Berkeley Unified Numident Mortality Database: Public Administrative Records for Individual Level Mortality Research

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Abstract

With the release of Social Security application and death records, the National Archives and Records Administration (NARA) has created a new administrative data resource for researchers studying mortality. This publicly available data provides demographic researchers access to over 49 million mortality records with rich geographic detail. We document the contents of this data set, provide free access to a cleaned and harmonized version of the data, and discuss statistical methods for estimating mortality differentials based on this deaths-only data set.

Introduction

The Numerical Identification System (Numident) forms the backbone of the U.S. Social Security Administration's record keeping system. For every person with a Social Security number, it tracks their earnings status, claims status, date of birth (and, if applicable, death), as well as other background information including birthplace, race, sex, and names of parents. In 2013, the Social Security Administration transferred a large portion of their Numident records to the National Archives and Records Administration (NARA). NARA completed a public release of these records, offering nearly complete coverage of those who died from 1988 to 2005. In this paper, we describe the contents of the publicly available NARA Numident records, introduce a cleaned and harmonized version of the data, show how the records can be used for the study of mortality in the United States, and provide new methods for estimating mortality from death records.

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The NARA Numident is an individual-level mortality data set with over 49 million death records. It includes variables describing race, sex, birthplace, ZIP Code of residence at time of death, and administrative variables, such as a person's age on their first first Social Security application and total number of Social Security applications. Notably, the death coverage is nearly complete for deaths to persons age 65+ between 1988-2005.

However, mortality est with the NARA Numident records presents challenges. The records lack any indicator of socioeconomic status. To overcome this, the records can be linked to other data sources, either by Social Security number or a combination of other key identifiers. Survivorship cannot be estimated, as the deaths do not have denominators. Further, the observed deaths are left and right truncated, which makes calculating unbiased estimates of mortality difficult. We introduce methods to overcome this.

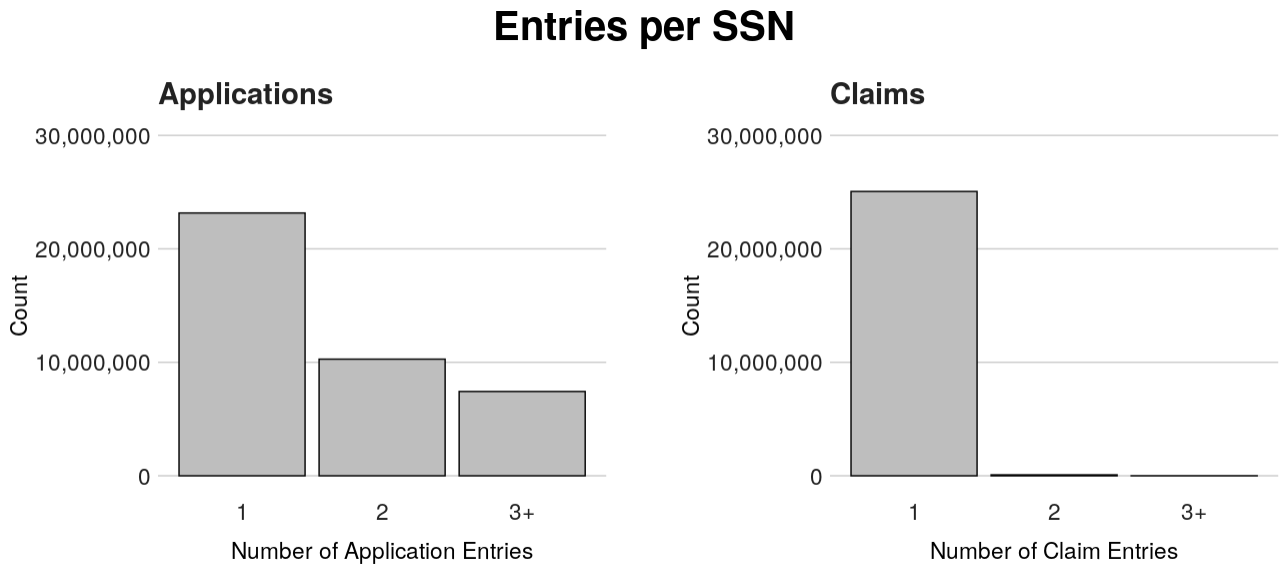
While administrative mortality data sets have been used by a small set of researchers who have been able to work with government employees inside restricted computing environments (Chetty et al. 2016; Mehta et al. 2016), the Numident data is openly accessible to all researchers. Our hope is that the public availability of this data will encourage more mortality research using administrative records, enhance the replicability and debate about results, and open up new avenues of research. To facilitate mortality research with the Numident records, we have created a cleaned and harmonized version of the Numident records with enhanced documentation: the Berkeley Unified Numident Mortality Database (BUNMD).

Another publicly available data resource for mortality research is the Social Security Death Master File (DMF). The DMF was first made available in 1988, and is extracted quarterly from the Numident records (Hill and Rosenwaike, n.d.). The file has been used by some researchers to study mortality, particularly at older ages (Gavrilov and Gavrilova 2012). While the file has high death coverage for deaths of persons aged 65 or older from 1975 - 2005, it lacks covariates, such as sex, race, or place of birth (Hill and Rosenwaike, n.d.). The methods we provide here are also useful for researchers working with the DMF.

We are also in the process of linking both the DMF and the Numident files to the 1940 census, to create a rich, public linked administrative dataset for the study of mortality (CENSOC).

The Content of the NARA Numident files

The NARA Numident records contain three types of entries: applications, claims, and deaths. The Social Security Administration adds a new entry to the Numident when a Social Security cardholder submits a new application or claim. New entries never overlay old entries. Instead, a new entry is added to the Numident. Figure 1 shows the distribution



(a)

Figure 1: Number of entries per SSN for the Numident Application and Claims files.

of application and claim entries per SSN. While 43.3% of individuals in the Numident have multiple application entries, only 0.3% of individuals have multiple claims.

To illustrate the structure and content of the publicly-released National Archive Numident files, we show in figure 1 the records that were released for the actress Lana Turner who died in 1995 and for the Supreme Justice Thurgood Marshall, who died in 1993.

