The Mean Lifetime of Famous People from Hammurabi to Einstein*

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Abstract

This paper builds a unique dataset of around 300,000 famous people born between Hammurabi's epoch and 1879, Albert Einstein's birth year. It includes the vital dates, occupations, and locations of celebrities from the *Index Bio-bibliographicus Notorum Hominum* (IBN), a very comprehensive biographical tool. The main contribution of this paper is fourfold. First, it shows, using for the first time a worldwide, long-running, consistent database, that mortality displays no trend during the Malthusian era. Second, after correction for selection and composition biases, it dates the beginning of the steadily improvements in longevity to the cohort born in 1640-9, clearly preceding the Industrial Revolution. Third, it finds that the timing of longevity improvements concerns most countries in Europe, as well as all types of skilled occupations. Finally, the reasons for this early rise in mean lifetime have to be found in age-dependent shifts in the survival law.

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Keywords: Longevity, Notoriety, Malthus, Gompertz-Makeham, Compensation Effect of Mortality.

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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 adult longevity displayed no trend during the Malthusian stagnation era, i.e. until about the industrial revolution. Even if the evidence remains scattered, the absence of a trend can hardly be contested, which is likely related to the steadiness of low living standards and the stagnation of medical practice (including nutritional and hygienic habits). This stagnation occurred despite that the Malthusian era is characterized by technological improvements covering many fields of human activity.

Extended evidence shows that adult life expectancy has increases widely and sustainedly from 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 the generations born in the nineteenth century, even if little information is available for those born before.[1] The earliest evidence on adult life expectancy improvement is in Wrigley et al. (1997). They find for English population an important reduction in adult mortality 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 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. Understanding adult longevity in the past has moreover implications for predicting future human lifespan (see Wilmoth (2007)).

The question of the timing of the rise in longevity finds a nice echo in what the contemporaneous of the industrial revolution wrote about life expectancy history and prospects. 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

[1]From the Human Mortality Database (HMD), cohort life expectancy at age 20 (males) starts to rise 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 in http://www.mortality.org/Public/Overview.php.

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."

This paper aims to document the long stagnation period and identify the time at which longevity started to rise above its stagnation mean. To this aim, we build a unique dataset of around 300,000 famous people born from the 24th century BCE (Hammurabi, king of Babylonia, is among the few firsts) to 1879 CE, year of Albert Einstein's birth. Individual 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, allows us to go beyond the current state of knowledge and provide a global picture. Existing estimations are local, mainly European centered, and start at the best at the 16th century.[2]

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

The main contribution of this paper is fourfold. First, it documents, using a world-wide, long-running, consistent database, that *adult longevity shows no trend during the Malthusian era*. The mean lifetime of famous people was equal to 59 ± 0.4 years during four millennia. Second, it shows that *permanent improvements in longevity precede 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 68.2 years for Einstein's cohort. Third, using the information about locations and occupations available in the database, we also find that the increase in longevity *occurred almost everywhere over Europe*, not only in the leading countries of the 17th-18th century, and *for all observed occupations*. Finally, we find that the reasons for this early

[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.

rise in mean lifetime has to be mainly found in *age-dependent shifts in the survival law*. To this purpose, we have grouped individuals in 150 cohorts of at least 1600 members and measured survival laws for these cohorts, then, following Gavrilov and Gavrilova (1991), we have estimated the Gompertz-Makeham mortality law for each cohort, and used the estimated coefficients to test the Compensation Effect of Mortality. We find that changes in mortality observed since the middle of the seventieth century are mainly due to changes in the Gompertz parameters consistently with the Compensation Effect. This shows an early tendency of the survival law to rectangularize.

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 rise in their longevity has a specific meaning for economic growth. This may support the hypothesis that longevity improvements were one cause of the industrial revolution. One mechanism can 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 goes through 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. Section 2 describes the data, studies their quality, and computes the unconditional mean lifetime of famous people. Section 3 reports a list of potential biases, defines a set of control variables and provides an estimation of the conditional mean lifetime of famous people, after controlling for the reported biases. It also studies 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. Section 5 compares the survival probabilities of our famous people for specific places and time with similar case studies from the literature. Section 6 suggests criteria any good interpretation of these events should meet and concludes.

2 Data and Descriptive Statistics

2.1 The *Index Biobibliographicus Notorum Hominum*

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

FAMOUS PEOPLE: People referred 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 him/her including some broad information about occupation and nationality, and the list of biographical sources where 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 to the same person):

- Hammurapi; 1792-1750 (1728-1686) ante chr.;[3] ... ; 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 whom last names begin with letters A to L, since those from M to Z were not yet available in electronic format when we received the data. However, this criteria is not expected to introduce any selection bias in the estimation of famous people cohort mean lifetime.

[3]Notice that two different years of birth are reported for Hammurabi (Hammurapi in German), but a unique lifespan of 58 years. The places of birth and death are not reported.

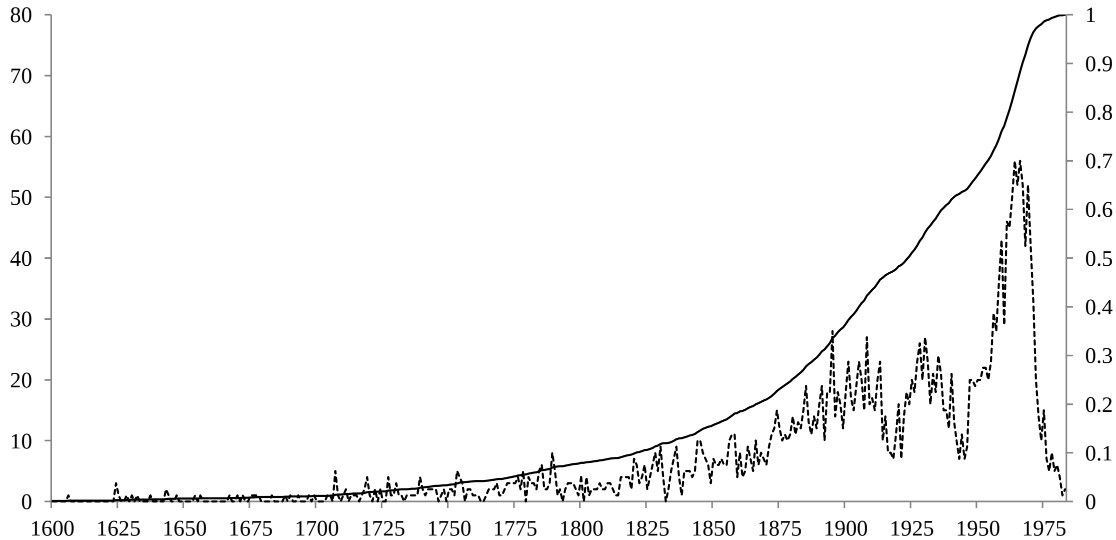

Figure 1: Time Distribution of Biographic Sources. Frequency (dashed line, left axis), cumulative (solid line, right axis)

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 lifespan smaller than 15 or larger than 100 years were excluded, 729 and 872 respectively. Note that the IBN reports information on very few people dying during childhood, and most centenarians in the database are likely to be measurement errors.

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

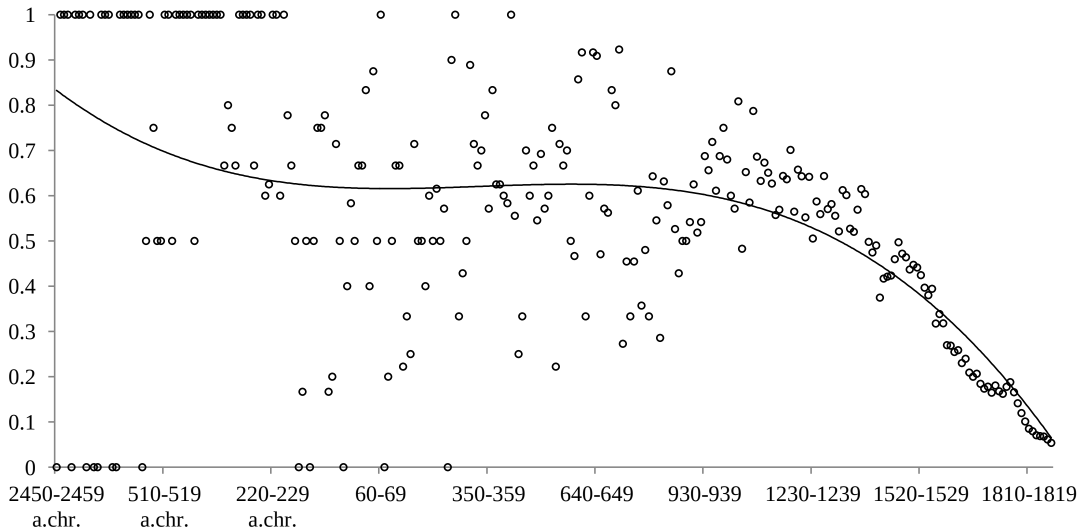

Figure 2: Frequency of Imprecise Observations

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

2.2 Data Precision

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

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

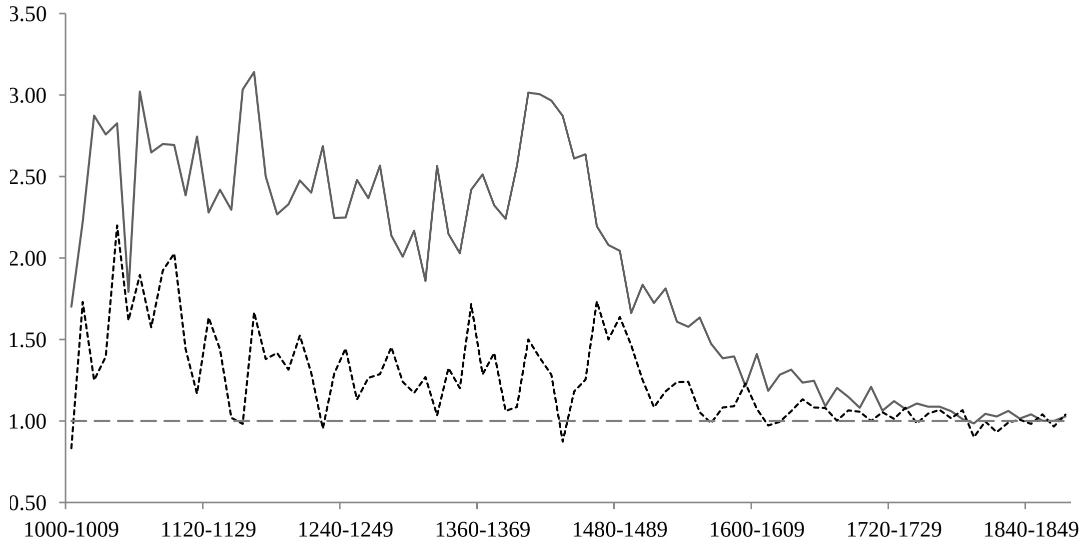

Figure 3: Heaping Index. birth year (solid line), death year (dashed line)

sons, 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 o 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 presents the two heaping indexes by decades up to 1879.[4] Death date heaping is low, indicating that the sources know quite well the death of famous people. Birth dates are much more uncertain, as the heaping index is about three before 1450, indicating that there are three times more dates finishing in 0 and 5 than there should be. It appears that the improvements start around 1450. This is consistent with the finding 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 been filled 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 of a major increase in human capital preceding the industrial revolution.

