Berkeley Unified Numident Mortality Database: Public administrative records for individual-level mortality research

Full Count Census Data II: Record Linkage and Databases

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Motivation

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- Mortality research is often hampered by **data limitations**
  - U.S. has no population-level registry like Scandinavian countries
- Researchers are increasingly turning to administrative datasets (Chetty et al., 2016; Card, Dobkin and Maestas, 2008; Card et al., 2010; Meyer and Mittag, 2019; Ruggles, 2014)

Numident: Backbone of SSA record keeping system

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  - Date of birth, date of death, birthplace, race, sex, parents names, etc.
- Internal restricted version used for research by SSA researchers and collaborators (Mehta et al., 2016; Elo et al., 2004; Waldron, 2007)

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- A subset of Numident records were transferred from the Social Security Administration to the National Archives
- National Archives made these records available — 60 **text files** with 120+ fields with many missing values
- Messy, challenging data structure

The structure of the National Archives Numident records

Record type	Total entries	Total records (persons)	Entries per person
Death	49,459,293	49,459,293	1.000
Applications	72,120,516	40,870,455	1.765
Claims	25,228,257	25,140,847	1.004

Creating the BUNMD

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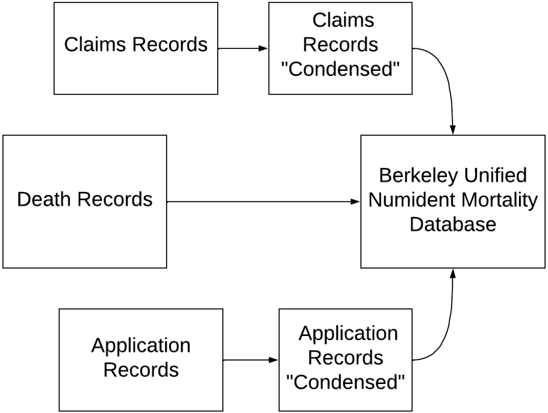
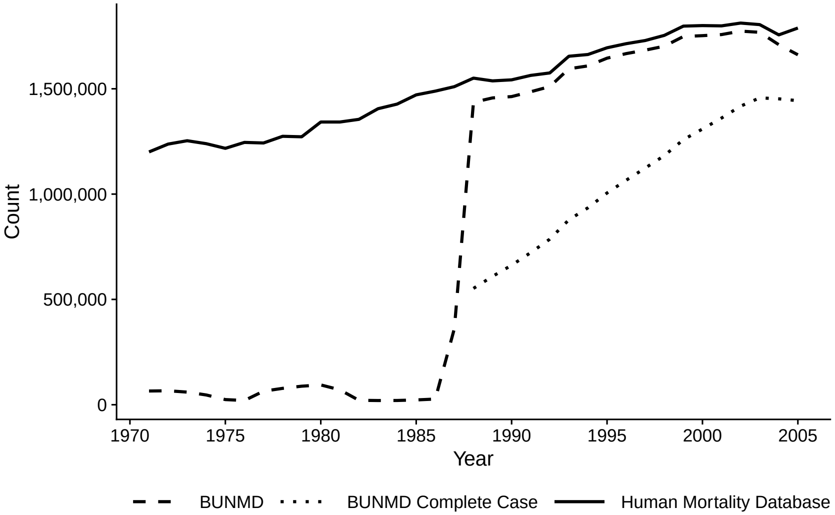