Thurgood Marshall

For Thurgood Marshall, we have one application and one death record:

Application Record:

ssn	citizenship_code	cycle_date	entry_code	dob	sex
131074264		193712XX	0	07021908	1

race	pob_state_country	year_cycle	month_cycle	pob_foreign_ind
2	MD	1937	12	

fname	mname	lname	mother_fname	mother_mname	mother_lname
THURGOOD		MARSHALL	NORMA	A	WILLIAMS

father_fname	father_mname	father_lname
WILLIAM	C	MARSHALL

Death Record:

ssn	sex	zip_residence	lname	mname	fname	byear
131074264	1	220411335	MARSHALL		THURGOOD	1908

dyear	socstate	bmonth	dmonth	bday	dday
1993	36	7	1	2	24

Lana Turner

For Lana Turner we have four application records, corresponding it seems to name changes each time she was married.

Application Record:

ssn	citizenship_code	cycle_date	entry_code	dob	sex	race	pob_state_country
567183907		193703XX	0	02081921	2	1	ID
567183907		194907XX	2	02081921	2	1	ID
567183907		195611XX	2	02081921	2	1	
567183907		197009XX	2	02081921	2	0	UN

pob_foreign_ind	fname	mname	lname	mother_fname	mother_mname	mother_lname
	LANA		TURNER	MILDRED	F	COWAN
	LANA	TURNER	TOPPING	MILDRED	F	TURNER
	LANA	TURNER	BARKER			
	LANA	TURNER	DANTE			

father_fname	father_mname	father_lname	year_cycle	month_cycle
JOHN	M	TURNER	1937	3
JOHN	V	TURNER	1949	7
			1956	11
			1970	9

Death Record:

ssn	sex	zip_residence	lname	mname	fname	byear	dyear	socstate	bmonth
567183907	2	900255240	TURNER		LANA	1921	1995	6	2

dmonth	bday	dday
6	8	29

In order to facilitate analysis of the Numident dataset, we have created the Berkeley Unified Numident Mortality Database. This file condenses the Numident death, application, and claims records into a single file with one record per person. This file is available for download at ____ . The file includes about 49 million records, 28 variables, and is about 5.7 Gb in size.

For Lana Turner, the BUNMD data record is:

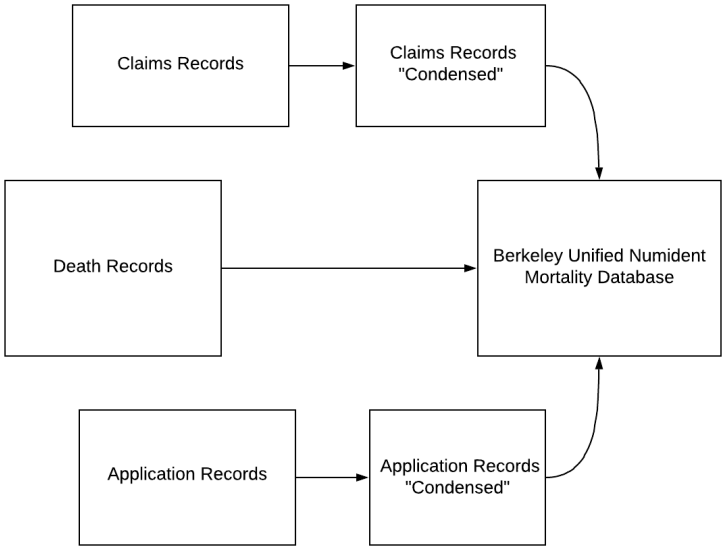
ssn	zip_residence	lname	mname	fname	byear	dyear	socstate	bmonth	dmonth
567183907	900255240	TURNER		LANA	1921	1995	600	2	6

bday	dday	number_apps	race	race_change	number_claims	sex	bpl	father_fname
8	29	4	1	0	0	2	1600	JOHN

father_mname	father_lname	weight	death_age	cweight
NA	TURNER	1.047614	74	1.105444

To faciliate analysis with the Numident files, we have created a cleaned and harmonized version of the file: Berkeley Unified Mortality Numident Database (BUNMD). The Numident records released by NARA contain 49,459,293 death records entries, 72,120,516 applications entries corresponding to 40,870,455 unique individuals, and 25,228,257 claims entries corresponding to 25,140,847 unique individuals. The BUNMD file takes the most important information in these files and condenses it into one database with one record per person. Every death from the original Numident record was included in the BUNMD, and other covariates were added on from the application and claims records. See Figure xx. We have condensed the multiple numident entries, choosing a single value for sex, race, birthplace, and parents' names across multiple applications. The BUNMD file contains constructed variables indicating the total number of application and claim entries per person. It also includes constructed variables for date of first application and state in which social security number was issued. Please see the technical appendix for more details on the construction of this file.

In order to study name changes, race changes, and other features, the original Numident files are useful.



(a)

Figure 2: Berkeley Unified Numident Mortality Database creation flowchart.

Numident Coverage

The Numident records publicly released by the National Archives are a subset of the master Numident records. Specifically, the release contained records for individuals with a verified death between 1936 and 2007 or persons over 110 years of age as of December 31st, 2018. The process by which records were selected into this public released Numident is not well defined. Figure XX shows the total count of deaths in the BUNMD (age 65+) compared to the Human Mortality Database (HMD). Numident Sample 1 corresponds to all deaths restricted to age 65+, occurring between 1988 and 2005, to the cohorts of 1900-1940. Sample 2 corresponds to deaths restricted to age 65+ occurring between 1988 and 2005, to the cohorts of 1900-1940, with complete information on sex, place of birth, and race.

Figure 3 shows the death coverage of the BUNMD file for persons 65+. Coverage is highest for the years 1988-2005, at over 95%.

- Coverage
- the material below we've mostly done — we're going to weight by age*dyear*sex. TODO
- check on race
- check on state
- comparison with HMD (year, age.at.death, sex)
- race (maybe NCHS) see Berkeley Mortality Database for nice versions of Black, White death counts.