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

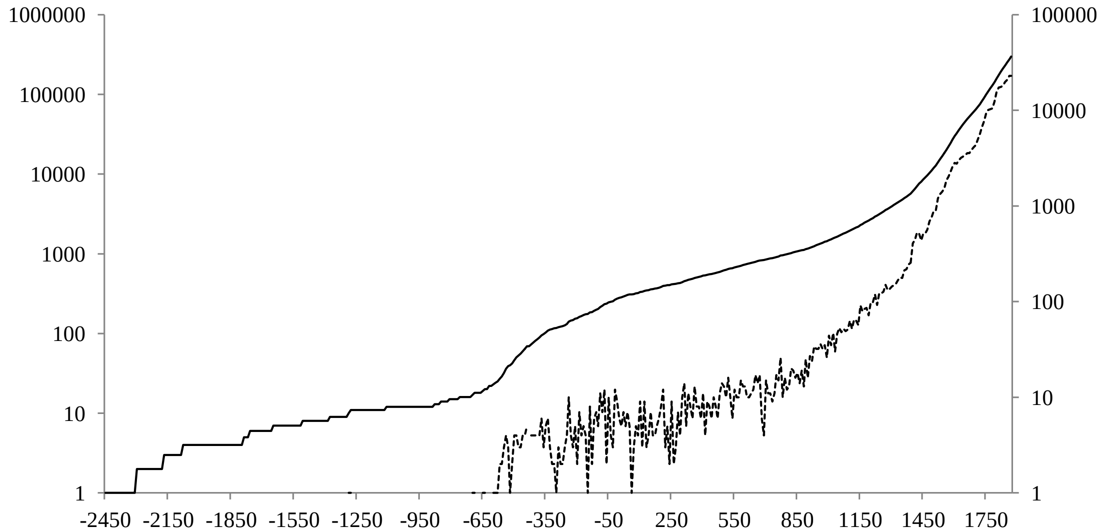

Figure 4: Number of Observations by Decade, density (dots) and cumulative (solid line)

2.3 Unconditional Cohort Mean Lifetime

This paper focuses on the estimation of famous people mean lifetime, not on life expectancy at birth or at any other particular age. To be more precise, celebrities' mean lifetime measures life expectancy conditional on the age at which people become 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. The latter can be used to estimate life expectancy at birth. The former, however, allows measuring 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 is changing over time (Bongaarts and Feeney 2003). Individuals in the database are 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 are only 274 individuals born before Christ, 400 individuals before 230 CE, and 1600 before 1040 CE.

Before estimating conditional mean lifetime, let us represent the unconditional mean lifetime implied by the data by grouping individuals in ten-year cohorts. To overcome the representativity problem, which is very important at the beginning of the sample,

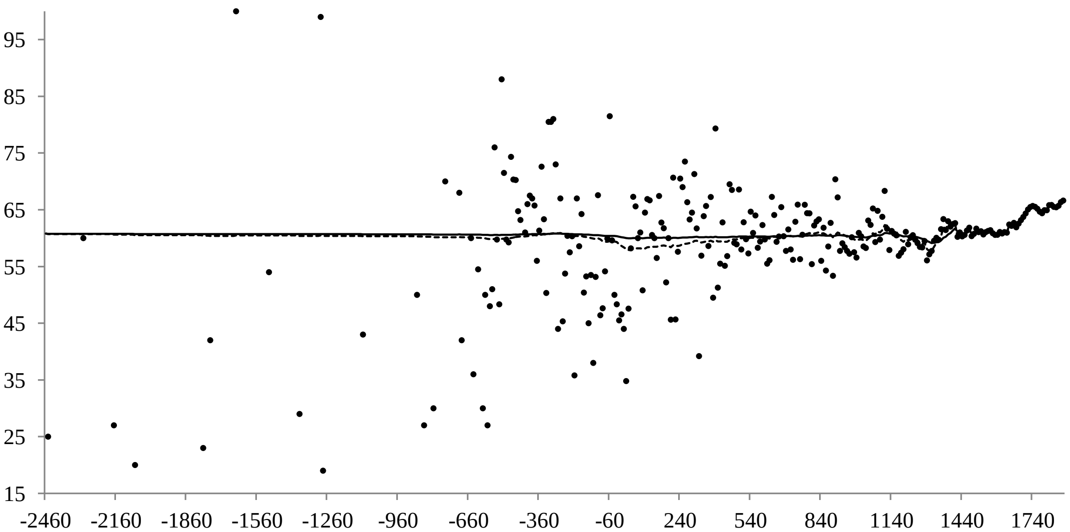

Figure 5: Unconditional Mean Lifetime. data (dots), smoothing with $x = 400$ (dotted line), smoothing with $x = 1600$ (solid line)

when representing the data, we apply a simple adaptive rule

- when $n_t < x$ $\qquad \lambda_t = (n_t/x)\, l_t + (1 - n_t/x)\lambda_{t-1}$
- otherwise, $\qquad \lambda_t = l_t$

where l_t and λ_t are the actual and smoothed mean lifetimes, n_t represents the actual cohort size, and x is an arbitrary representative size. The choice of x is based on the idea that if people lifespan 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 be in a 95% confidence interval ± 1.5 (± 0.75).

As initial condition we use $\lambda_{-\infty} = 60.8$, taken from Clark (2007) for the hunter-gatherers.[5] 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.

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

Figure 5 reports the actual mean lifetime and the corrected mean lifetime of ten-years cohorts for both $x = 400$ and $x = 1600$. The actual mean lifetime fluctuates dramatically around 60.9 until the 14th Century, due to the small size of 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 shows movements around the mean until it starts increasing from the cohort born 1640-1649.

3 Famous People Conditional Mean Lifetime

3.1 Possible Biases

When estimating famous people mean lifetime, we have to be seriously concerned with different type of selection and composition biases. 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 getting such a status increases with age, famous people mortality rates tend to be underestimated, particularly at young ages. The notoriety bias arrives because potential celebrities dying before getting the needed reputation are excluded from the database by construction. Moreover, in some métiers, occupations are hierarchically ranked with ranks highly correlated with seniority. It is the clear case of military and clerical occupations. Since high rank occupations are more reputed, we expect to observe them more frequently in the IBN than low ranks. In order to control for the notoriety bias, we include occupational dummies in the regressions. Occupation 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 includes famous people for whom the years of both birth and death are reported. For this reason, celebrities in the IBN still alive at the publication of a biographic dictionary or encyclopedia are excluded from our database by construction, 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 distance between birth dates and publications dates is short. Let us call it the *source bias*. After dating the sources, we have computed for each individual the age of her/his cohort at the 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 have been published during the 19th and 20th centuries (see Figure 1), we have decided to exclude people born after 1880.

Occupation Bias. The database is built on existing biographic publications reporting people that were famous at their time. However, fame was not always related to the same human achievements, implying that the weight of some occupations may have change substantially over time. This is, for example, the case of nobility and religious occupations. The case of martyrs, even if less frequent, is more striking since they used to live short, by definition, and they were concentrated in a particular period of human history. For this motive, changes in the occupational composition of the database may generate artificial changes in the survival probabilities. Occupation dummies are used to control for the potential occupation bias.

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

Migration Bias. Since the probability of migrating at least once in life is positively correlated with the individual lifespan, we expect that migrants have on average a larger lifespan than non-migrants. We refer to it as migration bias. The IBN provides for most individuals information on both the city of birth and the city of death. To control for the migration bias, we have created a migration variable taking the value of one when the place of birth and death are different, zero otherwise.[6]

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.[7]

[6] Mokyr (2005) measures the mobility of 1185 "creative people" in Europe over 1450-1750 and shows it is large, with 3.72 mean number of moves per person. Longer lived people, as one would have expected, moved somewhat more.

[7] It is important to notice that some cells in the IBN are empty, and when complete some are meaningless, 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. I does imply that we tend to underestimate the dummy coefficients, since the excluded group may include individuals belonging the control group.

In order to locate individuals in cities, we have used the information in the *places of birth and death* cells. From the 297,651 individuals in the database, a place of birth or death was missing for 60,637 among them only (20% of the sample). For the remaining 237,014 individuals, we have first counted words using *Hermetic Word Frequency Counter 1089t* and identified 56,574 birth places and 35,852 death places. We have dealt with the issue that some cities have composed names, such as New York. We have then translated city names for birth (resp. death) places with at least 30 (resp. 20) observations into 22 languages,[8] and search again to identify all individuals that were born or dead in the same city. We have checked for historical names for these cities (if possible) using Wikipedia.[9] This procedure leads to identify 584 and 603 birth and death cities, respectively. With translation, the sample for some cities more than double its size. We have finally retained the 77 cities with at least 300 observations – as either birth or death place (see Appendix A). For the statistical analysis below, we have created a dummy for each of the 77 cities. For individuals born and dead in different cities two different city dummies are included. 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 large cities, zero otherwise. Finally, for all individuals with observed birth and death places, we have created a *migration* dummy that takes value one only if the places of birth and death are different.

