Developing job linkages for the Health and Retirement Study

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Outline

- Background on HRS, CenHRS
- Approach to linkage
- Work using a small set of HRS jobs
- Some preliminary results
- Challenges

HEALTH AND RETIREMENT STUDY

A Longitudinal Study of Health, Retirement, and Aging
Sponsored by the National Institute on Aging

37,000 + Americans over the age of 50

- Surveyed every two years since 1992
- New cohorts added in 1993, 1998, 2004, 2010, 2016
- Includes both spouses
- Oversamples minorities
- Follows respondents through death

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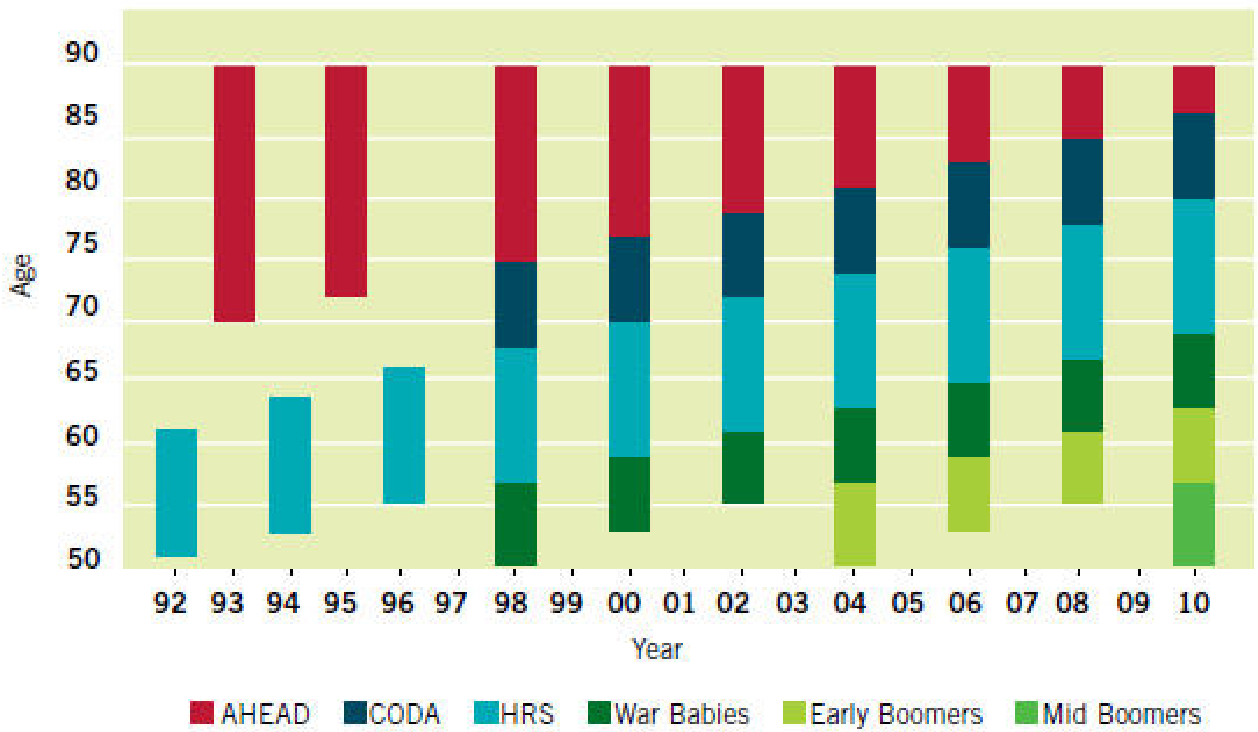
THE HRS LONGITUDINAL SAMPLE DESIGN