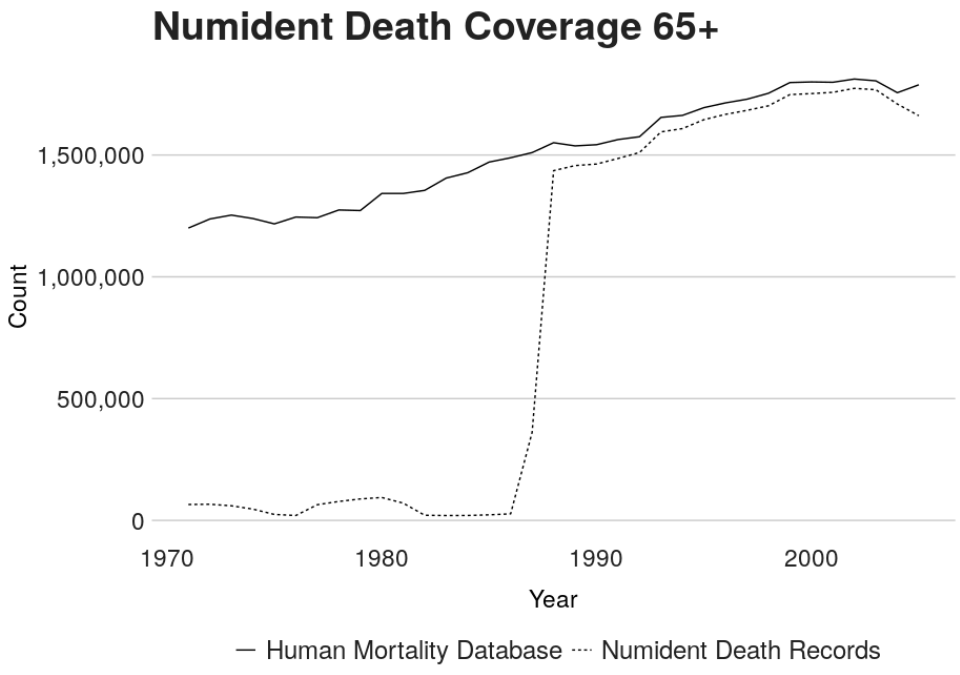


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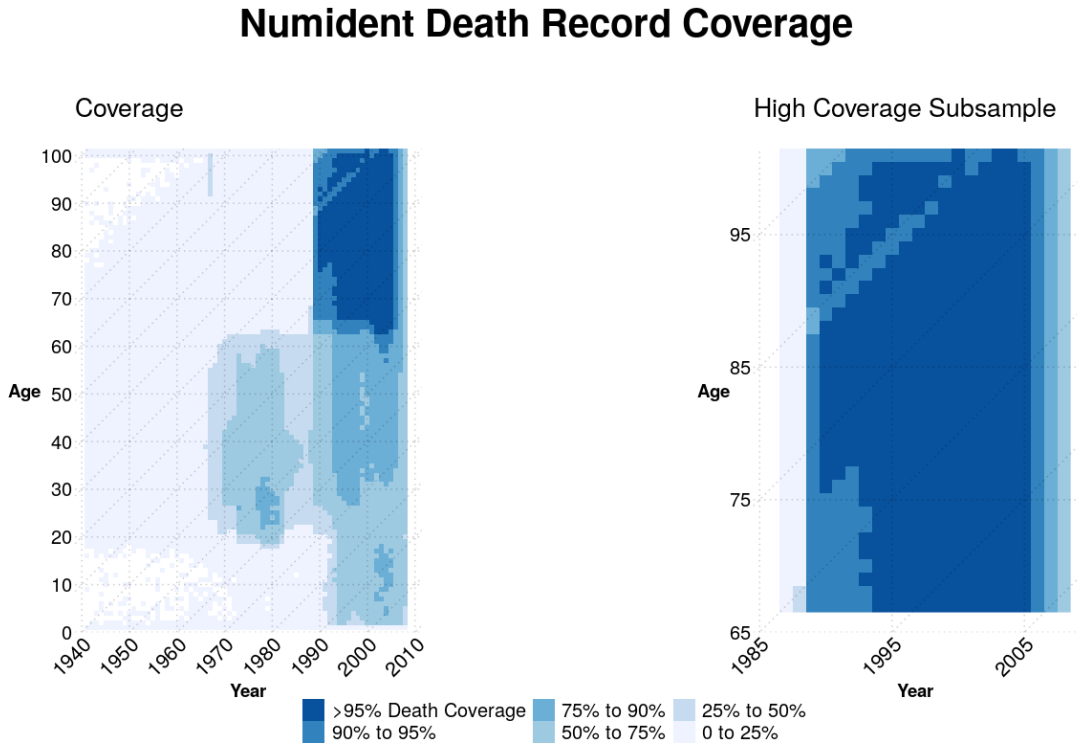
Figure 3: Berkeley Unified Numident Mortality Database creation flowchart.



(a)

Figure 4: Berkeley Unified Numident Mortality Database creation flowchart.

- key thing is if inverse HMD weights which are not based on race work.
- real issue here is weights and their pros and cons. and what we can give evidence for about pros and cons.
- Variables

Estimation: Deaths without Denominators

The BUNMD file includes only individuals who have died. For extinct cohorts (in which all members have died), it is possible to use classical methods of "extinct generations" to calculate mortality rates. These methods are appropriate for the cohorts born before 1900, for which only a few survivors to age 105 will die after 2005. For later cohorts, however, we have developed several different methods, which can be chosen based on suitability for the research question of interest.

The first method is to fit parametric survival models (Gompertz and Makeham), using maximum likelihood for doubly-truncated cohorts. The second method is to use ordinary regression, inflating the observed coefficients in order to account for truncation. Finally, we introduce the cox regression method

Method 1: Parametric survival models

Human mortality has a characteristic pattern in older ages. To a first approximation — first noticed by Benjamin Gompertz — mortality hazards rise exponential with age.

$$h(x) = a * exp(b * x) \tag{1}$$

The constant exponential rate of increase is most pronounced from ages in the 70s to ages in the 90s. At younger ages, say between 40 and 70, mortality is often somewhat higher than would be predicted by a Gompertz model. This was first noted by Makeham, who suggested that adding a constant term, would be a better description of observed mortality.

$$h(x) = c + a \cdot exp(b \cdot x) \tag{2}$$

Finally, at older ages, although there is still much debate, there may be a leveling of mortality. Thus the logistic ... model has been introduced to account for this leveling of mortality. For any parametric model, it is possible to write down the likelihood given the deaths we observe.

For truncated cohorts, with known left-truncation L and known right truncation R, we can write down the likelihood as

$$L = \prod (f_i(\theta)/(F_R(\theta) - F_L(\theta))) \tag{3}$$

The estimates of the vector θ of parameters can be obtained by maximizing the likelihood, or, equivalently, the log-likelihood. We have written functions in the computer language R that can be used to obtain maximum likelihood estimates of these parametric models.