Information in the *statement* cells is more complex. Only 1,274 observations have a missing statement cell. We have identified 81,078 unique words using the *Hermetic Word Frequency Counter 1089t*. Among those with at least 200 observations, we have translated them into the same 22 languages as we did for cities and merge all observations corresponding to the same occupation, nationality or religion. They collapsed into 171 occupations, 65 nationalities and 10 religions. Using these categories, 278,084 individuals have at least one occupation (94.4% of the sample) and 207,049 have more than one; 218,530 have at least one nationality (73.4%) and 11,929 have more than one. We have finally retained all relevant words with at least 300 observations. This has allowed us to identify 33 nationalities, 8 religions, and 148 occupations (see Appendix A). Occupations were grouped in nine occupational categories: Arts and métiers, business, clerical, education, humanities, law and government, military, nobility, and sciences (see

[8] For that, we have used Nice Translator –http://nicetranslator.com/. The list of languages includes are 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.

Appendix B). There were 6 other repeated words that we also use as controls.[10]

Finally, the *source* cells have been used to single out for each individual the publication year of the biographical source citing her/him. We have identified it for 290,528 individuals, 99.9% of total observations. To control for the source bias explained above, we would like to know for each individual the date of publication of the most recent source. Unfortunately, because of the way data are organized in the IBN, when an individual is cited by more than one source, we can only identify one of these sources automatically, not necessarily the most recent. In particular, it arrives that for 42,600 observations, the year of publication precedes the year of death, which we take as evidence on the existence of another source published latter. For all these reasons, we have measured for each individual the age of her/his cohort at the publication of the source in the following way. When the individual's death year is smaller than the publication year of the source, we take 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 have created eight *cohort age at source publication* dummies for ages {15-29, 30-39, ..., 90-99}. The dummies take value one for individual which cohort age at publication of the source is in the age group, zero otherwise.

3.3 Estimation

The unconditional picture described 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 with the following regression:

$$m_{i,t} = m + d_t + \alpha\, x_{i,t} + \varepsilon_{i,t} \tag{1}$$

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 and 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

[10] Chief, bengali, founder, landowner, servant and unionist. We do include bengali in this group, because most of them concerns 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.

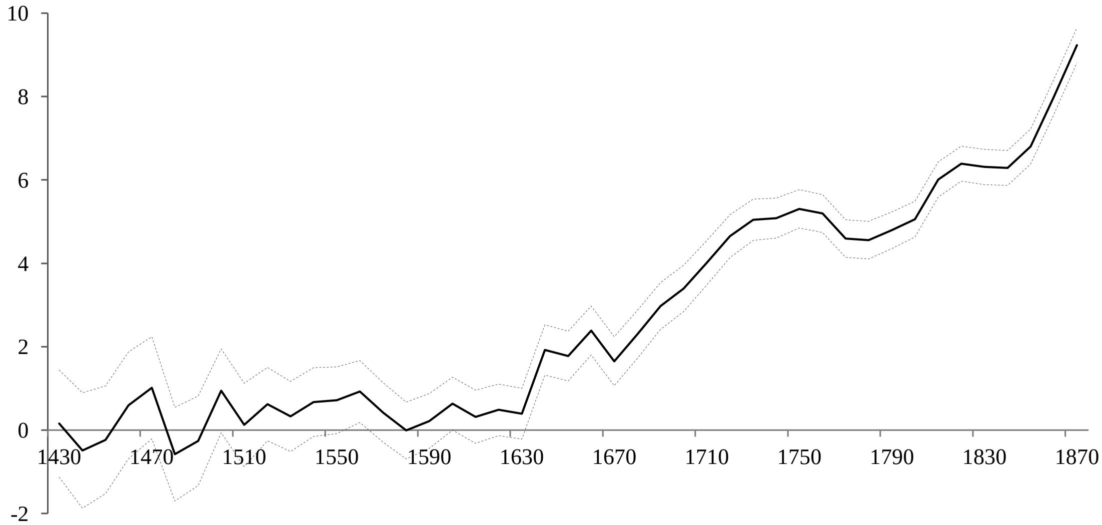

Figure 6: Conditional Mean Life: Cohort dummies and 95% confidence interval

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 (1) has been estimated using Ordinary Least Squares. The detailed results are in Appendix A.

Since one important question is to identify the precise cohort from which the mean lifetime of famous people starts growing, and we have few observations per decade before the fifteen century, we have created cohorts dummies by decade starting in 1430-1439, the first decade with more than 300 observations. The conditional mean lifetime of all previous cohorts, consistently with the observation in Figure 5, is 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 is not significantly different from the mean lifetime of celebrities born before 1430. Indeed, the mean lifetime of celebrities starts growing from the cohort born in 1640-49, to gain nine years over around two centuries. This figure reinforces the conclusion already stated for the unconditional means that longevity improvements for celebrities started well before the Industrial Revolution.

The estimated constant term is 59.04 years, which is one year and a half smaller 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, since the constant term measures the age of the mean celebrity born before 1430 with precise lifespan, non migrating and without identified city, nationality or occupation. The precision dummy is estimated at -0.82 years, which is small but significantly different from zero –the standard deviation is 0.08. The negative sign is fundamentally due to the fact that imprecise observations occur more frequently before 1640. Consequently, controlling for imprecise reported lifespans, if something, reduces the gains in mean lifetime observed after 1640.

More interestingly, the estimation also shows clear evidence that the other dummies are effectively controlling for the different biases referred in Section 3.1. From our estimation, a person living in one of the 77 retained, large cities has on average no survival advantage with respect to the rest of the population, since the estimated coefficient of the *large cities* dummy is small, 0.27 years, and not significantly different from zero –the standard deviation is 0.19. Figure 22, in Appendix, shows the distribution of the 77 city dummies. The standard deviations of the estimated coefficients are in the interval $(0.21, 0.79)$, meaning that they are 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– is -0.45 with a standard deviation of 0.18. Figure 23, in Appendix, shows the distribution of the 33 retained nationality dummies. Australians have 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 groups dummies are represented in Figure 25, in Appendix, with the corresponding 95% confidence intervals. It does clearly illustrate that the regression effectively controls for occupational composition bias, since the difference in mean lifetime between an average military occupation and an average science occupation is slightly larger than four years. The composition is also changing. Nobility, for example, moves down from 28% to 22% of the observed occupations before and after 1640, while *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 represented in Figure 24, in

Clerical		Military		Education	
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 Education Occupations.

Appendix. They are mainly concentrated around one-two in the interval $(-2, 4)$, even if a few occupations show large negative dummies, in some cases larger than 10 years. Within and between occupational groups inequality, however, is very similar for most occupational groups. In facts, the standard deviation of occupational dummies is 1.3 years, close to the standard deviation of occupations in most occupational groups at the exception of *clerical*, *military* and *education*, with 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 occupations in these groups are famous because of violent death.

Seniority is one of the main cause of the notoriety bias referred to in Section 3.1. Table 1 illustrates for clerical, military and education occupations the extend of the notoriety bias. High ranks in both occupations have 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 present a highly significant negative dummy. As said above, it likely reflects the fact that these people became famous because they are heroes who died young on the battlefield.

To control for the source bias, we have included in the regression eight dummies for cohort ages at source's publication going from 15-29 years, 30-39 up to 90-99. All coefficients, as reported in Figure 7, are negative, sizable and statistically significant

–the dotted lines correspond to the 95% confidence interval. As expected, the coefficient of the dummy shrinks in absolute value with the cohort age at publication going from around 40.2 to 2.7 years. The source bias is then high for people dying close to the publication of the source. Notice that, by construction, people lifespan in the first group is in between fifteen and thirty years, when added to the estimated dummy the sum is closed to the mean lifetime of the representative celebrity (20+40=60).

To estimate the extent of the source bias, we run the regression without the cohort age at publication dummies, and then measure 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, while the dotted line is twice the standard deviation of the cohort dummies in the benchmark estimation. The source bias is close to zero until the seventeenth century, then starts slowly growing but remains small and non-significant until the cohort born in 1700. It grows from then until reaching more than 4 years for the last cohort. Controlling for the source bias does not affect the main result that celebrities mean lifetime starts growing in 1640, as we have already observed in Figure 5. However, controlling for the source bias significantly increases the size of the improvement at the end of sample: it almost doubles the 5 years 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 increases from around 5% of total observations in the first half of the eighteen century to 60% in the last decade. It does explain why controlling for the source bias has such a large impact at the end of the sample.

