are clearly log-linear, which is consistent with our previous finding that the Makeham constants of survivals of famous people were not significantly different from zero. For the Swedish, however, the Makeham constant is not nil.

To better understand the effect of the notoriety bias in the estimation of Gompertz-Makeham mortality laws of famous people let us make the following assumptions. First, let us denote by $\delta_p(a)$ the mortality rates of the population of potentially famous people, which includes not only those observed in the IBN but also those that had the potential to be included but died

[18] To make both pictures as comparable as possible, we have conditioned IBN individual lifespans $r_{i,t}$ on being Swedish too.

before achieving the required prestige and fame. Let us then assume that the Gompertz-Makeham mortality law holds for the population of potential celebrities. For the sake of simplicity, let us substitute $\delta_p(a)$ in the left hand side of equation (4). Let us denote by $\Phi(a)$ the probability that potentially famous people achieve notoriety before age a. Consequently, death rates of famous people are

$$\delta(a) = \Phi(a)\delta_p(a),$$

the product of those that die conditional on being already famous.

Different theories may be elaborated to predict the age at which a potentially notorious person acquires the needed reputation to become famous. In this section, we build a simple theory based on the assumption that potentially famous people belong to dynasties, each one undertaking a single prominent job. Potentially famous members of the dynasty are sitting in a queue waiting for the death of the dynasty member currently holding the job. This is clearly the case for hereditary occupations like nobility where, for example, a prince has to wait for the death of the king to accede to the throne.[19] It is also the case of ranked occupations, such as religious or military occupations, in which people move up in a grade scale and then hold the position until death. In occupations such as arts and sciences, things are more complex, since the number of jobs is somewhat endogenous. However, some form of congestion may also operate, making it more difficult to become famous when the pool of famous people is large.

Let us take the case of princes and kings as our benchmark. A prince has to wait until his father's death to become king. The probability of becoming king as a function of his age thus depends on the probability of death of his father. Given that both belong to the same population, the probability of a prince's accession depends on the death of the reigning king, i.e.,

$$\Phi(a) = 1 - S_p(a + b),$$

where a is the age of the prince and $a + b$ is the age of his father. Of course, $S_p(a + b)$ depends on the same parameters as the Gomperzt-Makeham function $\delta_p(a)$ –see equation (5). We can then use non-linear least square methods to estimate parameters A, ρ and α for the population of potentially famous people on the death rates of observed celebrities by

[19] This is relevant, since princes are not reported in any dictionary or encyclopedia of kings, even though they can be reported in royal family books. Consequently, they are underrepresented in the IBN. In any case, they will never be reported as kings.

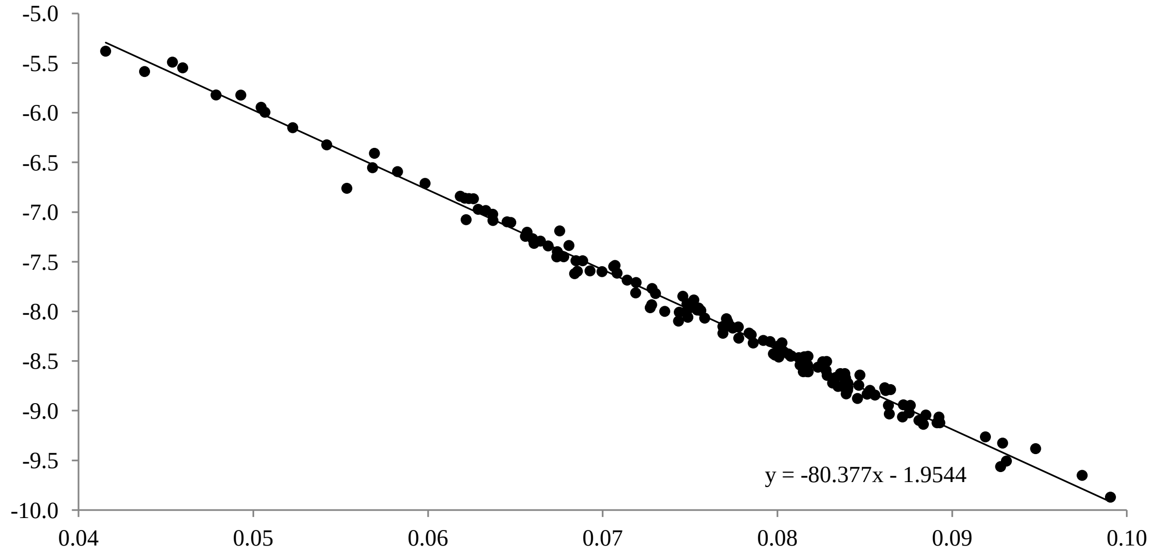

Figure 16: The Compensation Effect of Mortality of potentially Famous People: ρ (Y-axis), α (X-axis)

estimating:

$$\delta(a) = \left(A + e^{\rho+\alpha a}\right)\left(1 - \exp\{-A(a+b) - (e^{\rho+\alpha(a+b)} - 1)/\alpha\}\right) \tag{7}$$

for some given b.

In order to illustrate the effect, we estimated the parameters of $\delta(a)$ for the 1600-cohorts, under the assumption that $b = 25$. The Makeham constant became positive and significant; it displayed no particular trend over the whole sample, except for a (non significant) decrease in the nineteenth century, which is consistent with the observations in Gavrilov and Gavrilova (1991). More interestingly, the estimated parameters ρ and α with this correction for the notoriety bias are shown in Figure 16. They follow a similar pattern as the parameters estimated in Figure 14.[20] The estimated life span was 80.4 years, as in the benchmark estimation.

Figure 17 represents the estimated $\delta(a)$ and $\delta_p(a)$ for the last nine cohorts living at the same time as the Swedish of Figure 15. We observe that the correction for the bias we have imposed into the model qualitatively replicates the observed differences in mortality rates between the IBN famous people and the Swedish population.

[20] We have obtained similar results by simply assuming that the probability $\Phi(a)$ follows the uniform law rather than a survival probability.