Method 2: Ordinary Least Squares Regression

Regression on age at death is an easy and effective way to analyze the Numident mortality data. Regression coefficients tell the effect of covariates on the mean age at death. Because left and right truncation ages vary by cohort, it is important to include fixed effect terms for each year of birth. Models of the form:

$$\text{Age\_at\_death} = \text{birth\_year\_dummy} + \text{covariates of interest} \tag{4}$$

Provide estimates of the effect of the covariates on the age of death in the sample, controlling for birth cohort truncation effects.

Truncation, however, will tend to bias downward the estimated effects of any covariates. (need citation). Truncaction excludes the tails of the distribution, thus reducing the average difference between groups.

The idea is that the average differences between groups will be measured to be much smaller if we exclude the tails of the distribution.

Simulation tells us that the magnitudes of the regression coefficients need to be inflated by a factor of about 2 or 3 for many of the cohorts that are covered by the Numident files. The table below gives the inflation factors for each cohort, based on a simulation of a Gompertz distribution with M = xxx and b = xxx (the values found by fitting to the untruncated cohort of 1910 using HMD data). The interpretation of these numbers is that a regression coefficient of 0.5, say comparing Men and Women, found using the data from the cohort of 1910 (observed from 1988 to 2005) translates to a difference of life expectancy at age 65 of 0.5 x 2.3 = 1.15 years.

Method 3: Cox regression for extinct cohorts

For cohorts that are extinct (or very nearly so), Cox regression provides a convenient method. Cohorts born in 1900 or earlier are observed to age 105. Cox regression makes no distributional assumptions about the shape of mortality, but does assume proportional effects on the hazards. (cite).

Case Studies

Geography

The BUNMD contains place of birth and residence of death geographic data. For place of birth, the resolution is state-level for those born within the United States and country-level for those born outside of the United States. Geographic codes for birthplace are identical to the IPUMS BPL codes. The geographic resolution for residence of death is at the ZIP code level; occasionally, the resolution is ZIP+4. The use of ZIP codes for spatial analysis has an accompanying set of challenges ((**???**)). Figure xx shows life expectancy at age 65 by ZIP code for Ohio. Figure xx+1 shows life expectancy by ZIP code for Cayuga county. Life expectancy is lowest within Cleveland, and higher in the suburbs surrounding Cleveland, suggesting a large life expectancy gap. Differences in life expectancy can be explained by race and educational differences. These health disparities — well-documented in the United States — are likely driven by racial segregation.

Conclusion

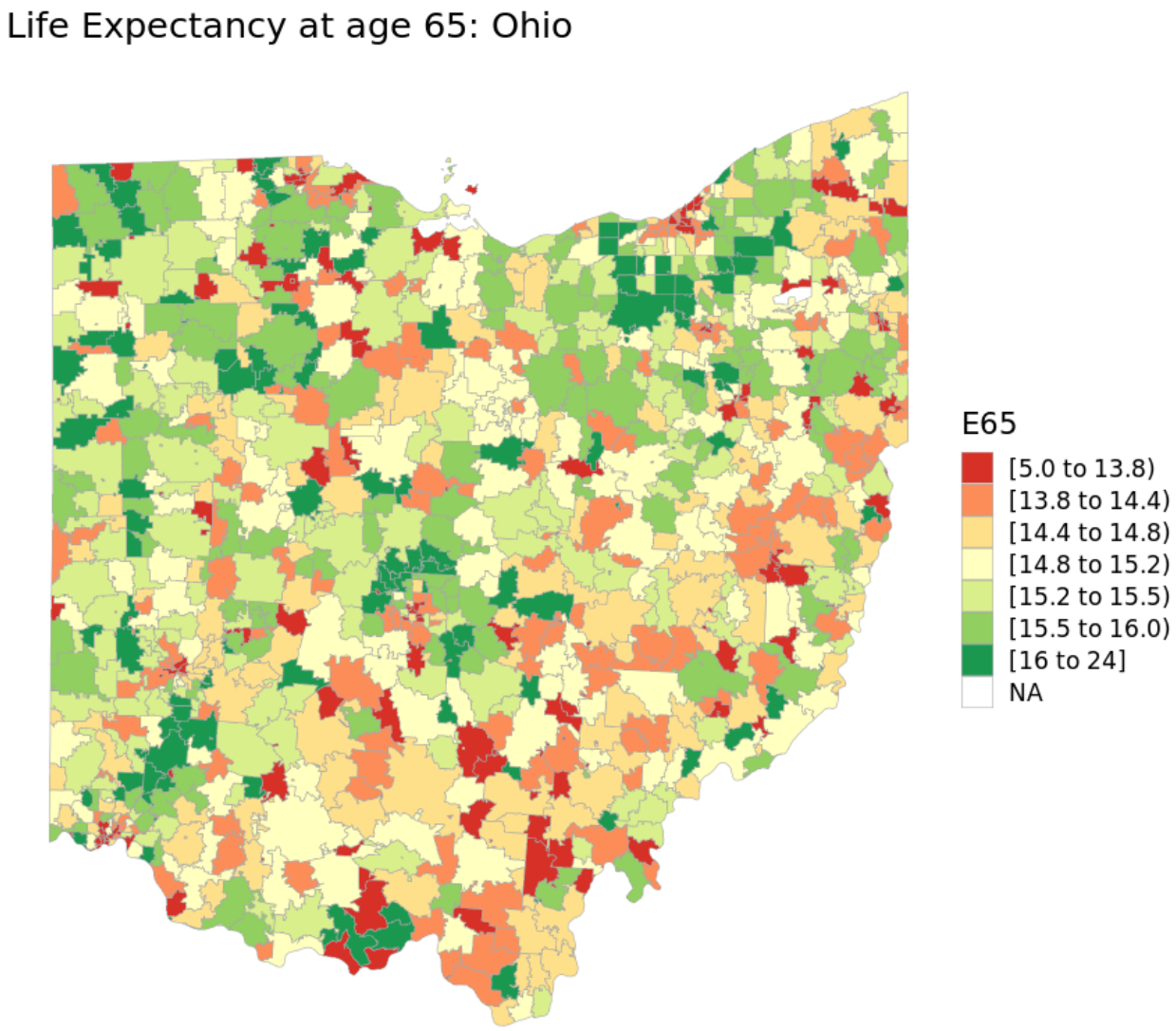


Figure 5: Ohio expectancy at age 65 for ohio, disaggregated by ZIP code. Cohorts of 1915 to 1920.