Census-Enhanced HRS

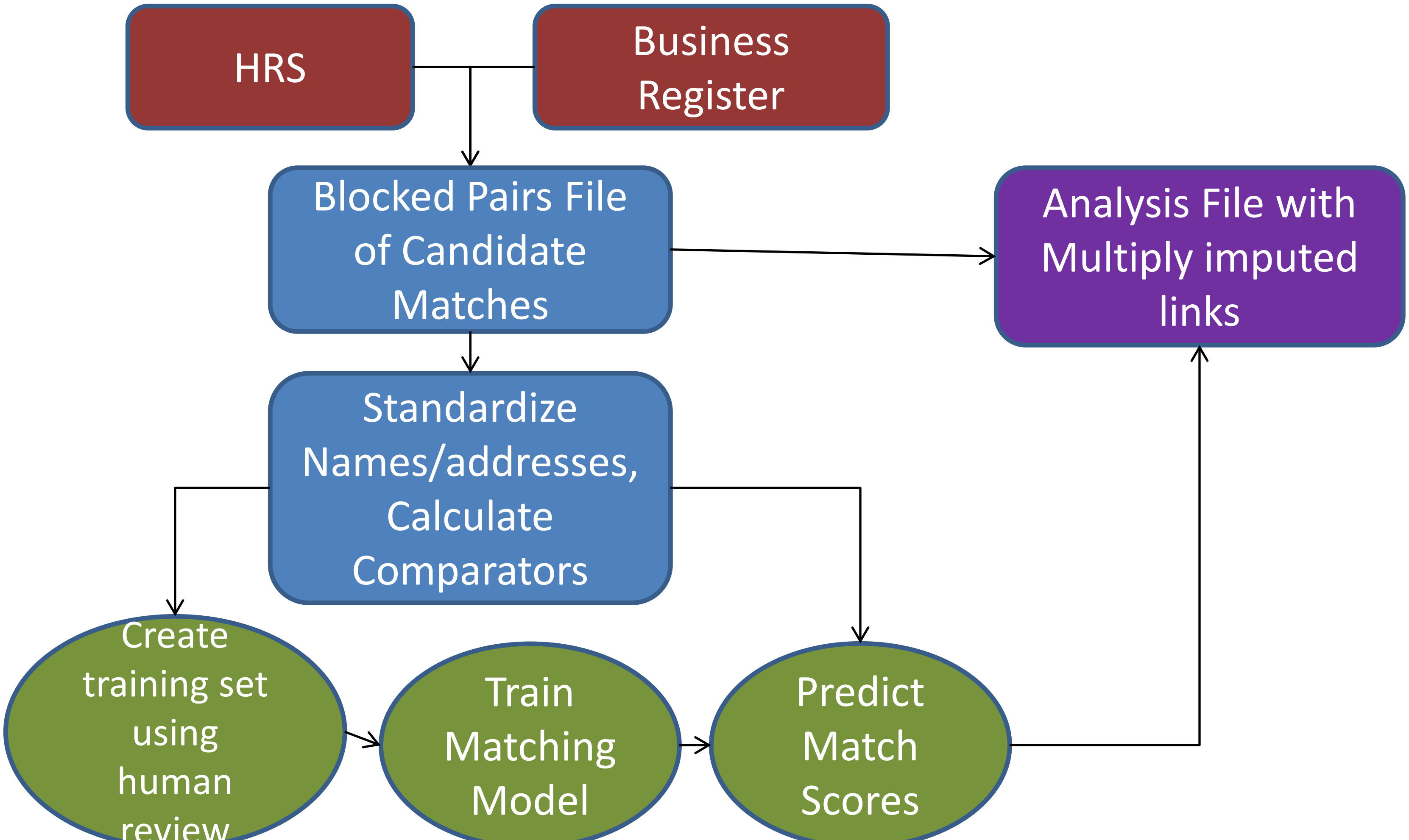
UMichigan/Cornell/Census collaboration

Goal: New info on HRS respondents in employer and co-worker context

Develop new data infrastructure:

- HRS-BR Crosswalk
- New measures of employer characteristics
- Enhance HRS public-use datasets

Linkage Process Flow



First steps:

- Use a subset of 1992 HRS private-sector jobs, 1992 BR to work out methods
- Block on:
  - 10-digit phone number, where possible
  - 3-digit zip code, otherwise
- Standardize address and name fields, using rules developed specifically for business names
- Compute Jaro-Winkler string comparator scores for names and addresses

Construct set of pairs

- 1,232 1992 HRS jobs from 7 states
- Exclude if missing employer name or state, or missing both zip3 and phone # (10%)

- <10% of phone numbers successfully blocked
- Almost always at least 1 BR entry in zip3 block

Initial set of blocked pairs

- All possible within-block pairs = 18.3M
- JW scores comparing name, address
- Stratify using 4x4 cross-classification of JW scores
- Mean pairs per sampled HRS job=3,100, but varies from 1 to 20,000 across bins.
- Lowest JW scored bin accounts for:
  - 98% of pairs blocked on 3-digit zip
  - 42% of those blocked on 10-digit phone number

Creating training set

- Sample 100 pairs from each stratum
- Each sampled pair reviewed by >=2 reviewers
- Reviewers see 1 pair at a time
- Assign separate scores for firm, establishment
- Score as follows:

1	=	Yes, match
2	=	Probably match
3	=	Maybe-maybe not
4	=	Probably not match
5	=	Not match
6	=	Not enough information

Results of review

- 3,400 reviews, 7 reviewers

Match?	Establishment	Firm
Yes	10%	18%
Maybe	13%	11%
No	76%	71%
Not enough info	<1%	<1%

- Disagreement across reviewers:
  - 5% for yes/no reviews
  - 63% for maybe/not enough info
- Use only yes/no reviews in estimating model (3,100)

Match rates by blocking factor

Share of reviews scored as match		
Blocked on	Establishment	Firm
10-digit phone number	94%	100%
3-digit zipcode	11%	19%
Note: Reviews scored Probably match, maybe/maybe not, probably not match, or not enough information are excluded from denominator.		