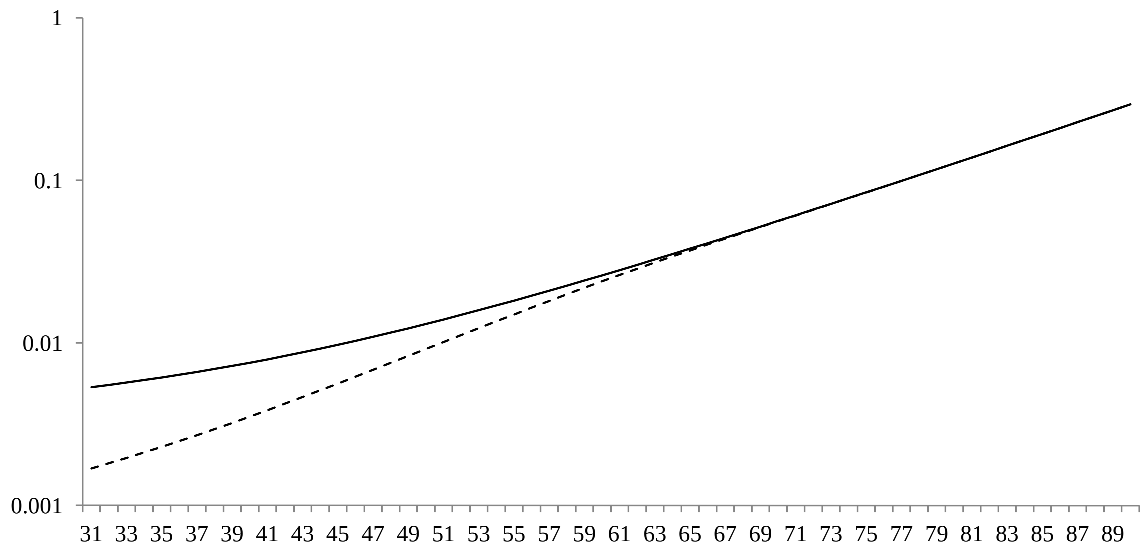

Figure 17: Simulated Mortality Rates 1871-79 for IBN people: Ages 30 to 90 (X-axis) and dead probabilities in log scale (Y-axis). $\delta_p(a)$ (solid line), $\delta(a)$ (dashed line)

One can conclude that the rectangularization of the survival laws initiated in 1640 was robust to the proposed correction of the notoriety bias, as well as the estimation of the life span T. The changes in the mean lifetime we measured in Section 3 are to be related to changes in the age-dependent Gompertz parameters ρ and α, and these changes occur by leaving the life span T unchanged (Compensation Effect).

5 Comparisons with Previous Studies

At least two questions are still open. First, to what extent are the famous people survival probabilities we estimated informative about the survival probabilities of the whole population? To address this issue, we compared our estimates with existing estimates using English data based on family reconstruction (1550-1820), and the Swedish census data (1750-). We also compare with existing estimates for the cities of Geneva (1625-1825) and Venice (1600-1700). Second, to what extent do we provide a different message from the few studies about specific groups of famous people, such as English aristocrats, or the Knights of the Golden Fleece?

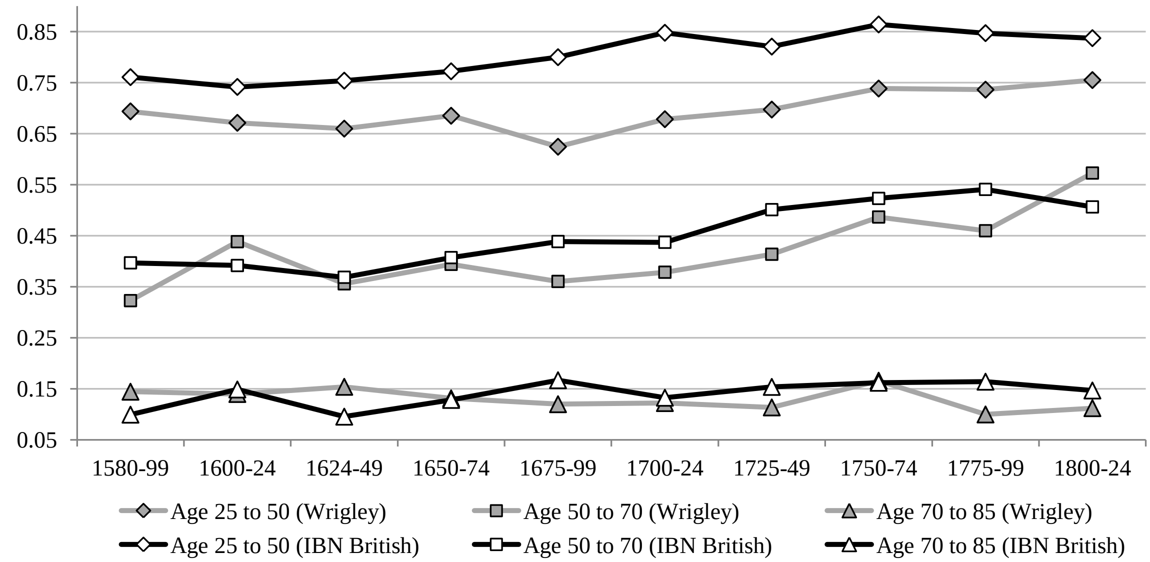

Figure 18: Survival Probabilities: England, Wrigley's data vs IBN

5.1 Comparison with Ordinary People

5.1.1 English Family Reconstitution Data 1580-1820

A global comparison between people and ordinary people in Europe cannot be performed over the past, as data for the whole population are usually not available. England is an exception in this respect, thanks to the work of Wrigley et al. (1997), who provide life tables for the English population from 1550 to 1820. We can compare their data for males with a subsample of our database that includes famous people with English nationality and/or London as city. Remember that our survival probabilities were computed from a measure of conditional lifespan for each individual, as described in Section 4.1, which results from adding the estimated constant term, cohort dummy and individual error. Taking periods of 25 years, as in Wrigley et al. (1997), our subsample had a large enough number of observations to compute sensible survival laws: from 408 individuals for 1580-1599 to 4794 individuals for 1800-1824.

Three main conclusions emerged when we compare the data of Wrigley et al. (1997) with ours, as can be seen in Figure 18 –the survival probabilities refer to the age intervals 25-50 (young adults), 50-70 (old adults), and 70-85 (late age). First, for young adults, the mortality rates of famous people underestimated the mortality of ordinary people. The survival probabilities of young adults were systematically larger for famous people. This observation may be due to the notoriety bias, as suggested throughout this paper. Second, there were no remarkable