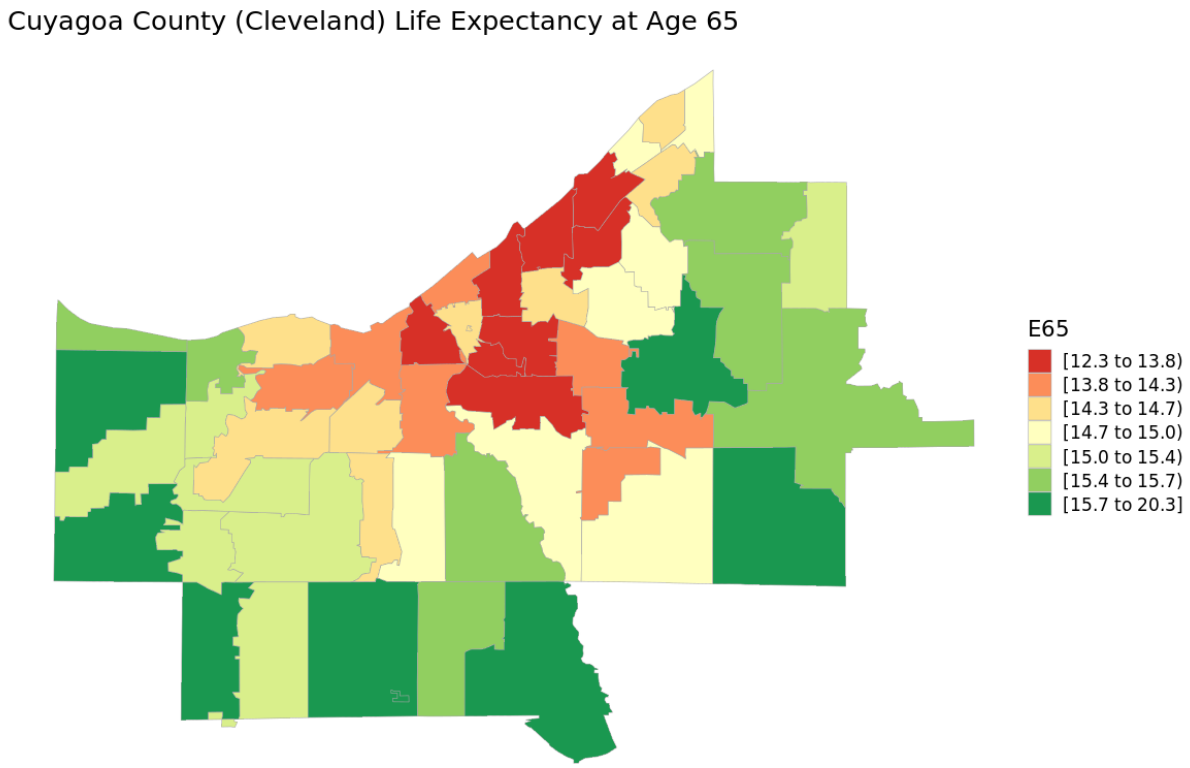


Figure 6: ZIP Codes surrounding Cleveland.

Notes

- can get old-age mortality using reverse survival (good application would be black/white , elo, preston et al)

? other approaches . . . no, but can mention in a few sentences and refer to Monica's paper / dissertation

Case studies:

Pick a subset that are the BEST. - Race x state (just black and white) - BPL x time of 1st application (proxy for time of arrival – Mexicans and Fillipinos) - Something with own name and name of parents - [So what this means is that we want "race", "bpl", time of first application, anything we might have on citizenship (but that's not crucial for the 1st data set production), and then we want all the name info there is]

Coverage

- state, not really for substance, but still good for coverage
- first name, last name
- could do an ancestry corrector. my guess is that last name doesn't matter much. and neither does 1st name ... but i don't know.
- Nicknames — as a proxy for social class. can distinguish blacks and whites.
- Yes, by country ... super interesting but a lot of detail (e.g., when people came to the U.S. that is a bit hard to infer — but can use 1st date ... this is kind of a paper in and of itself)
- n_ss5 applications: maybe a proxy for carelessness losing cards, life instability
- daylight savings time ...? No — too hard a topic ... but not bad for another paper
- ZIP code (say by income or house value or average educ): one illustrative example, e.g., Manhattan or NYC or Ohio
- Choose a case study that data is available for (like from NCHS) to validate our approach (daylight savings time?); (state?)
- Choose case studies that can't be done with other data ... (race x daylight savings time?)(BPL !!!)(anything involving names) (anything involving exact date of birth).
- Influenza?????
- Weighting and HMD comparison (casey can do this with Josh's old code – but it does need to be adapted, because I was using pre-tabled data from HMD, and if you use numideath, you have to table it yourself into a Dx vector with ages of death as names(Dx) for the functions to work) (also find an example where weighting makes a difference)
- Truncated gompertz vs regression (but this can be in one of the case studies)
- Case studies: all on age at death
- Race x state
- Nicknames (use 1940 to get social class score of nicknames ...?)

Public distribution, acknowledgement, conditions

Thank Lynn Goodsell, guy from SSA, Berkeley HMD.

Distribute file Distribute original SS-5 Files?

For: Demographic Research or Demography (DR has the advantage of infinite extra cool links etc and being totally free and accessible — which is probably what we want; prestige of Demography not really needed for this paper (and it might not get accepted because of its nature).

Reference:

Black, Dan. n.d. "The Methuselah Effect: The Pernicious Impact of Unreported Deaths on Old Age Mortality Estimates," 45.