3.4 Robustness: Is the Early Increase in Longevity General?

Model (1) assumes that the mean lifetime of celebrities in all occupations, cities and nationalities moved jointly over time. Any gain in longevity is then assumed to be common. However, it may b e 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 improving later. Perhaps, income started growing before the Industrial Revolution in the regions that led it, not in the others, making famous people mean lifetime increase only in these regions. In this line, this section tries to answer the following questions. Did some occupations, likely because they have profited from early improvements in income, or from some specific conditions, lead the reduction in mortality? Did life expectancy early increase only in those regions

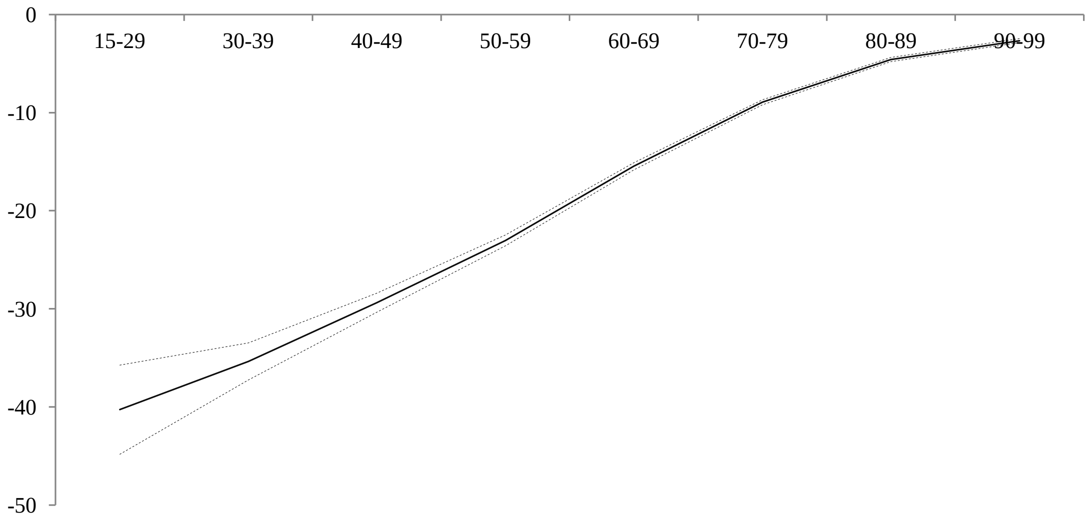

Figure 7: Cohort age at publication dummies

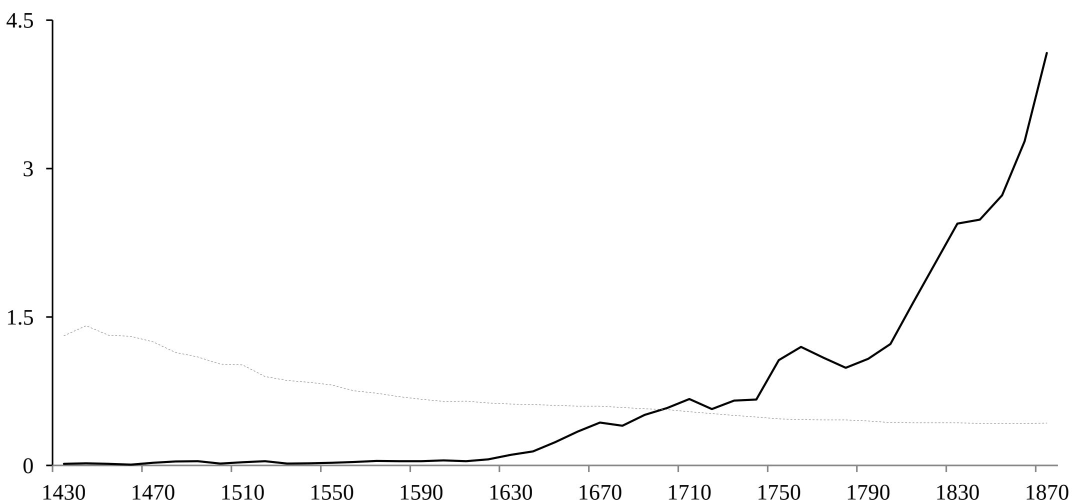

Figure 8: Source bias. Estimation (solid line), 2× std cohort dummies (dotted line)

leading the Industrial Revolution, Great Britain in particular? or was it a more general phenomenon? To answer these questions, we run regressions interacting in each case one of the potential candidate characteristics for early improvement in life expectancy with the cohort dummies. The model to be estimated becomes:

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

where $\tilde{d}_t$ measures the additional difference between the conditional mean lifetime of cohort t and the conditional mean lifetime of the excluded cohort for people endowed with this characteristic.

3.4.1 Occupations

Terms interacting the cohort dummies with an occupational group (arts and métiers, business, clerical, education, humanities, law and government, military, nobility and sciences), one at a time, were added to the regression. We find that none of these groups is individually running the main result. Figure 9 shows the coefficient of the cohort dummy d_t estimated when the interactive terms are 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 lives of famous people not belonging to each of the specified occupations. As can be observed in Figure 9, all of them are in the confidence interval of the cohort dummies in the benchmark estimation. In Appendix, it can be seen that, for each of the nine occupational groups, the interaction terms, measuring the differential changes of each occupational group mean lifetime, are always in the $(-2, 2)$ years interval, without showing any remarkable differential pattern.

3.4.2 Nationalities and Cities

Is it the case that celebrities' mean lifetime has increased first in those regions that leaded the industrial revolution? Having this hypothesis in mind, we have created three dummies. First, a *leading cities* dummy including the largest cities in the sample (Amsterdam, Berlin, Copenhagen, London, Paris, Rome, Stockholm, Wien). Second, a *British* dummy, including English and Scottish nationalities, as well as people born or dead in London and Edinburgh, the only two British cities among the retained 77 large cities. Third, a *leading nations* dummy taking the value one if an individual has the nationality of a selected group of countries, or was born or dead in a city, among the 77 selected

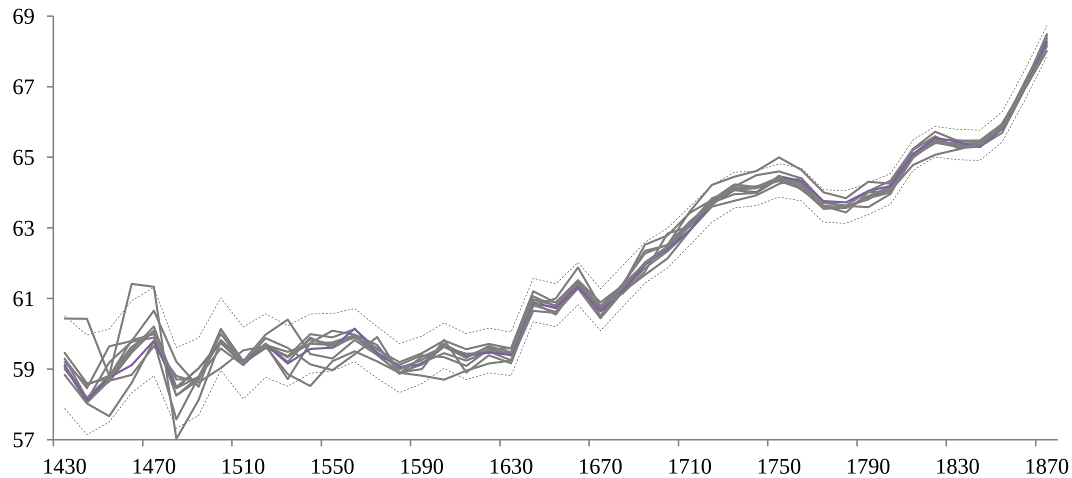

Figure 9: Robustness: Occupational groups

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

cities, in the actual territory of one of the leading nations. The set of selected countries includes those that, followingMaddison (2010), had in 1870 an annual GDP per capita at least equal to 1800 dollars per capita(Australia, Austria, Belgium, Denmark, France, Germany, Netherlands, Switzerland, UK and US). As in the previous subsection, we have added to the benchmark regression new terms interacting the cohort dummies with the three leading dummies above, one at each time. Figure 10 shows the cohort dummy coefficients estimated when the interactive terms are included. As can be observed, including the leading dummies do not affect significantly the estimation of the mean lifetime changes of the whole population, meaning that nor leading cities, neither Britain nor leading nations are behind our main result that the famous people mean lifetime started growing around the cohort born in 1640 after millennia of stagnation.

4 Survival Laws

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

4.1 Conditional Survival and Mortality Rates

Cohort dummies and residual terms of Equation (1), as estimated in Section 3.3, are used to measure *conditional survival laws* for all individuals in the sample. For each individual i belonging to cohort t, let us define $\hat{r}_{i,t} \equiv \hat{m} + \hat{d}_t + \hat{\varepsilon}_{i,t}$, where $\hat{m}$ is the estimated constant, $\hat{d}_t$ the estimated cohort dummy parameter and $\hat{\varepsilon}_{i,t}$ the estimated residual. Let us denote by $r_{i,t}$ the *conditional lifespan* of individual i belonging to cohort t, where $r_{i,t}$ is the integer part of $\hat{r}_{i,t}$.[11] It represents the lifespan of individual i after controlling for all individual i observed characteristics.

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

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

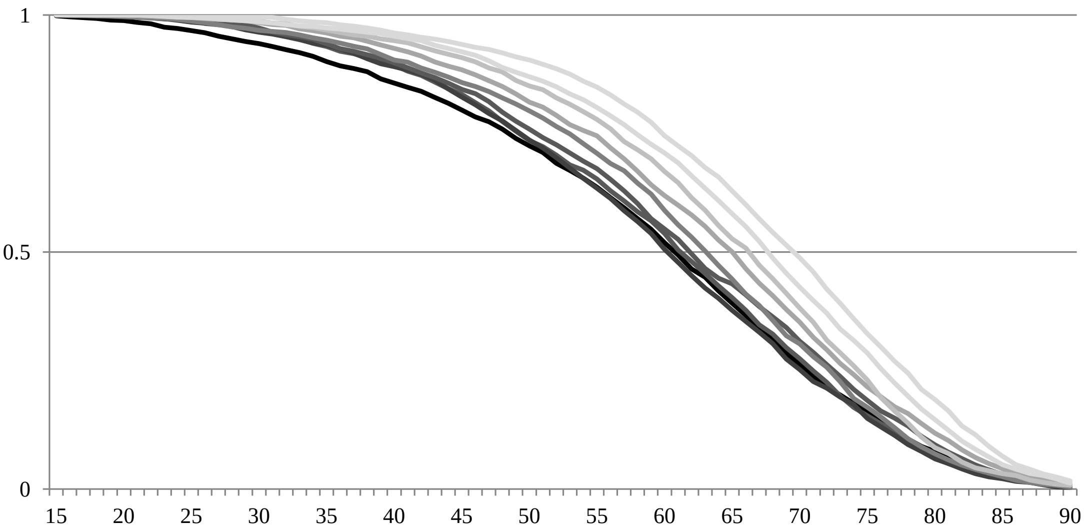

Figure 11: Conditional Survivals for some 1600-cohorts: from deep black to clear gray are cohorts 1040-1254, 1535-1546, 1623-1628, 1665-1669, 1714-1717, 1787-1788, 1807-1808, 1859, 1879.

conditional survival probabilities are then measured by computing the ratios $s_{t,h}/n_t$ for all h.[12]

In this section, following the argument developed in Section 2.3 concerning confidence intervals, we aggregate annual cohorts to measure survival probabilities and mortality rates for cohorts of at least 1600 individuals; individuals born the same year always belong to the same cohort.[13] We refer to them as the 1600-cohorts. Following this criterion, we have detected 150 1600-cohorts. Figure 11 shows the survival laws of some selected 1600-cohorts; they are ordered from deep black, the oldest, to clear grey, the youngest. The first three survival laws precede 1640; they are very similar to each other. The survival law moves to the right from the 17th century onward in a tendency to rectangularize.