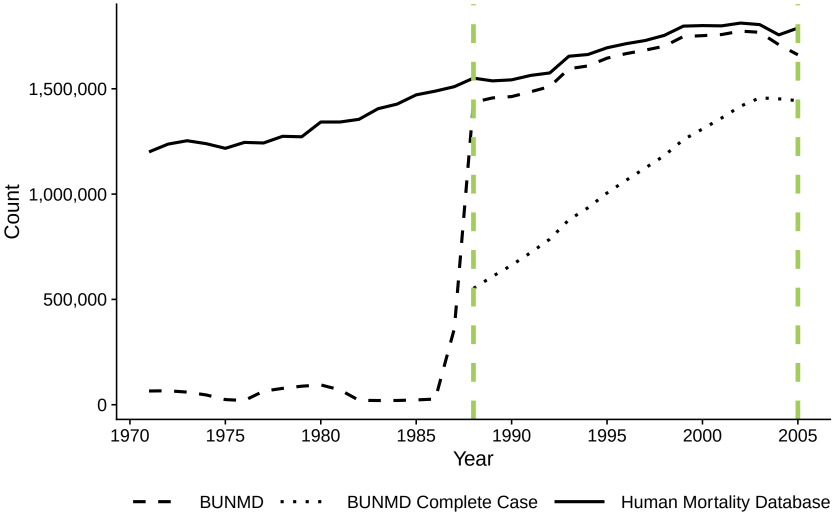
Variables in the BUNMD

Variable	Description	Numident Source
ssn	Social Security Number	Death Entry
fname	First name	Death Entry
mname	Middle name	Death Entry
lname	Last Name	Death Entry
byear	Year of birth	Death Entry
bmonth	Month of birth	Death Entry
bday	Day of birth	Death Entry
dyear	Year of death	Death Entry
dmonth	Month of death	Death Entry
dday	Day of death	Death Entry
zip_residence	ZIP Code of residence at death	Death Entry
sex	Sex	Death, Application, or Claim Entry
race_first	Race (first)	Application Entry
race_last	Race (last)	Application Entry
bpl	Place of birth	Application or Claim Entry
father_fname	Father's first name	Application or Claim Entry
father_mname	Father's middle name	Application or Claim Entry
father_lname	Father's last name	Application or Claim Entry
mother_fname	Mother's first name	Application or Claim Entry
mother_mname	Mother's middle name	Application or Claim Entry
mother_lname	Mother's last name	Application or Claim Entry
death_age	Age of death (years)	Constructed
socstate	State in which SS card issued	Constructed
age_first_app	Age of first application	Constructed
number_apps	Total number of applications	Constructed
number_claims	Total number of claims	Constructed
weight	Weight variable	Constructed
ccweight	Complete case person-weight	Constructed

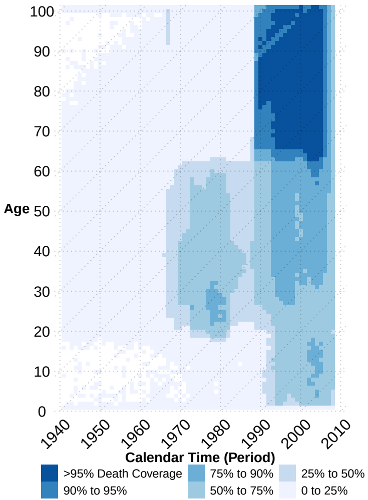
Mortality coverage ages 65+



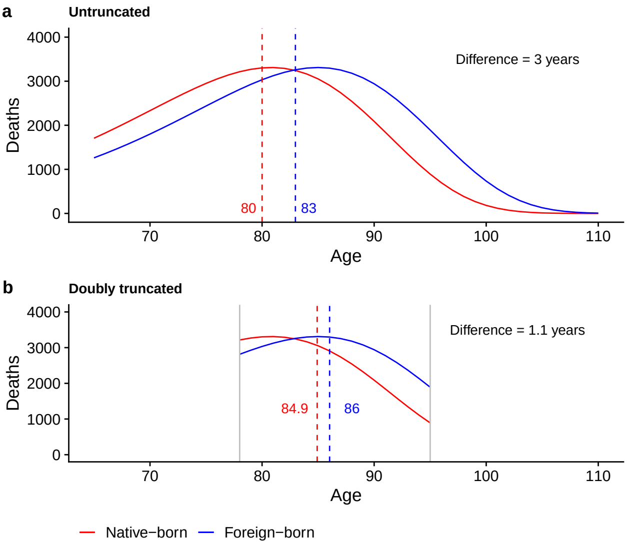
95%+ mortality coverage between 1988-2005