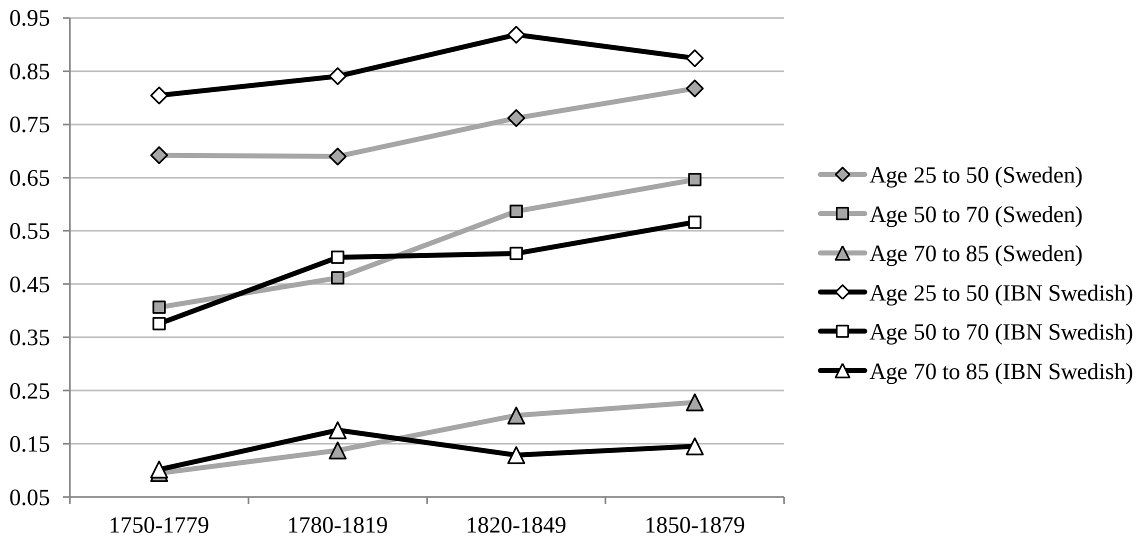

Figure 19: Survival Probabilities: Sweden, HMD vs IBN

differences between famous and ordinary late age individuals. Third, famous adult people were the forerunners in declining mortality. Their mortality rates decreased one century before those of ordinary adults. The survival of famous adults, both young and old, started increasing in the middle of the 17th century, creating an increasing gap from ordinary adults, who started catching-up around the middle of the 18th century.

5.1.2 Swedish Records, 1750-1879

As early as 1749, Sweden established a public agency responsible for producing population statistics. These statistics were based on population records kept by the Swedish Lutheran church. These data are available from the Human Mortality Database (HMD) and show that the demographic transition in Sweden followed the standard pattern. Adult life expectancy started to increase around 1825 (see e.g. de la Croix, Lindh, and Malmberg (2008)).

The survival probabilities of the whole Swedish population and IBN Swedish famous people are compared in Figure 19. The Swedish population in the IBN is large enough to make the comparison in Figure 19 meaningful: 1407 individuals born in 1750-1779, to 3400 individuals born in 1850-1879. As for England, we observed a systematic overestimation of young adult survival rates and a catching-up taking place at the beginning of the 19th century, 50 years later than in England.

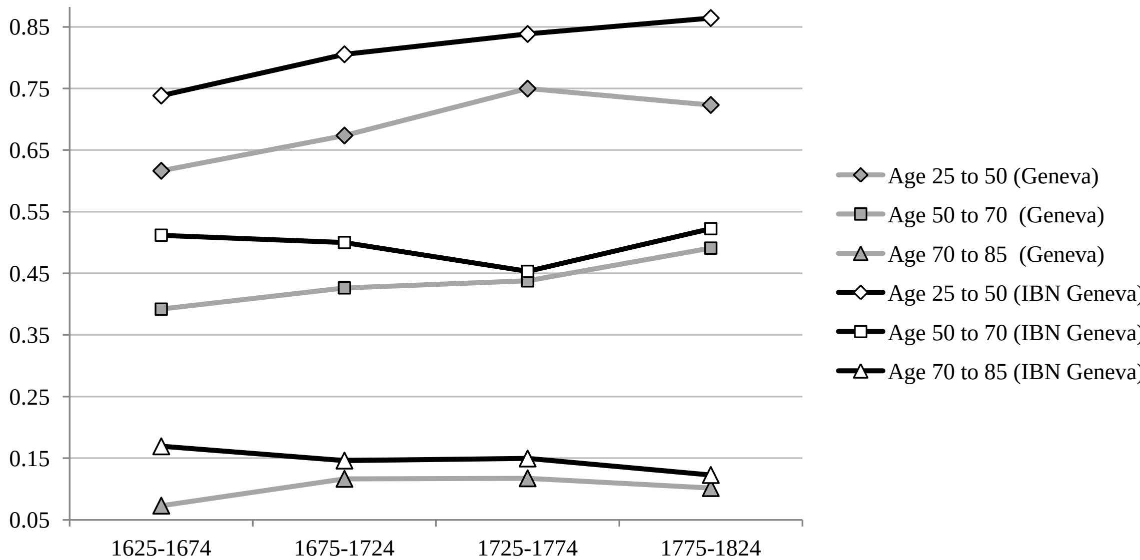

Figure 20: Survival Probabilities: Geneva, Perrenoud vs IBN

5.2 Comparison with Cities

5.2.1 Geneva, 1625-1825

Perrenoud (1978) provided very detailed demographic data for the city of Geneva (Switzerland) over two centuries. If we consider periods of 50 years covering the Perrenoud sample, we have about 200 famous persons born or dying in Geneva per subperiod. Results are presented in Figure 20. We first remark that Perrenoud's data display an upward trend as early as in the seventeenth century. This fact was already stressed by Boucekkine, de la Croix, and Licandro (2003) who used that evidence to claim that improvements in adult longevity preceded the industrial revolution, at least in some cities, and may have increased the incentives to acquire education. Comparing Perrenoud to IBN, we do not retrieve the pattern seen for Britain and Sweden of early improvement for famous people, followed by a catching-up phenomenon; here the people of the city seem to have the same global trend as IBN famous people: improvement in young adult survival rates through 1625-1774 in both samples; closing the gap between the samples in old adult survival and old age survival. This raises the question whether the trends we observed for famous people were in fact present in European cities (beyond Geneva).

Figure 21: Survival Probabilities: Venice, Beltrami vs IBN

5.2.2 Venice, 1600-1700

Beltrami (1951) provided demographic data for the city of Venice (Italy) over one and a half century. If we consider periods of 50 years covering the Beltrami sample, we have about 200-300 famous persons born or dying in Northern Italian cities (Bologna, Florence, Genoa, Turin, Venice) per subperiod. Results are presented in Figure 21. As in Geneva, Beltrami's data display an upward trend in the seventeenth century. Again, people from the cities seem to have the same global trend as IBN famous people, in particular as far as survival up to age 50 is concerned.

5.3 Comparison with Nobility

In order to study long-term trends in the mortality rates of adults of a given population, several others have used various types of records, usually available for high social classes, such as genealogical data or monographies about military or religious orders. These social classes are closer to our famous people than to the rest of the population. Comparing these studies with similar subsamples from our data is an interesting robustness check.