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

[13]For the latter reason, cohort sizes range between 1600 and 3200 individuals. Indeed, the mode is close to 1600 and 50% of the cohorts have less than 1900 observations.

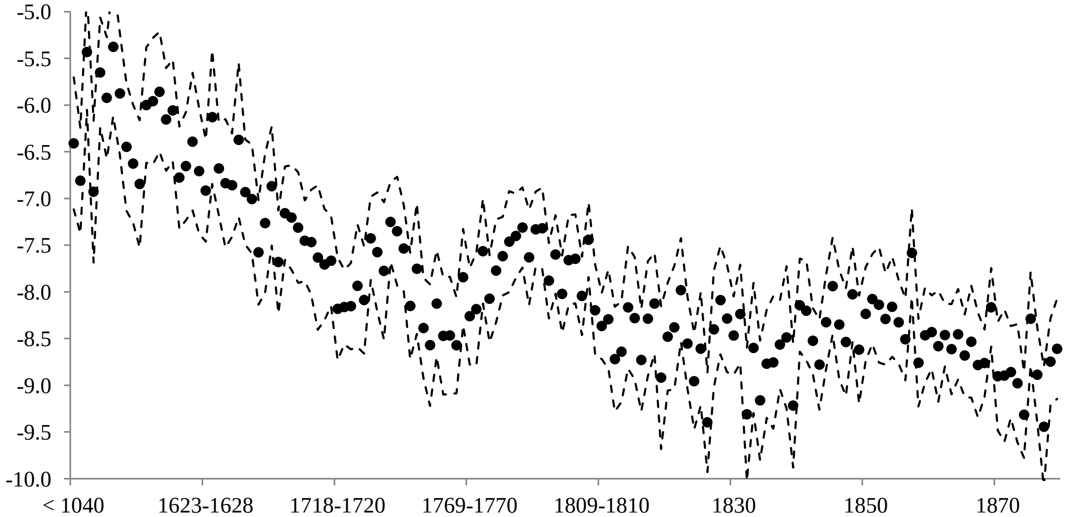

Figure 12: Estimated $\hat{\rho}$

4.2 Gompertz-Makeham and the Compensation Effect

We follow Gavrilov and Gavrilova (1991) to estimate and interpret the evolution of the survival law of famous people over the last millenium. The main argument is 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

$$\delta(a) = A + e^{\rho+\alpha a}. \tag{3}$$

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

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

In order to assess whether the observed shifts in the survival law are related to age dependent or age independent factors, we estimate by non-linear least squares the Gompertz-

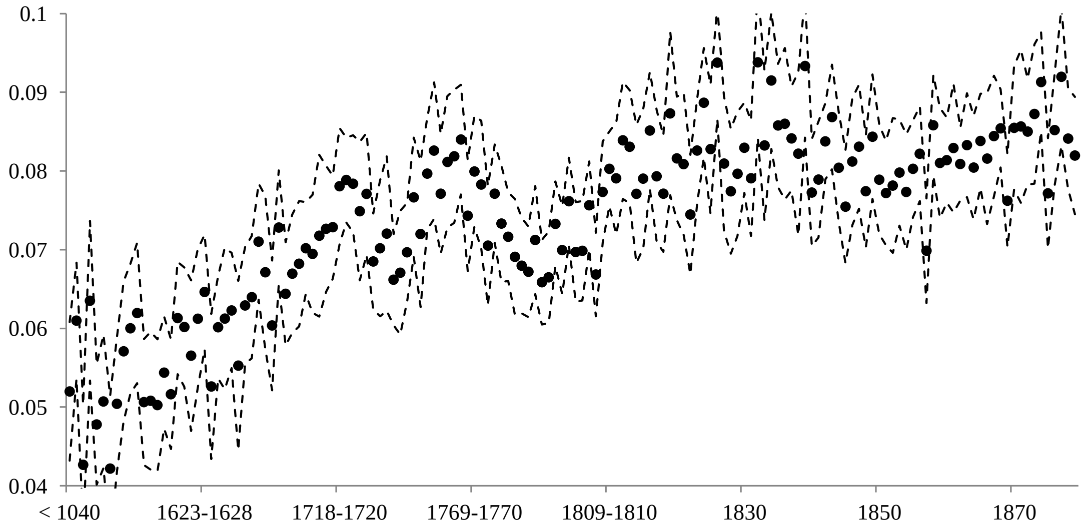

Figure 13: Estimated $\hat{\alpha}$

Makeham law (3) (in logs) for each of the 1600-cohorts. As usual in this literature, the estimation only considers the observed mortality rates between 30 and 90 years, since the Gomperz-Makeham law mainly applies to this age bracket.

Consistently with the main findings in Gavrilov and Gavrilova (1991), the estimated Gompertz parameter ρ is decreasing over time while the estimated Gompertz parameter α is increasing, as can be observed in Figures 12 and 13. However, these parameter changes take place as early as for the cohort born in 1640, i.e. earlier than in Gavrilov and Gavrilova (1991). Moreover, contrary to the estimations in Gavrilov and Gavrilova (1991), the age-independent parameter A is systematically non significantly different from zero. This last observations is due to the fact that famous people mortality rates are close to zero for ages close to 30. We develop this argument below in Section 4.3.

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

$$\rho = M - T\alpha, \tag{4}$$

where M and T, $T > 0$, are constant parameters, the same for all human populations. It is easy to see that under the Compensation Effect, the survival tends to rectangularize when $A = 0$ and α goes to infinity; in this case, the maximum life span of humanity is

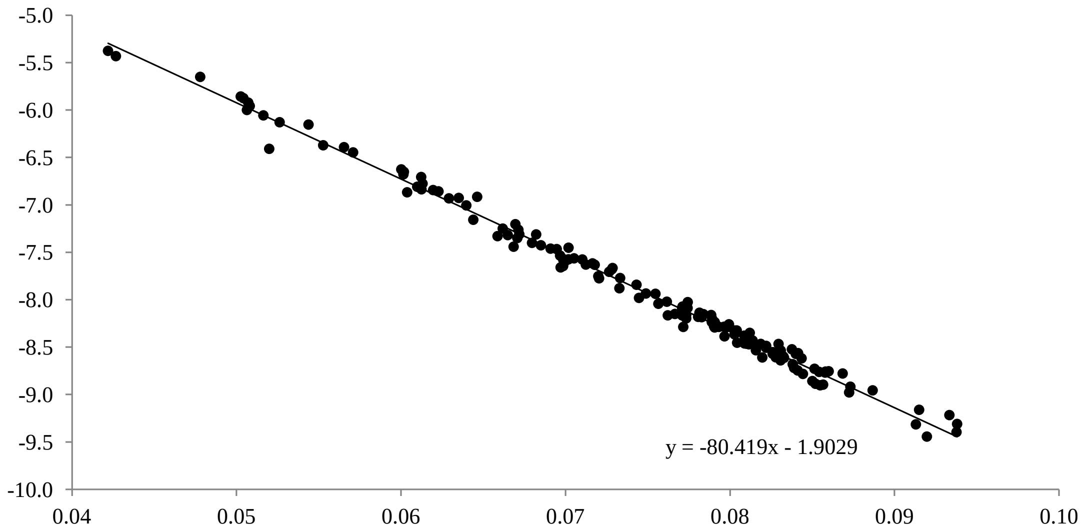

Figure 14: The Compensation Effect of Mortality: ρ (Y-axis), α (X-axis)

T.[14] Consequently, any reduction in ρ compensated following (4) by an increase in α, rectangularizes the survival and increases the mean life. However, such an improvement in the mean lifetime is bounded by the maximum lifespan T.

Indeed, as can be observed in Figure 14, the Compensation Effect of Mortality holds for famous people in the IBN, at least until the last retained cohort, the one born in 1879. This finding is also in line with Gavrilov and Gavrilova (1991).[15] Since ρ decreases and α increases consistently with the Compensation Effect, the survival law of famous people tends to rectangularize as observed in Section 4.1. The Compensation Effect has been estimated by OLS on the pairs ρ, α estimated for the 1600-cohorts. The life span parameter T has then been estimated at 80.4 years –with a standard deviation of 0.57 years.

4.3 Mortality of Potentially Famous People

As explained in Section 3.1, the IBN suffers from the *notoriety bias.* It does mean that some potentially famous people are excluded from the IBN because they died before

[14]For this purpose, take ρ in (4) and substitute it in (3). Then, let α goes to infinity, which implies that the death rates tend to zero for $a < T$ and to infinity when $a > T$.

[15]Strulik and Vollmer (2011) find changes in the Compensation Law in the last half of the 20th Century and increases in the maximum lifespan.