Lexis diagram of death coverage



Double truncation presents challenges for mortality estimation



Attenuation: Regression understates effects of predictors

$$\text{Age of Death} = \beta_0 + \lambda_t t + \mathbf{X}\boldsymbol{\beta} + \epsilon \tag{1}$$

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2. $\lambda_t t$ **are birth year fixed effects**
3. $\mathbf{X}$ **is a matrix of covariates and** $\boldsymbol{\beta}$ **is the coefficient vector**

Gompertz parametric MLE approach (no attenuation)

$$h_i(x|\beta) = a_0 e^{b_0 x} e^{\beta Z_i} \tag{2}$$

where

- $h_i(x|\beta)$ is the hazard at age x conditional on parameters

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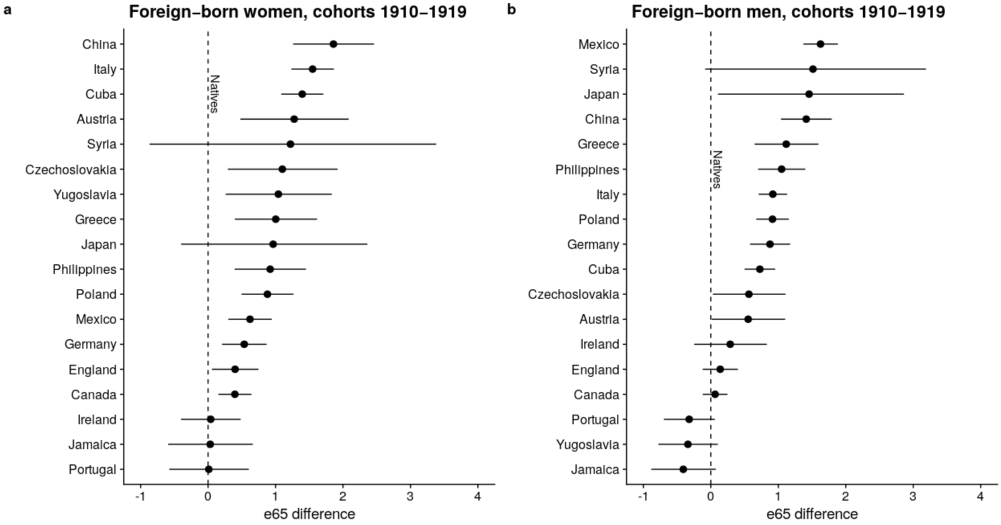
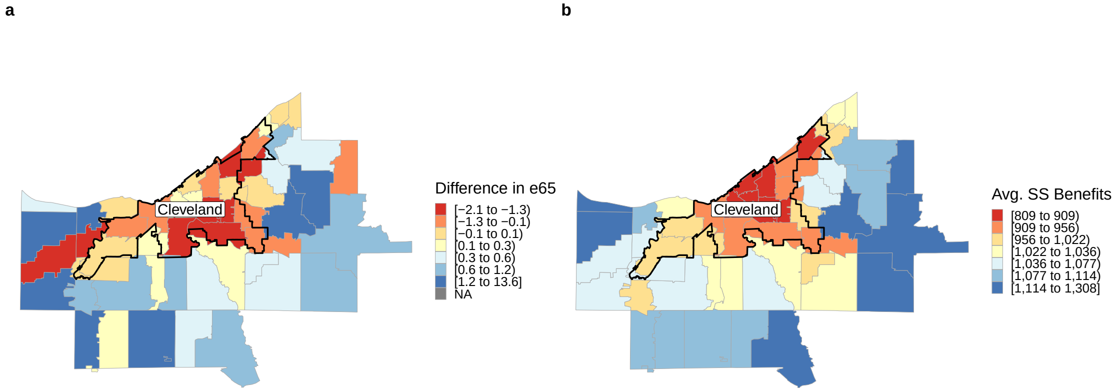
- **b_0 gives rate of increase of mortality over time**
- Z_i are the covariates for person i (e.g., years of education, place of birth)
- β is the set of coefficients

