Developing job linkages for the Health and Retirement Study

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Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.
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
- Includes both spouses
- Oversamples minorities
- Follows respondents through death
HEALTH AND RETIREMENT STUDY
A Longitudinal Study of Health, Retirement, and Aging
Sponsored by the National Institute on Aging

THE HRS LONGITUDINAL SAMPLE DESIGN

Year

Age

50 55 60 65 70 75 80 85 90

92 93 94 95 96 97 98 99 00 01 02 03 04 05 06 07 08 09 10

AHEAD  CODA  HRS  War Babies  Early Boomers  Mid Boomers
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

- HRS
- Business Register
- Blocked Pairs File of Candidate Matches
- Standardize Names/addresses, Calculate Comparators
- Create training set using human review
- Train Matching Model
- Predict Match Scores
- Analysis File with Multiply imputed links
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

<table>
<thead>
<tr>
<th>Match?</th>
<th>Establishment</th>
<th>Firm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>10%</td>
<td>18%</td>
</tr>
<tr>
<td>Maybe</td>
<td>13%</td>
<td>11%</td>
</tr>
<tr>
<td>No</td>
<td>76%</td>
<td>71%</td>
</tr>
<tr>
<td>Not enough info</td>
<td>&lt;1%</td>
<td>&lt;1%</td>
</tr>
</tbody>
</table>

- Disagreement across reviewers:
  - 5% for yes/no reviews
  - 63% for maybe/not enough info
- Use only yes/no reviews in estimating model (3,100)
<table>
<thead>
<tr>
<th>Blocked on</th>
<th>Establishment</th>
<th>Firm</th>
</tr>
</thead>
<tbody>
<tr>
<td>10-digit phone number</td>
<td>94%</td>
<td>100%</td>
</tr>
<tr>
<td>3-digit zipcode</td>
<td>11%</td>
<td>19%</td>
</tr>
</tbody>
</table>

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
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