We used two such datasets, covering the period 1500 to 1900, which overlaps the period where the mean lifetime of famous people starts increasing: first, the mortality tables for British peers who died between 1603 and 1938 and their offsprings published by Hollingsworth

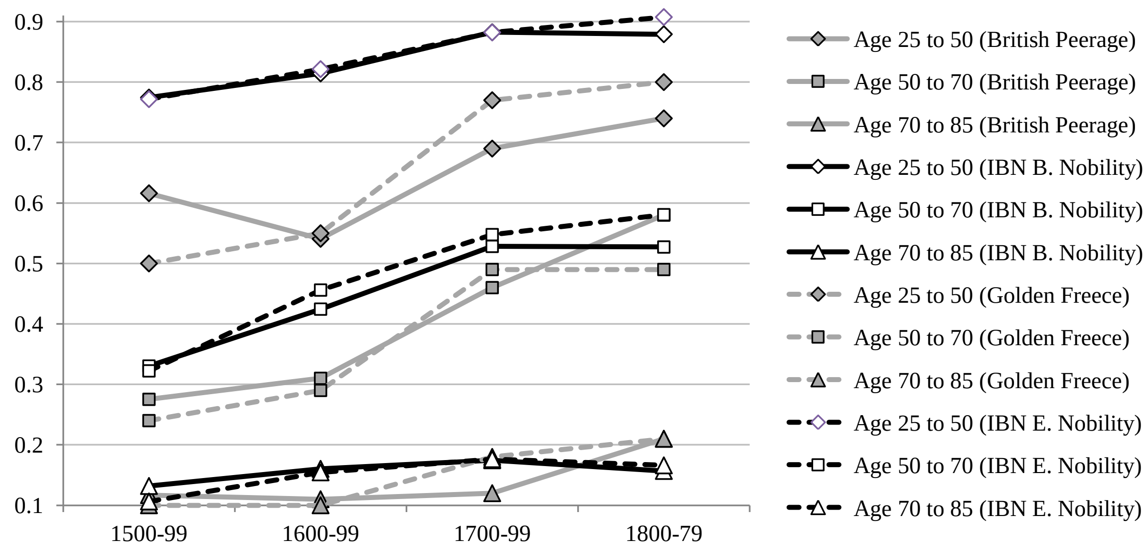

Figure 22: Survival Probabilities: Nobility

(1977).[21] A comparable subsample from our IBN database consists of British with a nobility occupation. We have many such individuals, from 577 for the 16th century to 3,324 for the 19th century. Second, Vandenbroucke (1985) provides vital statistics for the Knights of the Golden Fleece, an order started in 1430 with the Dukes of Burgundy and continued with the Hapsburg rulers, the kings of Spain and the Austrian emperors. A comparable subsample from our database consists of people with a nobility occupation and Austrian, Belgian, Dutch, German or Spanish nationality (all belonging to the former Hapsburg empire): 2,349 persons fall in this category in the 16th century, and 17,334 in the 19th century.

Several lessons can be drawn from Figure 22 . First, *the survival of IBN young adult nobles is overestimated* when compared with British peers and Golden Fleece members. Notice that, differently from the IBN, in both the British peers and Golden Fleece data, most individuals belong to the sample at birth, implying that the overestimation is due to the notoriety bias, i.e., nobles' offspring dying young are generally excluded from the IBN, reducing mortality rates at young ages. This observation reinforces the claim that the overestimation reported in Section 5.1 regarding ordinary people is also mainly due to the notoriety bias. Second, *mortality reductions for nobility take place in the 17th century* in the three databases, reinforcing the observation that improvements in the mean lifetime of famous people anticipate those of ordinary people by at least one hundred years.[22]

[21] The original data were sampled from genealogical data by Hollingsworth (1964).

[22] Incidentally, we remark that the initial decrease observed for young adult British peers does not appear in the IBN, which may cast doubts on its significance.

6 Interpretations and Conclusion

It is generally accepted that survival of ordinary adults started to increase permanently in the nineteenth century, with scattered evidence showing that in some places it started some decades before. The main causes of this observation are still under debate, but include higher income, better nutrition, better hygiene habits and sanitization of cities, more efficient medicine and public health.[23]

This paper uses for the first time the Index Bio-bibliographicus Notorum Hominum (IBN), a dataset containing information about vital dates, occupations, nationality and other relevant characteristics of hundreds of thousands of famous individuals from around the world. Exploiting observed individual characteristics to control for potential biases, we show, using a worldwide, long-running and consistent database, that there was no trend in mortality rates during the Malthusian era. Indeed, the conditional mean lifetime of all cohorts of famous people born before 1640 fluctuated around sixty years. Second, we date the beginning of the steady improvements in longevity to the cohorts born in 1640-9, clearly preceding the Industrial Revolution by one and a half centuries. Third, we find that improvements in longevity involved most countries in Europe, as well as all types of skilled occupations. Finally, the reasons for this early increase in mean lifetime were mainly related to age-dependent shifts in the survival law.

What could be the reasons for the reduction of famous people mortality rates in the seventeenth century? From the analysis above, a good explanation of this early improvement in longevity needs to fulfill the following conditions:

Selectivity. Reductions in mortality rates have to be restricted to people with some fame, not affecting the mean lifetime of the general population.

Regional Independence. The reductions should not be related to a particular location, since the improvements in the mean lifetime took place throughout Europe.

Occupational Independence. They have to affect similarly almost all skilled occupations.

Age Dependence/Life Span Constancy. They should not affect all adult ages in the same way, but mainly reduce the mortality rates of working age adults. In other

[23] For a general view on the main causes see Wilmoth (2007) and Cutler, Deaton, and Lleras-Muney (2006). The fundamental role of nutritional improvements on the reduction of mortality during the Industrial Revolution has been stressed by McKeown and Record (1962). Landes (1999), referring to the first half of the 19th century, argues that much of the increased life expectancy of these years came from gains in prevention, cleaner living rather than better medicine.

words, they should fundamentally generate a rectangularization of the human survival law without affecting the life span of human populations.

Urban Character. They should particularly affect ordinary people living in cities.

We see three possible candidate reasons, detailed below. We are not going to select one of them, but rather see if they can fulfill the necessary conditions suggested above.

The first candidate is the early *empowerment of the bourgeoisie*. We formulate this hypothesis in the following way. A major accumulation of capital, skills and technology has preceded the industrial revolution; a sort of necessary condition. From the seventeenth century onward, famous people directly or indirectly benefited from this change, through a substantial increase in their income. In other terms, during the 17th century, European society experienced the reinforcement and empowerment of the bourgeoisie. However, the rest of the population continued living under the same conditions as in the Malthusian era, generating a notorious increase in income inequality. This hypothesis, by assumption, fulfills the Selectivity requirement. As long as the emergence of the bourgeoisie is a European phenomenon, it also fulfills the Regional Independency requirement. Occupational Independence is also met because the increase in the surplus diffuses among the famous (e.g., even if the artists or the priests were not initially affected, the richest would buy more from them or make them larger transfers). The Urban Character would be met if the source of the increase in the income of famous people was an increase in urban efficiency or productivity, or if the gain of the bourgeoisie, fundamentally urban, benefitted all people in cities. Since the reductions in mortality are not induced for any improvement in medical technology, it has to be consistent with the rectangularization of the survival law, matching Age Dependence and Life Span Constancy.