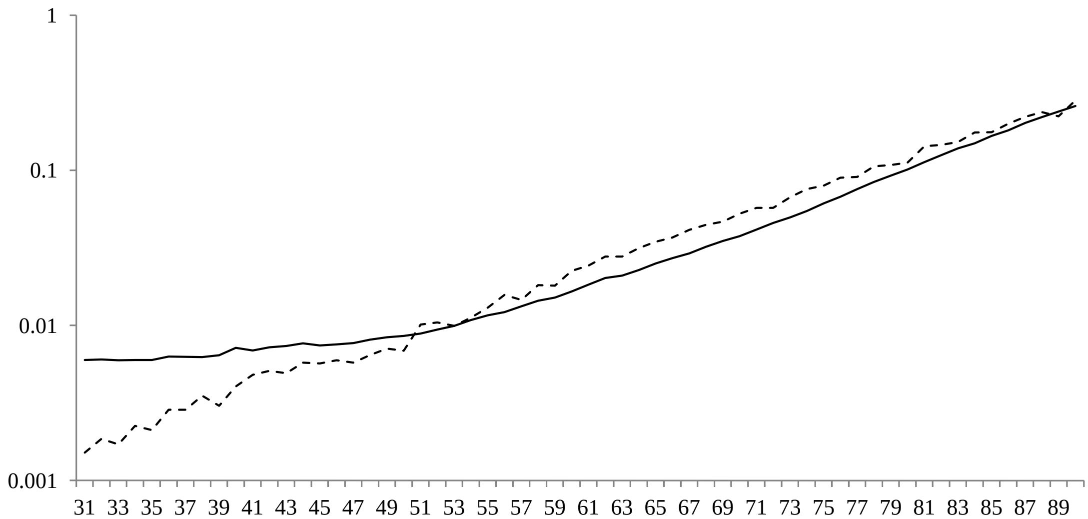

Figure 15: Mortality Rates 1871-79: Ages 30 to 90 (X-axis) and dead probabilities in log scale (Y-axis). Swedish from Human Mortality Database (solid line), IBN (dashed line)

becoming famous, which tends to underestimate mortality rates particularly at young ages. Figure 15 illustrates the 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.[16] Even if 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 famous people survivals are 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 before achieving the prestige and fame required to be in the IBN. 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 (3). Let us denote by $\Phi(a)$ the probability that potentially famous

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

people achieve notoriety before age a. Consequently, famous people death rates 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 one single prominent job. Potentially famous members of the dynasty are sitting on a queue waiting for the death of the dynasty member currently holding the job. This is clearly the case of hereditary occupations like nobility where, for example, a prince has to wait for the death of the king to accede to the throne.[17] It is also the case of ranked occupations as religious or military occupations, where 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 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. Then, the probability of becoming king as a function of his age depends on the probability of death of his father. Given that both belong to the same population, the probability of a prince 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 $\delta_p(a)$. We can then use non-linear least square methods to estimate parameters A, ρ and α for the population of potentially famous people for the death rates of observed celebrities by estimating:

$$\delta(a) = \left(A + e^{\rho+\alpha a}\right)\left(1 - \exp\{-A(a + b) - (e^{\rho+\alpha(a+b)} - 1)/\alpha\}\right) \tag{5}$$

for some given b.

[17]This is relevant, since princes are not reported in any dictionary or encyclopedia of kings, even if 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.

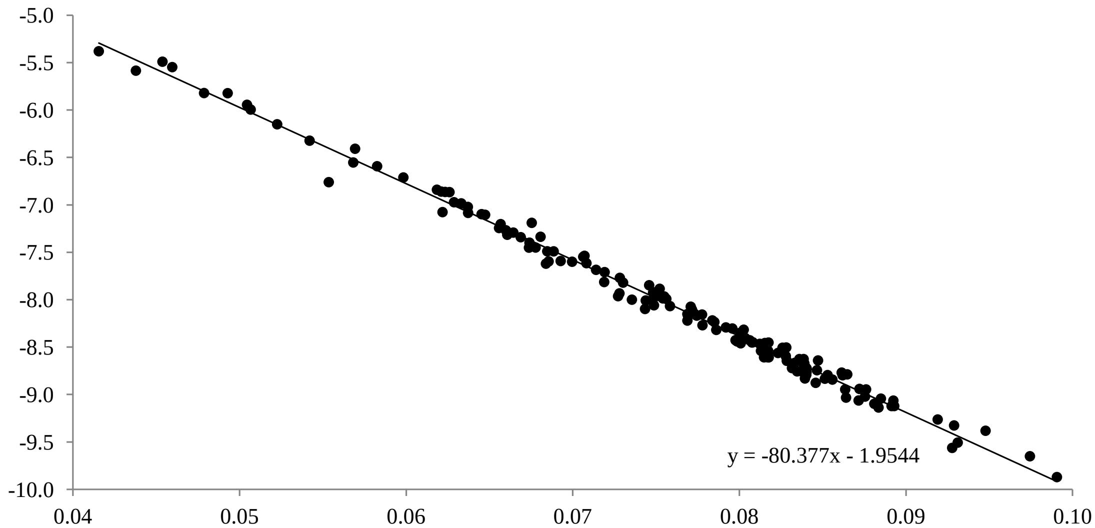

Figure 16: The Compensation Effect of Mortality of potentially Famous People: ρ (Y-axis), α (X-axis)

In order to illustrate the effect, we have estimated the parameters of $\delta(a)$ for the 1600-cohorts, under the assumption that $b = 25$. The Makeham constant becomes now positive and significant; it displays no particular trend over the whole sample, except for a (non significant) drop 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 represented in Figure 16. They follow a similar pattern as the parameters estimated in Figure 14.[18] The estimated life span is 80.4 years, as in the benchmark estimation.

Figure 17 represent 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.

One can conclude that the rectangularization of the survival laws initiated in 1640 is robust to the proposed correction of the notoriety bias and the life span T as well. 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).

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

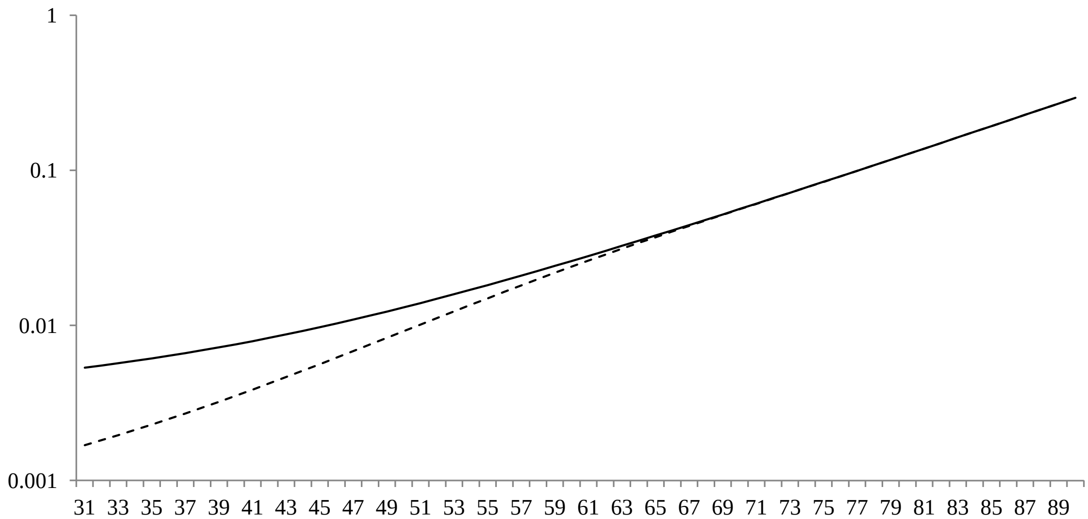

Figure 17: Simulated Mortality Rates 1871-79 for IBN people: Ages 30 to 90 (X-axis) and dead probabilities in log scale (Y-axis). $\delta_p(a)$ (solid line), $\delta(a)$ (dashed line)

5 Comparisons with Previous Studies

At least two questions are still open. First, to what extent the survival probabilities we estimate for the famous people are informative about the survival probabilities of the whole population? To address this issue, we can compare our estimates with those which exist for whole populations, such as the English data based on family reconstruction (1550-1820), and the Swedish census data (1750-). Second, to what extent do we provide a different message from the various studies which have studied specific groups of famous people, such as the English aristocrats, or the Knights of the Golden Fleece?

5.1 Comparison with Ordinary People

5.1.1 English Family Reconstitution Data 1580-1820

A global comparison between famous people and ordinary people of 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

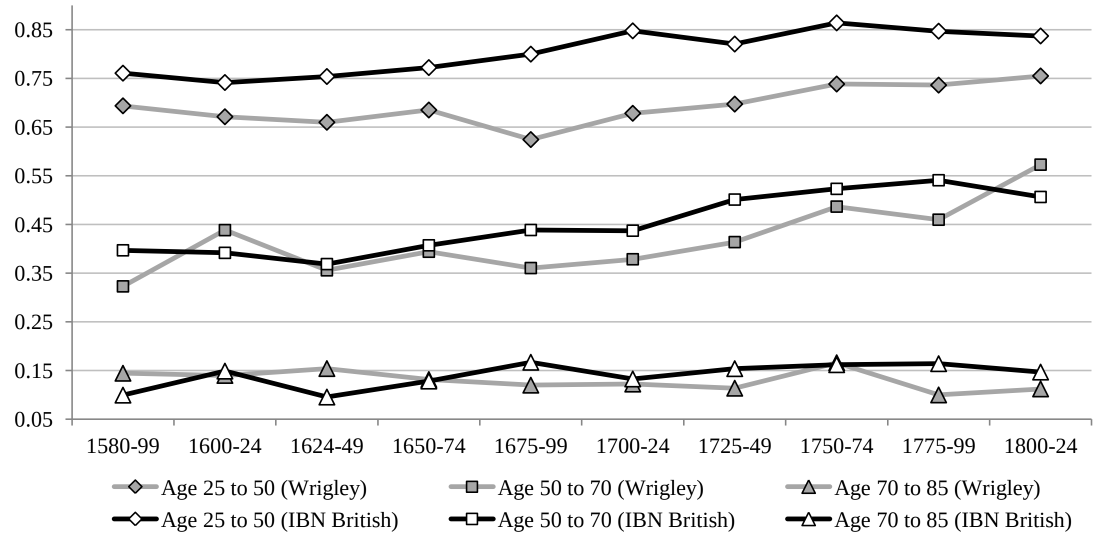

Figure 18: Wrigley's data vs IBN British: Probability of survival from one age to the other

English nationality and/or London as city. Remember that our survival probabilities are 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 has a number of observations high enough to compute sensible survival laws: from 408 individuals for 1580-1599 to 4794 individuals for 1800-1824.