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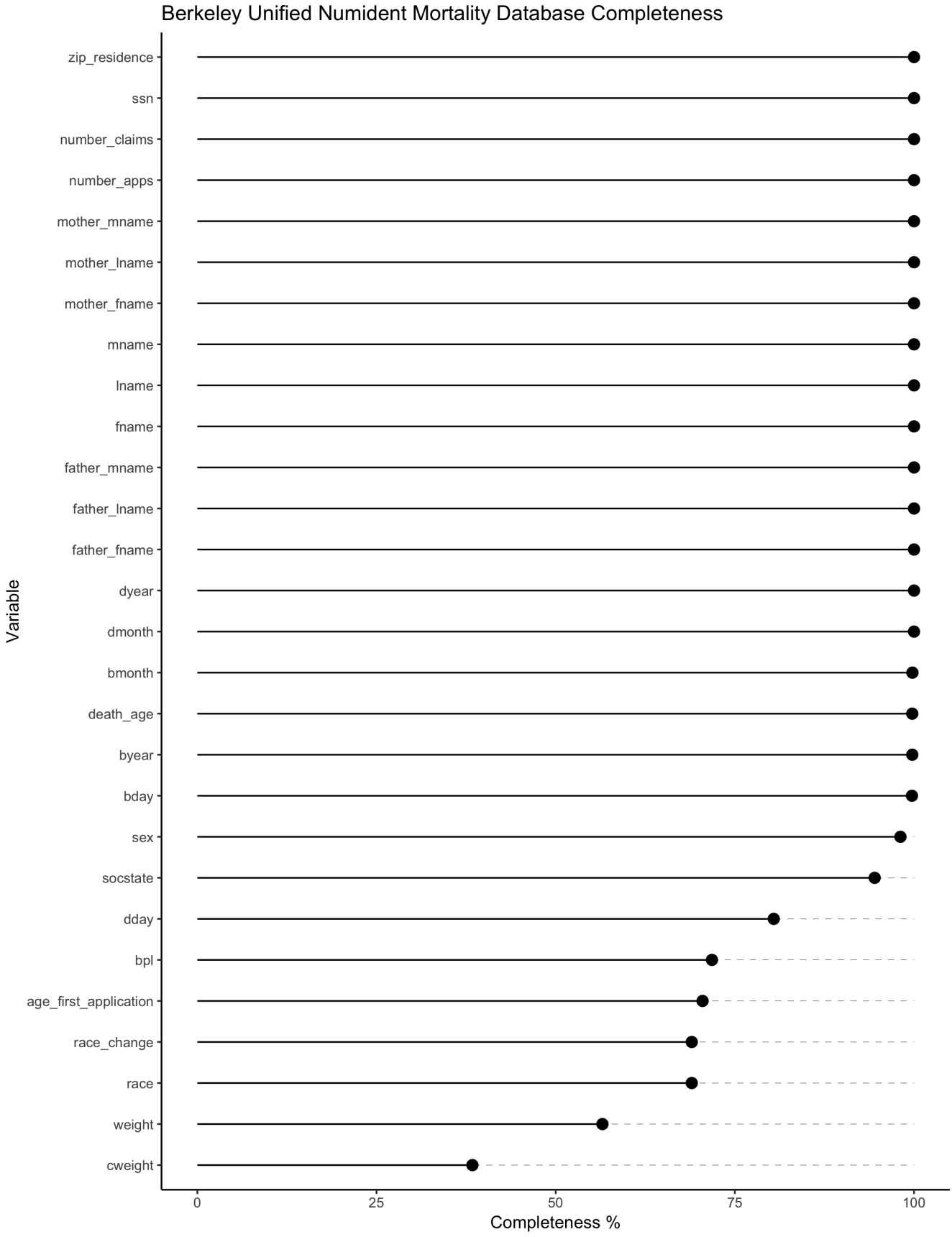
Mehta, Neil K., Irma T. Elo, Michal Engelman, Diane S. Lauderdale, and Bert M. Kestenbaum. 2016. "Life Expectancy Among U.S.-born and Foreign-Born Older Adults in the United States: Estimates from Linked Social Security and Medicare Data." *Demography* 53 (4): 1109–34. https://doi.org/10.1007/s13524-016-0488-4.

Puckett, Carolyn. 2009. "The Story of the Social Security Number." *Social Security Bulletin* 69 (2): 21.

Scott, Charles G. n.d. "Identifying the Race or Ethnicity of SSI Recipients," 12.