Hoffman et al. (2002) studied inequality in Europe from 1500 onward. They looked at the purchasing powers of different income classes based on changes in relative prices. They concluded that luxury goods, especially servants, became cheaper, greatly widening the inequality of lifestyles before the Industrial Revolution. The evidence they provide on relative prices offers another rationale for an early increase in inequality in Europe.

One specific channel from real wealth to longevity could be through childhood development of the famous. Low level of health in childhood is not only conducive to death at an early age, but may also affect life at later stages. The relationship between early development and late mortality is well-established. Fogel (2004) emphasizes that nutrition and physiological status are the basis of the link between childhood development and longevity. Another important mechanism stressed by epidemiologists links infections and related inflammation

during childhood to the appearance of specific diseases in old age (Crimmins and Finch 2006). Similarly, Barker and Osmond (1986) related lower childhood health status to higher incidence of heart disease in later life.

Receding pandemics is the second candidate. The last plague in England was clearly identified in 1666-1667 (see Creighton (1891)). After this date, Europe could have been free of plagues by chance (Lagerlöf (2003), for example), or because of the natural evolution of the disease itself. Famous people belong to the upper social classes and are, therefore, shielded from certain diseases that are the prime cause of mortality for the rest of the population, such as infectious diseases, but cannot escape plagues. For example, suppose that the causes of death for famous people are 50% ordinary infection, 30% plagues, 20% others, whereas for the rest of the population they are 75% infection, 5% plagues, 20% others. If plagues are receding, as was shown to be the case after 1640 by Biraben (1975), then one should observe an improvement in the longevity of the upper classes, without much effect on the rest of the population, which remains primarily affected by other types of diseases. This type of explanation would fit Regional Independence, as plagues know no borders. The Urban Character of this explanation is also likely, as contagion is amplified by the high density of population. However, it is not clear how receding pandemics could satisfy the Age Dependence criterion; one would indeed a priori expect that pandemics are included in the (age-independent) Makeham constant, rather than in the Gompertz parameters. Finally, note that, for receding pandemics to drive the increase in the mean lifetime of famous people, plagues would need to have been a main factor of human mortality since Babylonian times and recede at the end of the 17th century. In this case, the estimated 60 years mean lifespan until 1640 includes the mortality induced by pandemics. The observed increase after 1640-9 is because this component of mortality starts to decrease.

The third candidate is *medical progress*. According to some authors (e.g. Omran (1971)), the influence of medical factors was largely inadvertent until the twentieth century, by which time pandemics of infection had already receded significantly. However, in the period 1500-1800, medicine showed an increasingly experimental attitude: no improvement was effected on the grounds of the disease theory (which was still mainly based on traditional ideas), but significant advances were made based on practice and empirical observations. For example, although the theoretical understanding of how drugs work only developed progressively in the nineteenth century with the development of chemistry (Weatherall 1996), the effectiveness of treatment of some important diseases was improved thanks to the practical use of new

drugs coming from the New World.[24] Another example is the use of the condom as a way to prevent spread of sexually transmitted diseases.[25] Note that the benefits of better medical practice could fit Selectivity if it was affordable and/or known only to the rich –see Johansson (1999). Regional Independence would be satisfied if medical knowledge spread easily across Europe.

A variation of the medical progress theory would be the Enlightenment hypothesis. The decrease in superstition that emerged from the new approach to the world promoted by the Enlightenment could have led the elite to consider that they indeed had some hold on their length of life, and that diseases were not necessarily sent by god. This view of the world could have easily spread among the upper classes in Europe through the network effect highlighted in Mokyr (2005) but taken centuries to percolate into the rest of the population.

Our criteria could also be used to reject explanations. For example the introduction and diffusion of the potato across Europe (widespread cultivation beginning in the late seventeenth and early eighteenth centuries) improved nutritional standards, increased population size and urbanization (Nunn and Qian 2011), and may have increased longevity, but such an explanation would violate the Selectivity criterion. Further research may try to use the criteria highlighted here to discriminate among possible explanations.

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[24] For example, according to Hawkins (1829) leprosy, plague, sweating sickness, ague, typhus, smallpox, syphilis and scurvy were leading causes of death in the past but could be treated effectively at the time he wrote his book.

[25] According to Collier (2007), In "1666, the year of the Great Fire of London, the English Birth Rate Commission officially documented the condom's popular use throughout the country by explaining that the significant decrease in births at the time was due to the use of "condons." This is the first time that spelling, or anything close to it, was used in an official government document." In the same book it is also noted that promiscuous aristocrats used the condom invented under Charles II (1630-1685) and officers of his army using it during the English Revolution of the 1640s.

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A Detailed Regression Results

Number of obs		297651	R-squared		0.1345	Root MSE		14.292
	coef	s.e.	dist. source	coef	s.e.	religion	coef	s.e.
constant	59.086	0.192	15	-40.280	2.320	methodist	-0.007	0.705
			30	-35.364	0.963	protestant	-0.318	0.356
occup. groups	coef	s.e.	40	-29.380	0.498	catholic	1.292	0.316
military	-2.733	0.204	50	-23.035	0.281	reformed	1.143	0.384
arts & métiers	-1.021	0.185	60	-15.469	0.185	baptist	0.009	0.570
nobility	0.084	0.202	70	-8.939	0.132	lutheran	-2.005	0.599
clerical	0.228	0.179	80	-4.595	0.111	mennonite	5.108	0.626
humanities	0.635	0.315	90	-2.675	0.104			
educational	0.645	0.129						
business	1.054	0.247	others	coef	s.e.		coef	s.e.
law and			servant	2.319	0.629	nationality	-0.458	0.181
government	1.177	0.132	unionist	3.900	0.733	city	0.275	0.189
sciences	1.415	0.250	founder	3.013	0.252	precision	-0.825	0.080
			chief	0.885	0.250	migration	0.486	0.059
			landowner	3.501	0.401			
			bengali	-13.333	0.480			
			jewish	0.089	0.529			
cohort	coef	s.e.	cohort	coef	s.e.	cohort	coef	s.e.
1430-9	0.157	0.656	1580-9	-0.007	0.348	1730-9	5.043	0.253
1440-9	-0.489	0.707	1590-9	0.219	0.335	1740-9	5.084	0.245
1450-9	-0.231	0.658	1600-9	0.633	0.324	1750-9	5.307	0.235
1460-9	0.596	0.653	1610-9	0.319	0.325	1760-9	5.195	0.231
1470-9	1.015	0.625	1620-9	0.487	0.316	1770-9	4.593	0.231
1480-9	-0.577	0.572	1630-9	0.395	0.311	1780-9	4.555	0.231
1490-9	-0.258	0.548	1640-9	1.925	0.308	1790-9	4.794	0.225
1500-9	0.944	0.512	1650-9	1.776	0.304	1800-9	5.059	0.217
1510-9	0.125	0.509	1660-9	2.387	0.299	1810-9	6.011	0.215
1520-9	0.625	0.449	1670-9	1.651	0.299	1820-9	6.388	0.215
1530-9	0.328	0.429	1680-9	2.301	0.293	1830-9	6.311	0.215
1540-9	0.671	0.421	1690-9	2.978	0.287	1840-9	6.287	0.213
1550-9	0.718	0.407	1700-9	3.397	0.283	1850-9	6.801	0.213
1560-9	0.927	0.377	1710-9	4.015	0.272	1860-9	7.979	0.213
1570-9	0.421	0.365	1720-9	4.652	0.262	1870-9	9.228	0.214