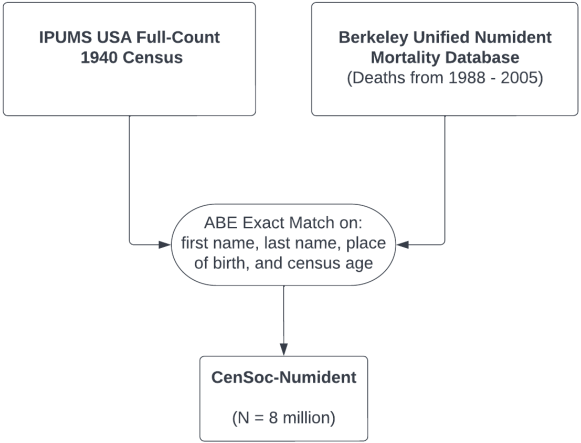
Case study 1: Mortality advantage of the foreign born



Case study 2: ZIP Code level mortality estimation



CenSoc-Numident: Linking BUNMD with the 1940 Census



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- Identify siblings using parents names and machine learning techniques (Joo et al.)

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- **Problem** Double truncation can downwardly attenuate estimates from conventional regression
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- Identify siblings using parents names and machine learning techniques (Joo et al.)
- Link onto 1950 Census, WWII enlistment records

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- Linked onto the 1940 Census ($N = 9$ million)
- **Publicly Available:** Reproducible, extendable science. No barriers to entry.

Thank You

Download: CenSoc.Berkeley.edu

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Research Material

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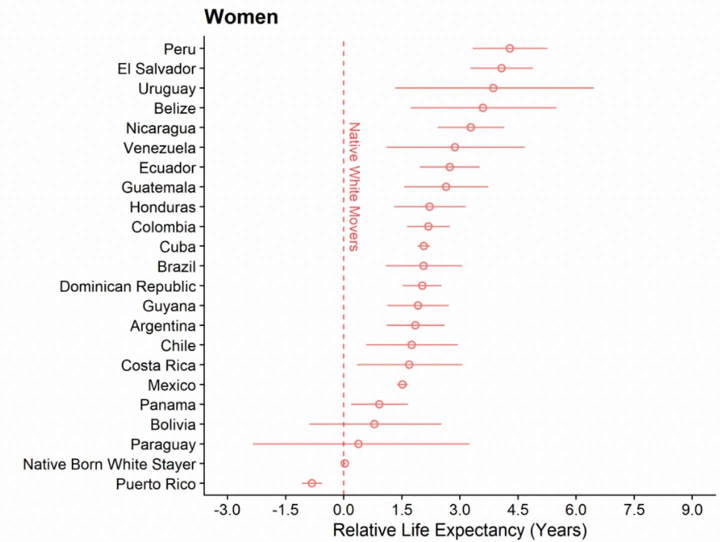
Reserve Slides

González et al. — Hispanic mortality paradox



Goldstein et al. — Black names and longevity

Dependent Variable:	Death Age			
	Pooled	**Family FE**		
Model:	(1)	(3)	(4)	(5)
BNI (Standardized)	-0.2386	-0.6258*	-0.6273*	-0.4696
	(0.2301)	(0.3060)	(0.3055)	(0.4380)
Birth Year FE	Yes	Yes	Yes	Yes
Family FE	-	Yes	Yes	Yes
Birth Order FE	-	-	Yes	Yes
Mortality Window	1988-2005	1988-2005	1988-2005	1941-2007
Observations	30,429	30,429	30,429	45,893
R^2	0.21029	0.61428	0.61430	0.56402
Within R^2	5.35×10^{-5}	0.00036	0.00036	8.14×10^{-5}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