Three main conclusions emerge when we compare Wrigley et al. (1997) data 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, mortality rates of famous people underestimate the mortality of ordinary people. The survival probabilities of young adults are systematically larger for famous people. It may be due to the notoriety bias, as suggested all along this paper. Second, there are no remarkable differences between famous and ordinary late age individuals. Third, famous adult people are forerunners in mortality decline. They reduce their mortality one century in advance than ordinary adults. The survival of famous adults, both young and old, starts increasing at the middle of the 17th century, generating an increasing gap with ordinary adults, who start catching-up around the middle of the 18th century.

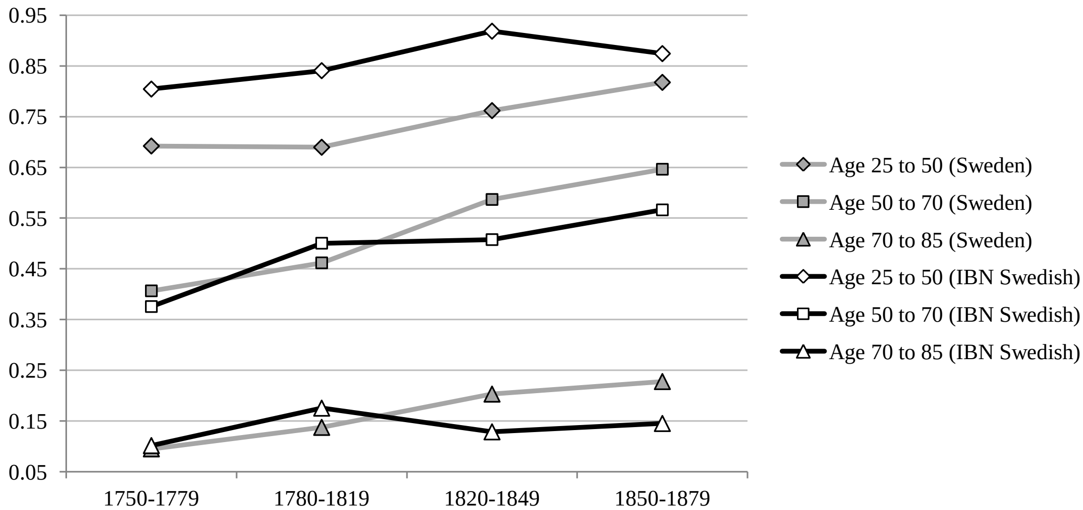

Figure 19: Probability of survival from one age to the other: Sweden

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. Those data are available from the Human Mortality Database. They show that the demographic transition in Sweden follows the standard pattern. Adult life expectancy starts 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. 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 observe a systematic underestimation of young adult survivals and a catching-up taking place likely at the beginning of the 19th century, 50 years later than in England.

5.2 Comparison with Nobility

In order to study long-term trends in the mortality 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

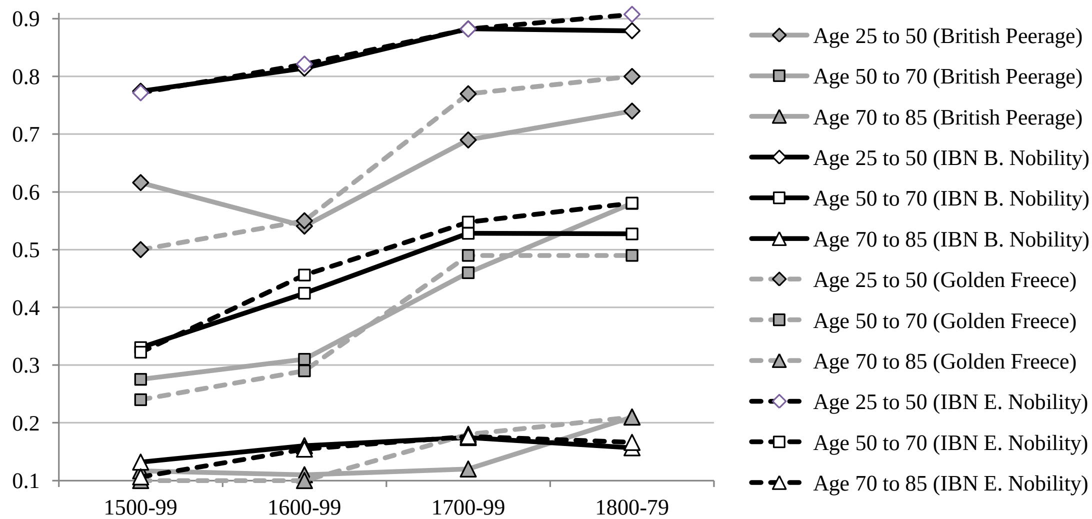

Figure 20: Probability of survival from one age to the other: Nobility

classes are closer to our famous people than the rest of the population. Comparing these studies with similar subsamples in our data is an interesting robustness check.

We use two of such datasets, covering the period 1500 to 1900, which overlaps the period where famous people mean lifetime starts increasing. First, the mortality tables for British peers died between 1603 and 1938 and their offsprings published by Hollingsworth (1977).[19] A comparable subsample from our IBN database consists of British with a nobility occupation. We have many of 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 (belonging all 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 20 . First, *the survival of IBN young adult nobles is overestimated* when compared with British peers and Golden Fleece's members. Notice that, differently from the IBN, in both the British peers and Golden Fleece data, most individuals belong to the sample at birth. It does imply that the overestimation is due to the notoriety bias, i.e., nobles' offsprings dying young are generally excluded from

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

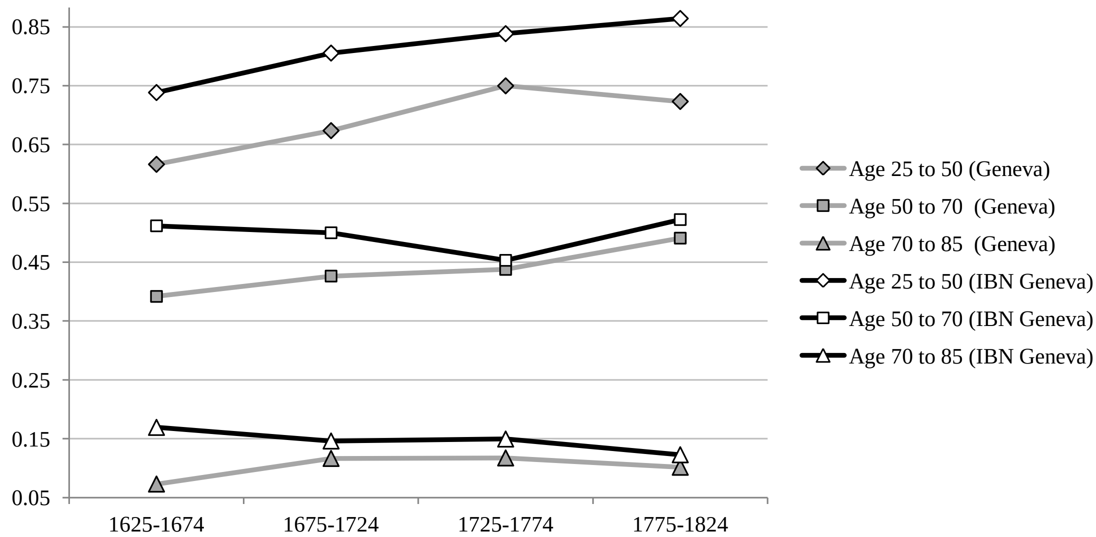

Figure 21: Probability of survival from one age to the other: Geneva, Perrenoud vs IBN

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 mainly due to the notoriety bias too. Second, *mortality reductions for nobility take place in the 17th century* in the three databases, reinforcing the observation that famous people mean lifetime improvements anticipate those of ordinary people by at least one hundred years.[20]

5.3 Comparison with Cities

5.3.1 Geneva, 1625-1825

Perrenoud (1978) provides 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 dead in Geneva per subperiod. Results are presented in Figure 21. We first remark that Perrenoud's data themselves display an upward trend as early as in the seventeenth century. This was already stressed by Boucekkine, de la Croix, and Licandro (2003) who use that evidence to claim that improvements in adult longevity precede the industrial revolution, at least in some cities, and may have increased the incentives to acquire education. Comparing Perrenoud to

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

IBN, we do not retrieve the pattern seen for Britain and Sweden of early improvement for famous people, following by a catching-up phenomenon; here the people of the city seem to have the same global trend as IBN famous people: improvement of young adult survival over 1625-1774 in both samples; closing gap between the samples for the old adult survival and old age survival. This raises the question whether the trends we observe for famous people was in fact a trend present in European cities (beyond Geneva).

5.3.2 Venice, 1600-1700

[to be done with Beltrami's data]

6 Interpretations and Conclusion

It is generally accepted that adult survival of ordinary people started to increase permanently in the nineteenth century, with scatter evidence showing that in some places it started some decades before. However, its main causes are still under debate, including higher income, better nutrition, better hygienic habits and sanitization of cities, more efficient medicine and public health.[21]

This paper exploits 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 people around the world. Exploiting observed individual characteristics to control for potential biases, we show for the first time, using a worldwide, long-running and consistent database, that mortality showed no trend during the Malthusian era. Indeed, the conditional mean lifetime of all cohorts of famous people born before 1640 fluctuates around 59 years. Second, we date the beginning of the steadily improvements in longevity to the cohorts born in 1640-9, clearly preceding the Industrial Revolution by one and a half century. Third, we find that longevity improvements concern most countries in Europe, as well as all types of skilled occupations. Finally, the reasons for this early rise in mean lifetime has to be mainly found in age-dependent shifts in the survival law.

[21] For a general view on the main causes see Wilmoth (2007) and **?**). The fundamental role of nutrition 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 has come from gains in prevention, cleaner living rather than better medicine.