city	coef	s.e.	city	coef	s.e.	city	coef	s.e.
amsterdam	-0.785	0.366	freiburg	-0.319	0.693	newyork	0.280	0.345
antwerpen	-0.711	0.472	gdansk	-1.788	0.616	nuremberg	-2.491	0.463
augsburg	-0.575	0.635	geneve	-0.392	0.400	oslo	0.140	0.641
barcelona	-2.115	0.622	genoa	0.718	0.694	paris	0.034	0.215
basel	-1.079	0.634	ghent	0.772	0.583	philadelphia	-1.402	0.496
berlin	-0.444	0.267	graz	-0.991	0.518	prag	-1.623	0.349
bern	-0.583	0.628	hamburg	-1.502	0.382	riga	-3.171	0.570
bologna	0.737	0.615	hannover	1.385	0.588	riodejaneiro	0.681	0.688
bordeaux	1.032	0.493	helsinki	-0.690	0.701	roma	-0.501	0.337
boston	-0.120	0.564	kaliningrad	-1.602	0.527	rotterdam	-0.015	0.574
bremen	-0.694	0.600	krakow	0.004	0.496	rouen	1.114	0.520
breslau	-1.665	0.438	leiden	-1.770	0.620	saintpetersburg	-1.371	0.385
brno	-0.264	0.632	leipzig	-2.573	0.419	stockholm	-0.570	0.332
bruxelles	0.851	0.404	liege	0.439	0.549	strasbourg	-1.269	0.398
budapest	0.761	0.336	lisbon	-0.223	0.626	stuttgart	0.671	0.514
buenosaires	0.112	0.567	london	0.329	0.260	toulouse	1.909	0.653
chicago	0.119	0.711	lviv	-0.488	0.573	turin	-0.287	0.641
cologne	0.065	0.501	lyon	-1.727	0.426	utrecht	0.011	0.580
copenhagen	-1.294	0.368	madrid	-1.885	0.435	venezia	0.253	0.513
denhaag	1.932	0.422	marseille	1.128	0.642	versailles	1.826	0.629
dresden	-0.838	0.383	metz	1.459	0.697	warsaw	-0.992	0.395
dublin	0.280	0.598	milan	-0.457	0.525	washington	-0.694	0.596
edinburgh	-0.596	0.538	montreal	-0.181	0.718	wien	-1.074	0.266
florence	-0.221	0.475	moscow	0.768	0.476	wiesbaden	2.039	0.703
frankfurt	-0.822	0.468	munich	-0.077	0.354	zurich	-2.163	0.544
frederiksberg	4.748	0.782	napoli	-0.883	0.478			
nationality	coef	s.e.	nationality	coef	s.e.	nationality	coef	s.e.
german	-0.494	0.183	russian	-3.278	0.231	irish	1.240	0.356
french	1.281	0.198	polish	-0.976	0.250	canadian	3.116	0.459
british	1.571	0.201	spanish	-0.018	0.277	chinese	1.129	0.453
swedish	1.087	0.217	belgian	-0.837	0.295	roman	-0.621	0.299
american	2.578	0.210	icelandic	0.869	0.361	croatian	-1.226	0.602
hungarian	-1.947	0.238	czech	0.542	0.341	greek	2.371	0.478
dutch	-0.180	0.252	norwegian	-0.515	0.389	slovenian	-1.780	0.611
swiss	0.943	0.235	finnish	-0.838	0.383	japanese	0.202	0.650
austrian	0.358	0.257	brazilian	-4.740	0.483	australian	5.205	0.628
italian	1.635	0.239	argentinian	-1.949	0.486	indian	-1.342	0.533
danish	0.194	0.276	portuguese	0.448	0.479	slovak	1.782	0.710

occupation	coef	s.e.	occupation	coef	s.e.	occupation	coef	s.e.
franciscan	1.483	0.447	judge	2.083	0.252	notary	1.475	0.408
jesuit	-2.735	0.231	physician	-0.363	0.340	physicist	1.110	0.479
author	0.831	0.115	missionary	-0.777	0.278	violinist	0.648	0.473
professor	1.438	0.118	philologe	-0.688	0.371	illustrator	1.964	0.426
writer	1.135	0.135	singer	0.267	0.312	dean	3.989	0.447
painter	1.784	0.190	surgeon	0.245	0.370	administrator	0.750	0.419
doctor	-1.804	0.253	farmer	2.508	0.335	astronomer	-0.369	0.477
jurist	-0.507	0.149	soldier	-2.416	0.411	collector	4.222	0.459
officer	0.842	0.183	diplomat	1.702	0.314	geologist	1.092	0.505
poet	-0.837	0.210	publicist	-0.539	0.360	admiral	7.498	0.420
politician	1.606	0.166	king	0.175	0.197	commander	0.671	0.455
teacher	0.498	0.153	artist	0.506	0.284	inventor	1.874	0.516
pastor	0.773	0.196	congressman	-1.040	0.340	pianist	-0.865	0.485
general	6.597	0.206	mathematician	0.157	0.371	knight	0.090	0.396
lawyer	-0.239	0.168	botanist	0.292	0.358	scholar	0.196	0.276
theologian	1.311	0.190	benedictine	0.633	0.364	fighter	-4.349	0.511
historian	1.994	0.311	philosopher	-0.813	0.376	bailiff	-0.056	0.476
composer	0.796	0.250	magistrato	2.246	0.345	academician	3.475	0.556
musician	1.028	0.251	printer	-0.189	0.366	adviser	-0.095	0.312
director	0.488	0.329	secretary	-0.778	0.294	designer	-0.541	0.572
councillor	1.090	0.285	librarian	0.995	0.412	consul	0.456	0.297
journalist	-1.919	0.343	organist	1.316	0.372	prince	-1.405	0.312
priest	0.710	0.190	chemist	-0.250	0.370	cardinal	1.768	0.558
clergyman	1.050	0.235	banker	3.713	0.393	geograph	-0.283	0.499
editor	0.022	0.277	industrialist	3.431	0.373	builder	1.781	0.525
deputy	1.710	0.218	vicar	-0.467	0.341	agronomist	1.348	0.596
actor	0.967	0.204	lecturer	-0.938	0.328	chamberlain	0.906	0.602
preacher	-0.547	0.232	lord	0.841	0.225	procureur	-0.493	0.553
businessman	1.485	0.289	dramatist	-0.155	0.377	sheriff	1.406	0.609
mayor	2.593	0.219	inspector	0.229	0.355	deacon	-4.846	0.552
bishop	3.690	0.238	student	-9.214	0.380	economist	0.907	0.554
minister	1.089	0.211	merchant	1.227	0.337	rabbi	2.268	0.476
architect	1.217	0.317	earl	-2.146	0.389	pewterer	0.959	0.703
noble	-2.134	0.246	manufacturer	2.725	0.344	cantor	1.661	0.564
military	0.259	0.249	bookseller	0.849	0.396	cartographer	0.112	0.606
beamter	0.640	0.228	goldsmith	0.097	0.455	martyr	-14.648	0.600
engineer	0.378	0.293	duke	-0.822	0.246	regisseur	0.295	0.650
translator	-0.310	0.344	abbot	2.184	0.320	prefect	1.955	0.569
sculptor	2.065	0.273	major	2.071	0.394	zoologist	0.723	0.593
pedagogue	1.686	0.361	trader	-0.885	0.354	orientalist	-0.799	0.628
lieutenant	-1.646	0.243	archaeologist	1.699	0.484	wholesaler	1.342	0.748
captain	-0.212	0.281	lithograph	0.691	0.416	classicist	0.821	0.702
rector	0.809	0.220	pharmacist	0.258	0.456	archdeacon	6.856	0.818