Berkeley Unified Numident Mortality Database Completeness
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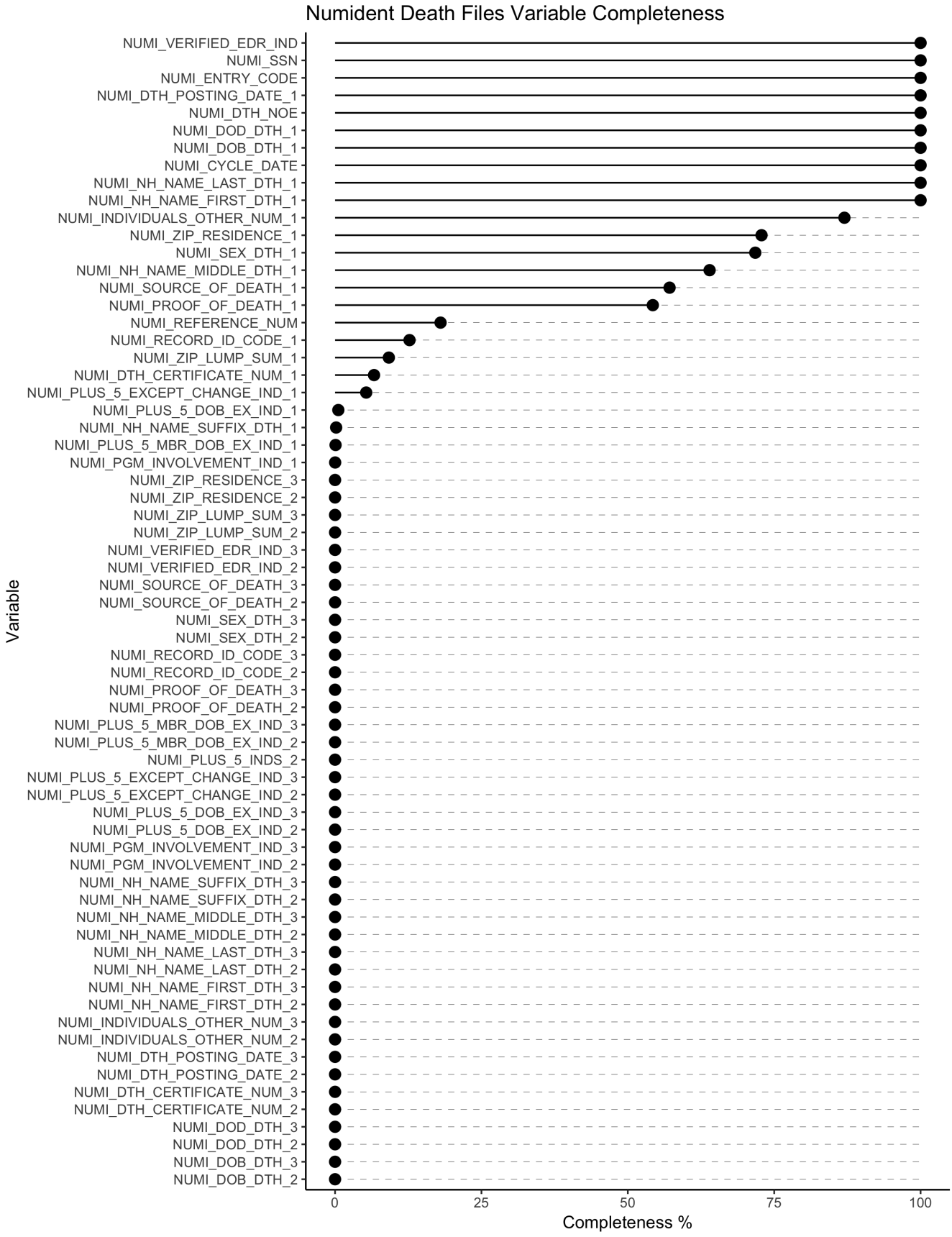
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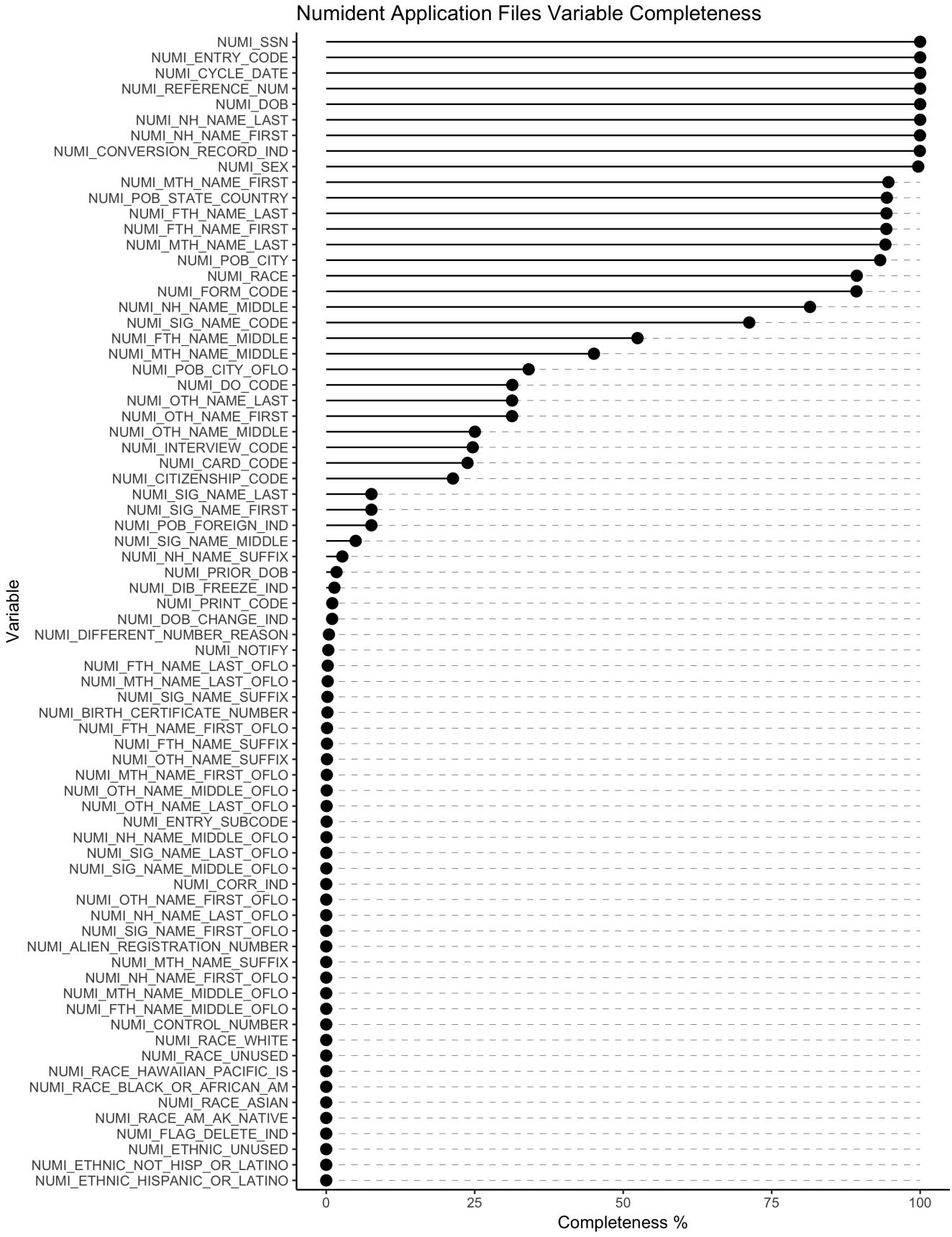
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NUMI_FTH_NAME_LAST
NUMI_FTH_NAME_FIRST
NUMI_MTH_NAME_LAST
NUMI_POB_CITY
NUMI_RACE
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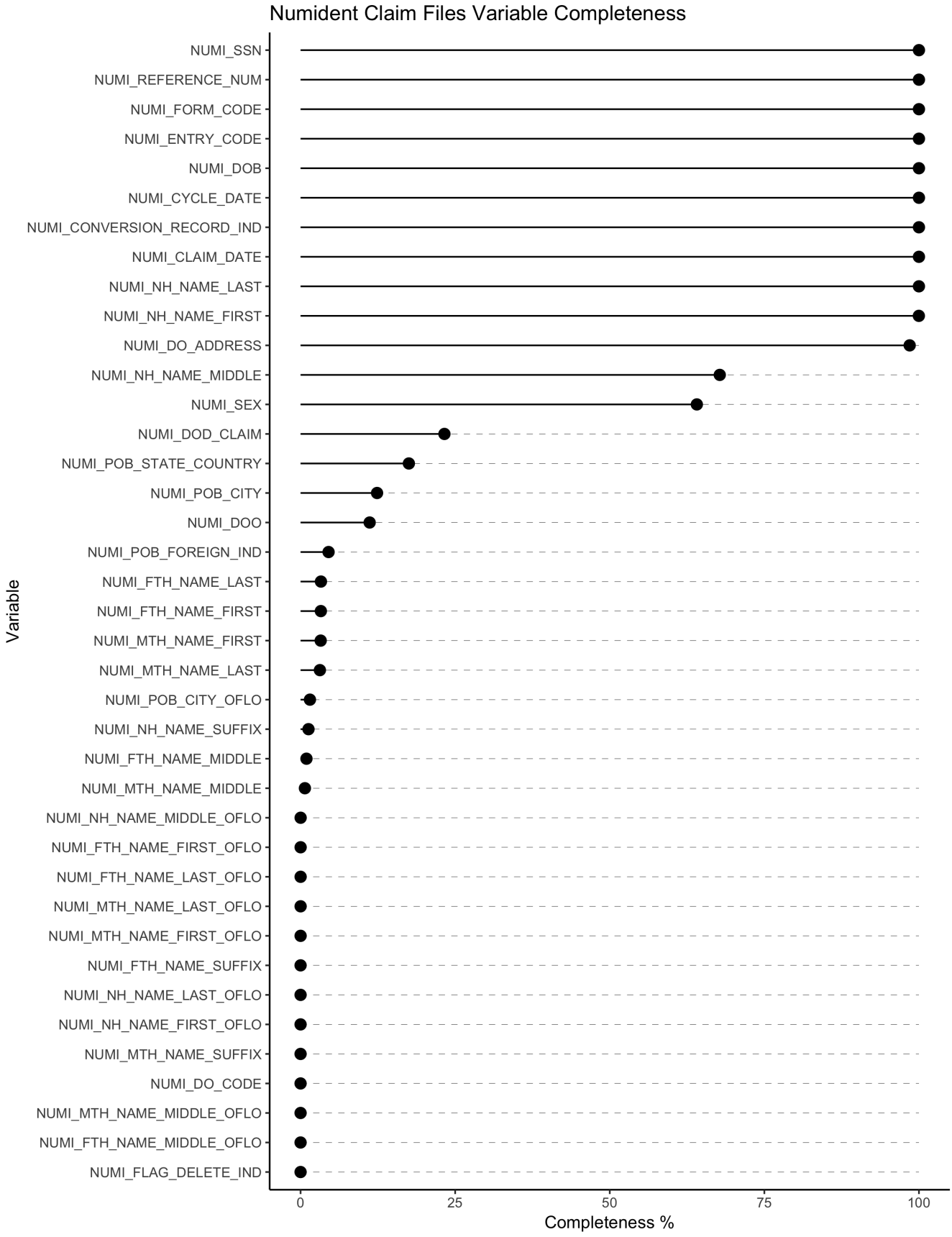
NUMI_OTH_NAME_LAST_OFLO
NUMI_ENTRY_SUBCODE
NUMI_NH_NAME_MIDDLE_OFLO
NUMI_SIG_NAME_LAST_OFLO
NUMI_SIG_NAME_MIDDLE_OFLO
NUMI_CORR_IND
NUMI_OTH_NAME_FIRST_OFLO
NUMI_NH_NAME_LAST_OFLO
NUMI_SIG_NAME_FIRST_OFLO
NUMI_ALIEN_REGISTRATION_NUMBER
NUMI_MTH_NAME_SUFFIX
NUMI_NH_NAME_FIRST_OFLO
NUMI_MTH_NAME_MIDDLE_OFLO
NUMI_FTH_NAME_MIDDLE_OFLO
NUMI_CONTROL_NUMBER
NUMI_RACE_WHITE
NUMI_RACE_UNUSED
NUMI_RACE_HAWAIIAN_PACIFIC_IS
NUMI_RACE_BLACK_OR_AFRICAN_AM
NUMI_RACE_ASIAN
NUMI_RACE_AM_AK_NATIVE
NUMI_FLAG_DELETE_IND
NUMI_ETHNIC_UNUSED
NUMI_ETHNIC_NOT_HISP_OR_LATINO
NUMI_ETHNIC_HISPANIC_OR_LATINO
Variable
0
25
50
75
100
Completeness %