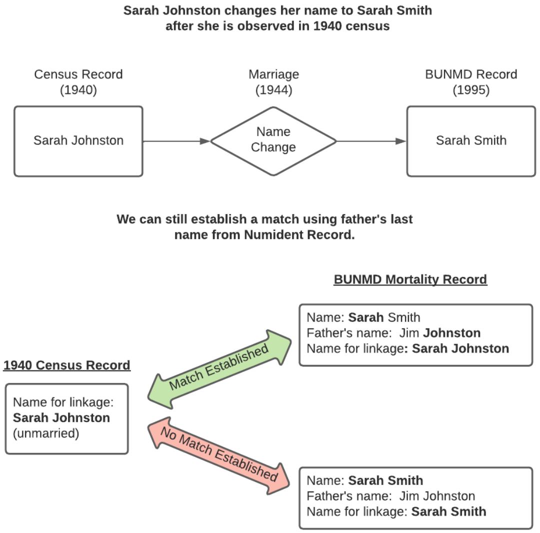
Joo et al. — Identifying siblings using machine learning

	ML, TH1		ML, TH2		EM		EM, within birthplace	
	Mean	Weighted mean	Mean	Weighted mean	Mean	Weighted mean	Mean	Weighted mean
Total	1.53	1.35	1.31	1.14	0.53	0.46	0.44	0.39
Race: White	1.43	1.26	1.23	1.07	0.54	0.48	0.46	0.40
Race: Black	2.33	2.01	1.85	1.57	0.47	0.40	0.38	0.31
Race: Others	2.15	1.92	1.78	1.55	0.23	0.21	0.19	0.17
Cohort: 1900-4	0.77	0.74	0.60	0.57	0.23	0.19	0.21	0.17
Cohort: 1905-9	1.15	1.11	0.92	0.88	0.33	0.28	0.31	0.26
Cohort: 1910-4	1.44	1.42	1.21	1.19	0.47	0.41	0.45	0.39
Cohort: 1915-9	1.56	1.56	1.35	1.34	0.55	0.49	0.55	0.48
Cohort: 1920-4	1.65	1.64	1.42	1.42	0.58	0.51	0.58	0.52
Cohort: 1925-9	1.61	1.61	1.38	1.38	0.55	0.49	0.55	0.49
Cohort: 1930-4	1.47	1.46	1.24	1.23	0.49	0.44	0.49	0.44
% of any sibling	53.8%		50.6%		27.7%		25.0%	

Variable source and selection rule

Variable	Numident source	Selection rule
ssn	Death Entry	-
fname	Death Entry	-
mname	Death Entry	-
lname	Death Entry	-
byear	Death Entry	-
bmonth	Death Entry	-
bday	Death Entry	-
dyear	Death Entry	-
dmonth	Death Entry	-
dday	Death Entry	-
zip_residence	Death Entry	-
sex	Death, Application, or Claim Entry	Last Recorded Sex
race_first	Application Entry	First Recorded Race
race_last	Application Entry	Last Recorded Race
bpl	Application or Claim Entry	Last Recorded BPL
father_fname	Application or Claim Entry	Maximum Characters
father_mname	Application or Claim Entry	Maximum Characters
father_lname	Application or Claim Entry	Maximum Characters
mother_fname	Application or Claim Entry	Maximum Characters
mother_mname	Application or Claim Entry	Maximum Characters
mother_lname	Application or Claim Entry	Maximum Characters
death_age	Constructed	-
socstate	Constructed	-
age_first_app	Constructed	-
number_apps	Constructed	-
number_claims	Constructed	-
weight	Constructed	-
ccweight	Constructed	-

Linking unmarried women in CenSoc-Numident



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