occupation	coef	s.e.	occupation	coef	s.e.
brigadier_general	-3.038	0.614	capuchin	2.053	0.489
major_general	-2.796	0.575	marshal	6.503	0.370
lieutenant_colonel	0.577	0.573	archbishop	1.713	0.449
violin_maker	-0.688	0.642	ambassador	0.814	0.462
colonel	4.052	0.287	naturalist	-0.829	0.475
engraver	0.177	0.285	baron	1.852	0.652
president	3.276	0.238	queen	-0.180	0.527
senator	3.659	0.292	antiquary	1.539	0.630
governor	0.710	0.265	piarist	-0.117	0.679
kapellmeister	1.405	0.549			

B Occupation categories

Arts and métiers: actor, artist, cantor, collector, composer, designer, dramatist, engraver, goldsmith, illustrator, kapellmeister, lithograph, musician, organist, painter, pewterer, pianist, poet, regisseur, sculptor, singer, violinmaker and violinist.

Business: antiquary, bookseller, banker, printer, publicist, businessman, director, editor, farmer, librarian, industrialist, merchant, trader, manufacturer and wholesaler.

Clerical: abbot, archbishop, archdeacon, capuchin, cardinal, clergyman, deacon, franciscan, jesuit, martyr, missionary, pastor, piarist, preacher, priest, rabbi, theologian and vicar.

educational: author, academician, dean, lecturer, professor, rector, scholar, student, teacher and writer.

Humanities: archaeologist, classicist, economist, historian, journalist, orientalist, pedagogue, philologe, philosopher and translator.

Law and government: administrator, adviser, ambassador, bailiff, beamter, congressman, consul, councillor, deputy, diplomat, governor, inspector, judge, jurist, lawyer, magistrato, mayor, minister, notary, politician, prefect, president, procureur, secretary, senator and sheriff.

Military: admiral, brigadier-general, captain, colonel, commander, fighter, general, lieutenant, lieutenant-colonel, major, major-general, marshal, military, officer and soldier.

Nobility: baron, chamberlain, duke, earl, king, knight, lord, noble, prince and queen.

Sciences: agronomist, architect, astronomer, botanist, builder, cartographer, chemist, doctor, engineer, geographer, geologist, inventor, mathematician,naturalist, pharmacist, physician, physicist, surgeon and zoologist.