Modeling approach

Model propensity for record from HRS to match record from the BR

- Estimate model parameters using training set
- Calculate agreement probability for all possible pairs within block

Multiply impute links using agreement probabilities

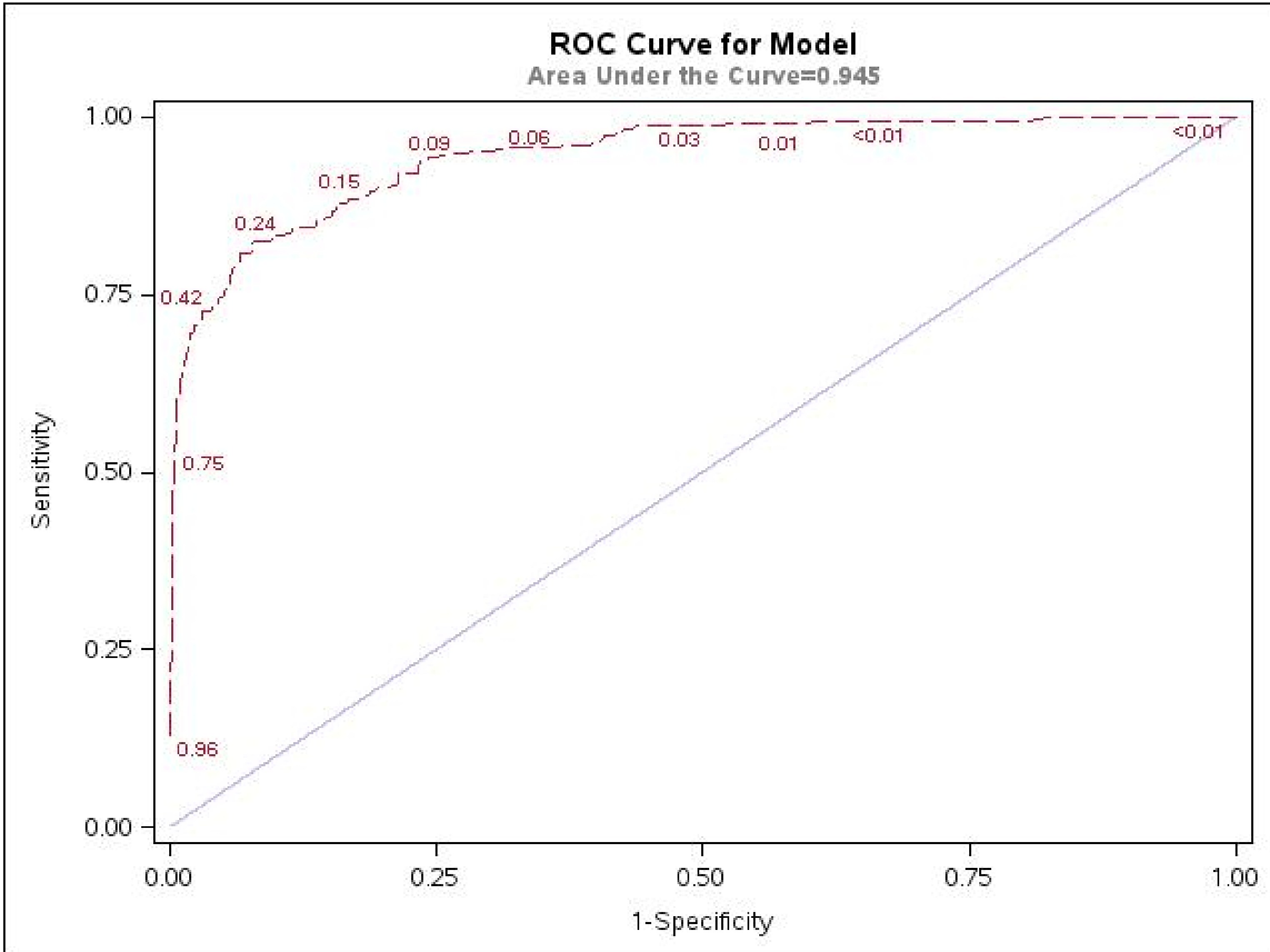
Training our matching model

- Using logistic model: dep var = 1 if pair is scored as a match, 0 otherwise
- Regressors: splines of continuous variables, indicators, and a full set of interactions
- To limit overfitting and to minimize out of sample error, we use elastic net shrinkage (Zou and Hastie, 2005)
  - Elastic net shrinkage reduces the dimensionality of the covariate vector
  - Idea: the optimal set of covariates is chosen to minimize cross-validated test error