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

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

Regional Independence. They should not be related to a particular location, since the improvements in the mean lifetime took place at least all around Europe.

Occupation Independence. They have to affect similarly almost all famous people occupations.

Age Dependence/Life Span Constancy. They should not affect all adult ages in the same way, but mainly reduce the mortality of the working age adults. In other 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 candidates, detailed below. We are not going to select one of them, but rather, see if they can fulfill the necessary conditions suggested above.

Increase in inequality: Let 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, famous people have directly or indirectly benefited from it, observing a substantial increase in their income. In other terms, during the 17th century human society experienced the emergence 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 an European phenomenon, it does also fulfill the Regional Independency requirement. Occupation Independence is also matched since the increase in the surplus diffuses among the famous (e.g. even if the artists or the priests are not hit at first by the shock, the richest would buy more stuff from them or make them larger transfers). The Urban Character would be matched either if the shock at the root of the increase in inequality is a rise in urban efficiency or productivity, or if the gain of the urban bourgeoisie benefits all people in cities. (check literature on inequality - Kuznetz, Marx)

One specific channel from wealth to longevity could be through childhood development of the famous. Child low level of health is not only conducing to death at early age, but may also affect life at later stage. The relationship between early development and late mortality has been well-established. Fogel (2004) emphases that nutrition and physiological status are at the basis of the link between childhood development and longevity. Another important mechanism stressed by epidemiologists links infections and related inflammations during childhood to the appearance of specific diseases in old age (Crimmins and Finch 2006). In the same direction, Barker and Osmond (1986) relates lower childhood health status to higher incidence of heart disease in later life.

Receding pandemics: The last plague in England is clearly identified in 1666-1667 (see Creighton (1891)). After this date, Europe could have been free of plagues by chance Lagerloef (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. To fix ideas, suppose that the causes of death for famous people is 50% ordinary infection diseases, 30% plagues, 20% others, while for the rest of the population it is 75% infection, 5% plagues, 20% others. If plagues are receding, as it is 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 border. The Urban Character of this explanation is also likely, as contagion is amplified by 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, notice that, for receding pandemics to drive the rise in the mean lifetime of famous people, it has to be the case that plagues were a main factor of human mortality since the Babylonian times and they recede at the end of the 17th century. In this case, the estimated 59 years of mean life until 1640 include the mortality induced by pandemics. The observed increase after 1640-9 is due to the fact that this component of mortality starts reducing.

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 came progressively in the nineteenth century with the development of chemistry, Weatherall (1996), the effectiveness of the treatment of some important diseases was improved thanks to the practical use of new drugs coming from the New World. 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. Notice that the benefits of better medical practice could fit Selectivity if it is affordable only to the rich Johansson (1999). Regional Independence would be satisfied if medical knowledge spreads easily across Europe.

Further research may try to use the criteria highlighted by our research to discriminate among possible explanations.

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A Detailed Regression Results

Number of obs		297651	R-squared		0.1345	Root MSE		14.292
constant	coef	s.e.	dist. source	coef	s.e.	religion	coef	s.e.
	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			
education	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			
decade	coef	s.e.	decade	coef	s.e.	decade	coef	s.e.
1430	0.157	0.656	1580	-0.007	0.348	1730	5.043	0.253
1440	-0.489	0.707	1590	0.219	0.335	1740	5.084	0.245
1450	-0.231	0.658	1600	0.633	0.324	1750	5.307	0.235
1460	0.596	0.653	1610	0.319	0.325	1760	5.195	0.231
1470	1.015	0.625	1620	0.487	0.316	1770	4.593	0.231
1480	-0.577	0.572	1630	0.395	0.311	1780	4.555	0.231
1490	-0.258	0.548	1640	1.925	0.308	1790	4.794	0.225
1500	0.944	0.512	1650	1.776	0.304	1800	5.059	0.217
1510	0.125	0.509	1660	2.387	0.299	1810	6.011	0.215
1520	0.625	0.449	1670	1.651	0.299	1820	6.388	0.215
1530	0.328	0.429	1680	2.301	0.293	1830	6.311	0.215
1540	0.671	0.421	1690	2.978	0.287	1840	6.287	0.213
1550	0.718	0.407	1700	3.397	0.283	1850	6.801	0.213
1560	0.927	0.377	1710	4.015	0.272	1860	7.979	0.213
1570	0.421	0.365	1720	4.652	0.262	1870	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.

Education: 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

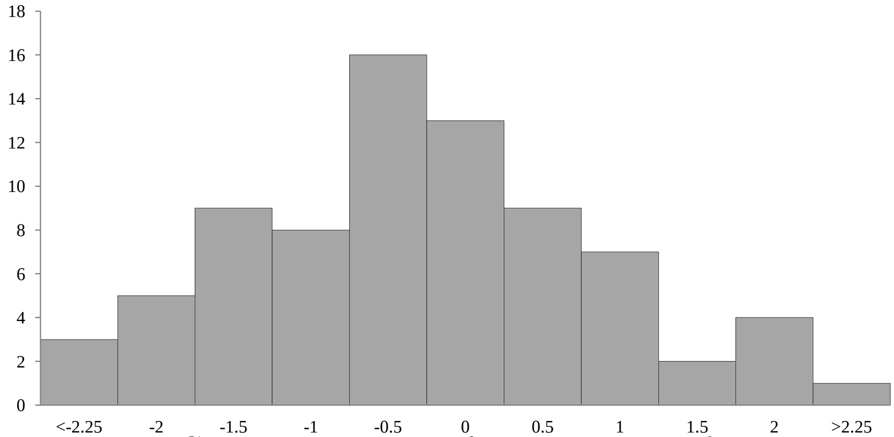

Figure 22: Conditional Mean Life: Distribution of city dummies

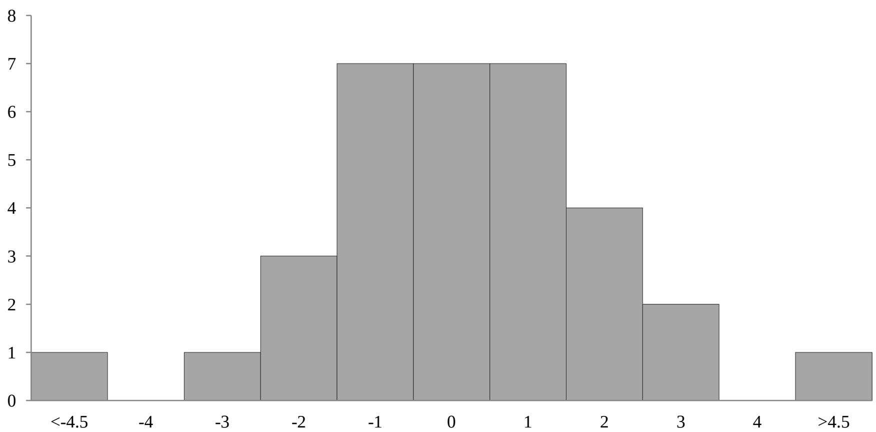

Figure 23: Conditional Mean Life: Distribution of nationality dummies

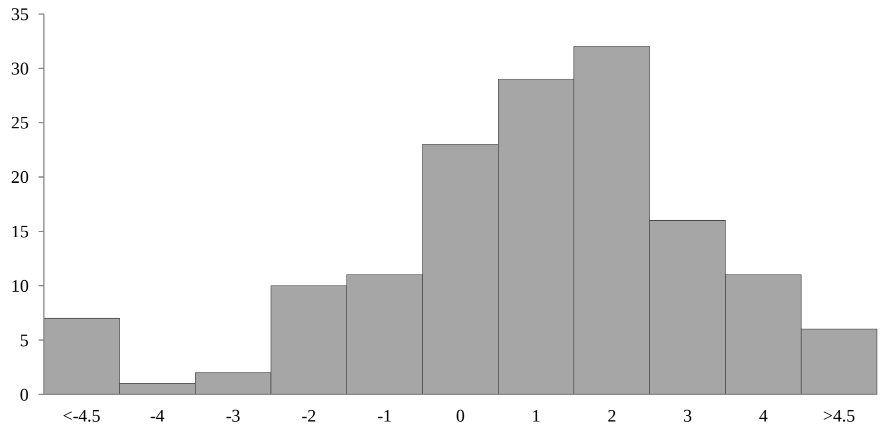

Figure 24: Conditional Mean Life: Distribution of occupation dummies

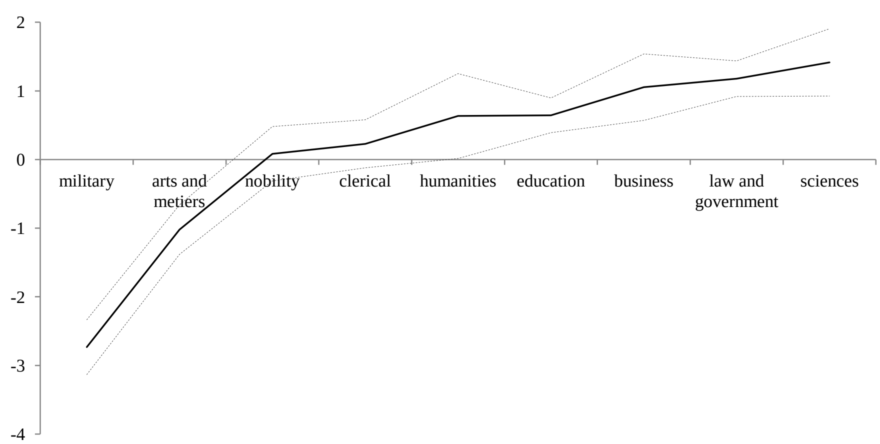

Figure 25: Conditional Mean Life: Main occupational groups

D The first life tables

The first life table had been published in London in 1662 in a book by Graunt (1661). His analysis is based on data originally collected 127 years earlier on the age at the time of death in London. 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	0.251163	0.351852	0
Halley's life table	Breslau 1687-1691	0.610229	0.410405	0.057803

Table 2: Survival Probabilities in various life tables