C Additional Figures

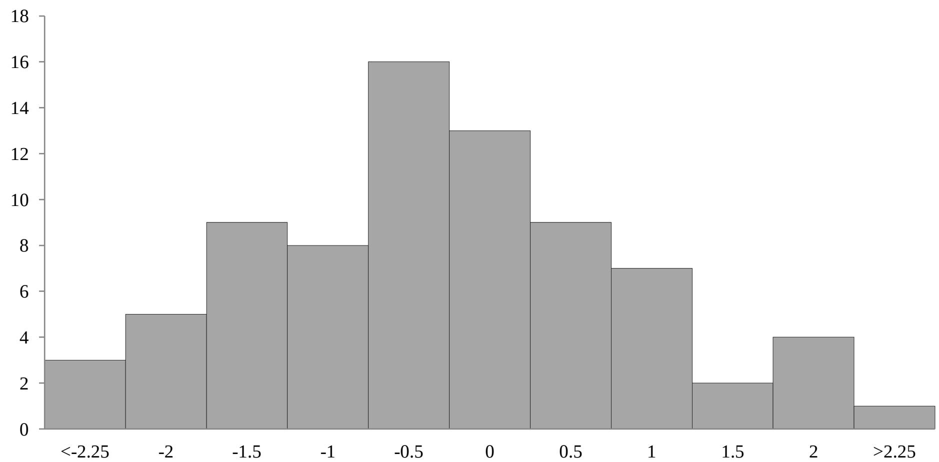

Figure A.1: Conditional Mean Life: Distribution of city dummies

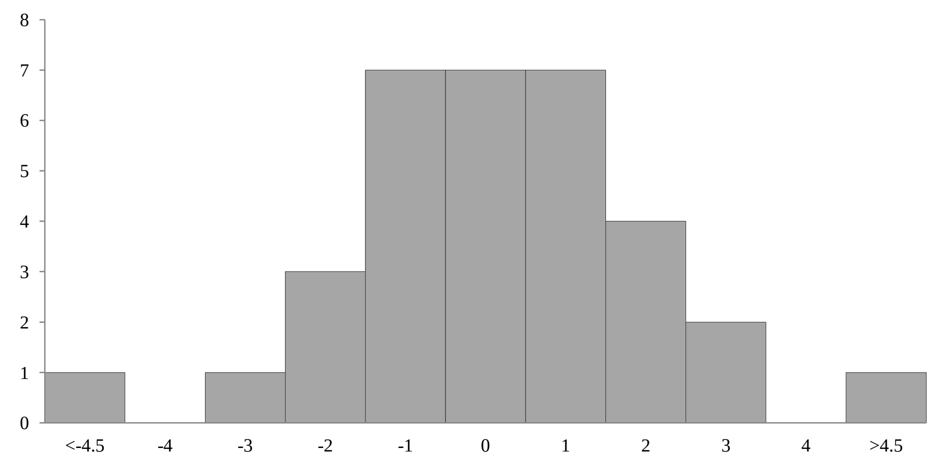

Figure A.2: Conditional Mean Life: Distribution of nationality dummies

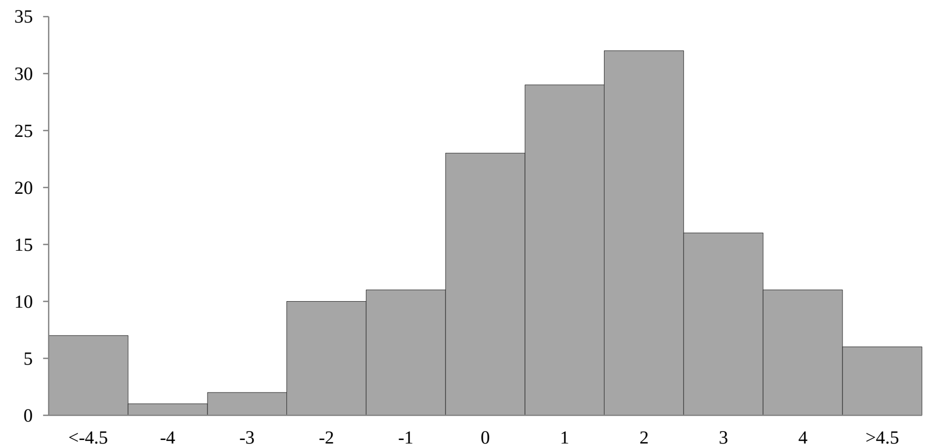

Figure A.3: Conditional Mean Life: Distribution of occupation dummies

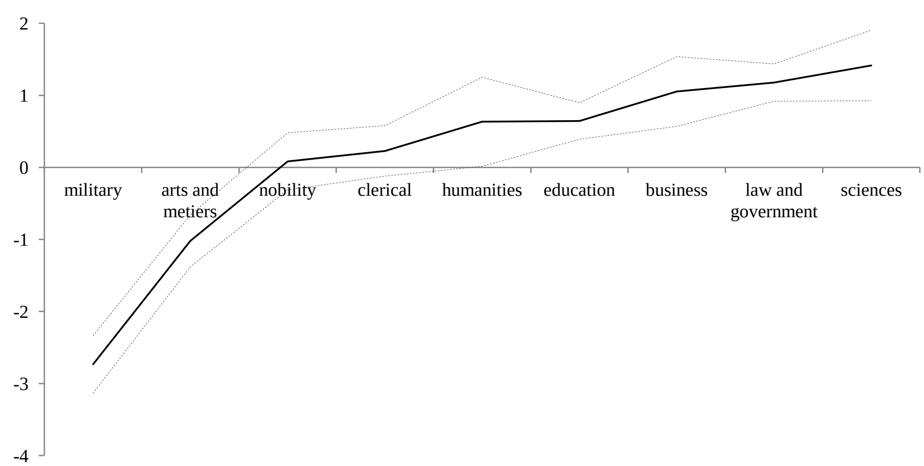

Figure A.4: Conditional Mean Life: Main occupational groups

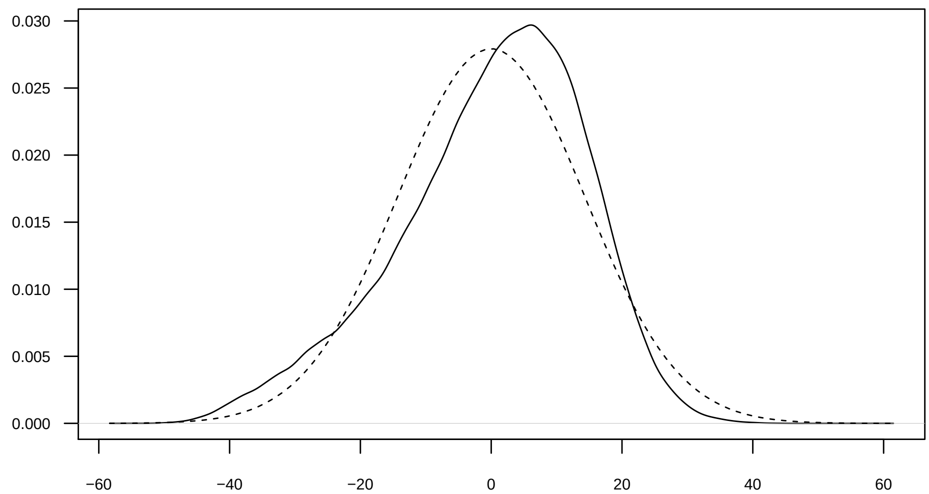

Figure A.5: Kernel Density of the Residuals (solid) and Normal density (dashes)

Figure A.6: Standard Deviation of Residuals by Decade, and 95% confidence interval

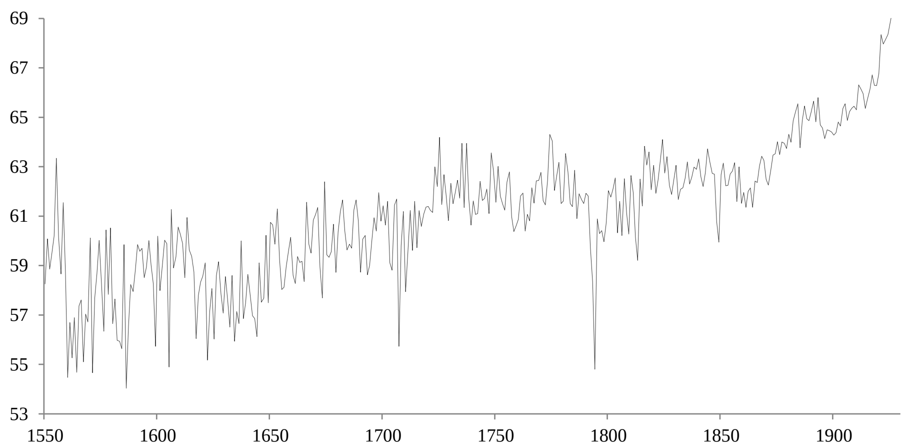

Figure A.7: Mean Lifetime per Year of Death

D The First Life Tables

The first life table was published in London in 1662 in a book by Graunt (1661). His analysis was based on data on the age at the time of death in London, originally collected 127 years earlier. Thirty years after this first life table Halley (1693) published results based on number of births and deaths in Breslau 1687-1691. (today called Wroclaw). For information, we provide in Table 2 some key survival rates from these tables.

		Age 25 to 50	Age 50 to 70	Age 70 to 85
Graunt's life table	London 1534	0.2512	0.3519	0
Halley's life table	Breslau 1687-1691	0.6102	0.4104	0.0578

Table 2: Survival Probabilities in various life tables