Numident Claim Files Variable Completeness
NUMI_SSN
NUMI_REFERENCE_NUM
NUMI_FORM_CODE
NUMI_ENTRY_CODE
NUMI_DOB
NUMI_CYCLE_DATE
NUMI_CONVERSION_RECORD_IND
NUMI_CLAIM_DATE
NUMI_NH_NAME_LAST
NUMI_NH_NAME_FIRST
NUMI_DO_ADDRESS
NUMI_NH_NAME_MIDDLE
NUMI_SEX
NUMI_DOD_CLAIM
NUMI_POB_STATE_COUNTRY
NUMI_POB_CITY
NUMI_DOO
NUMI_POB_FOREIGN_IND
NUMI_FTH_NAME_LAST
NUMI_FTH_NAME_FIRST
NUMI_MTH_NAME_FIRST
NUMI_MTH_NAME_LAST
NUMI_POB_CITY_OFLO
NUMI_NH_NAME_SUFFIX
NUMI_FTH_NAME_MIDDLE
NUMI_MTH_NAME_MIDDLE
NUMI_NH_NAME_MIDDLE_OFLO
NUMI_FTH_NAME_FIRST_OFLO
NUMI_FTH_NAME_LAST_OFLO
NUMI_MTH_NAME_LAST_OFLO
NUMI_MTH_NAME_FIRST_OFLO
NUMI_FTH_NAME_SUFFIX
NUMI_NH_NAME_LAST_OFLO
NUMI_NH_NAME_FIRST_OFLO
NUMI_MTH_NAME_SUFFIX
NUMI_DO_CODE
NUMI_MTH_NAME_MIDDLE_OFLO
NUMI_FTH_NAME_MIDDLE_OFLO
NUMI_FLAG_DELETE_IND
Variable
0
25
50
75
100
Completeness %