Available model covariates

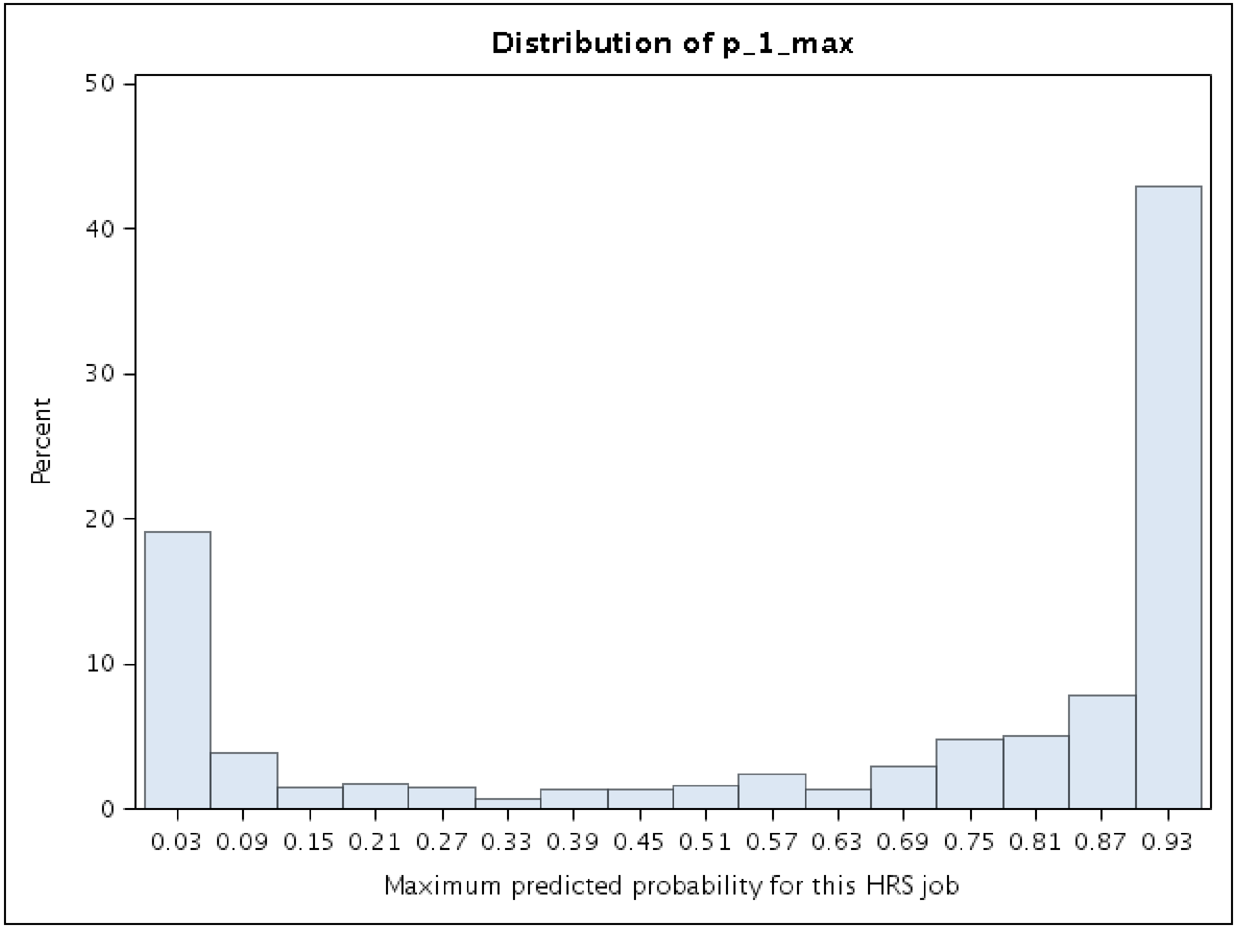
- JW scores for agreement of name, address fields
- Employment for establishment/employer for categories: 0/missing, 1-4, 5-14, 15-24,25-99, 100-499 500+
- Agreement on 3-digit, 5-digit zip code
- Agreement on industry—2 digit SIC
- Whether BR record is for single- or multi-unit
- Whether HRS employer offers health insurance/pension
- Business density—number of establishments in tract or per square mile

True positive rate



False positive rate

Distribution of maximum predicted probability using only JW scores



Challenges

- What to do when block does not include any high probability matches?
- Possible reasons
  - Blocking strategy excluded correct match
  - Blocking didn't fail:
    - Model failure
    - HRS information too garbled to support matching