# Non-Random Assignment of Individual Identifiers and Selection into Linked Data

# Implications for Research

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#### **Motivation**

Advances in the ability to link survey data to administrative records have generated wide-ranging benefits for measurement and inference

- Reducing measurement error from non-response, imputation, and misreporting (e.g., Bollinger, Hirsch, Hokayem, and Ziliak, 2019; Meyer, Mittag, and Goerge, 2022)
- Facilitating analyses of novel outcomes (e.g., Chetty, Hendren, Jones, and Porter, 2020)



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#### Selection into PIK assignment is likely non-random (Bond, Brown, Luque, and O'Hara, 2014)

- Can compromise the representativeness of linked data, leading to biased population estimates
- What should researchers do about it?



# Background

The Person Identification Validation System (PVS) assigns PIKs to individuals

- PVS matches individual records in an "incoming file" (e.g., a survey) to a "reference file" using a series of cascading probabilistic modules (see Layne and Wagner, 2014 for details)
- Reference file  $\approx$  crosswalk between universe of SSNs (with identifying information) and PIKs

Improvements in PVS have increased PIK rates (Bond et al., 2014)

- New modules
- Inclusion of Individual Taxpayer Identification Numbers (ITINs) in the reference file



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PIK rates have been shown to vary by race, Hispanic origin, citizenship, mobility, age, and socioeconomic status (Bond et al., 2014; Meyer and Goerge, 2011; Mulrow, Mushtaq, Pramanik, and Fontes, 2011; Bollinger et al., 2019)



#### **Research objectives**

- 1. Document variation in PIK rates in household surveys
- 2. Quantify the magnitude of linkage-induced bias
  - Bias = Difference between a restricted-sample (e.g., PIKed respondents) mean and a full-sample ("target") mean
- 3. Evaluate the performance of bias mitigation methods used in the literature
  - Most common: Inverse probability weighting (IPW)
  - Ongoing work to incorporate newer state-of-the-art methods



#### Data

American Community Survey (ACS), 2005-2022

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Internal Revenue Service Form W-2 records (W-2s), 2005-2022

- Near-full coverage of formally employed workers
- Source of administrative records for an actual linkage
  - Not all ACS respondents are linked due to differences in PIK assignment or misalignment of the target population across data sources



#### **PIK rates**

#### ACS respondents



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#### **PIK rates**

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# Linkage-induced bias

#### Definition

$$ext{Linkage-induced bias} := \mathbb{E}(y_i | z_i = 1) - \mathbb{E}(y_i)$$

- $y_i$  is the outcome of respondent  $i \in \{1,\ldots,n\}$
- $z_i=1$  if i has a PIK
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**Bias correction:** Wooldridge (2007) shows that Inverse Probability Weighting (IPW) estimation for missing data problems is consistent under selection-on-observables

- Meyer and Goerge (2011) and Bollinger et al. (2019) invoke selection-on-observables and use IPW to recover respresentative samples from linked data
- But IPW can be biased, inefficient, or unstable in finite samples (Busso, DiNardo, and McCrary, 2014; Li, Qin, and Liu, 2023; Liu and Fan, 2023)



#### **IPW steps**

- 1. Specify a model of selection into linkage
- 2. Estimate the selection equation and obtain propensity scores
- 3. Calculate IPW weight = 1 / propensity score
- 4. Reweight the linked sample by multiplying IPW weights with survey weights
- 5. Estimate an outcome equation using the reweighted linked sample



# **Evaluating the performance of IPW**

**Question:** Does reweighting reduce linkage-induced bias?

Approach: Compare the means of linked samples and reweighted linked samples to the mean of the target sample



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- Survey outcome: Wage income
- Samples
  - 1. Target: ACS wage earners (government and private-sector workers only)
  - 2. PIKed: Target sample restricted to PIKed respondents
  - 3. *IPW:* PIKed sample reweighted using IPW
- Propensity scores from a logistic regression of PIK assignment on a "typical" set of predictors
  - "Basic" (e.g., observable in administrative records): sex + race/ethnicity + quartic in age
  - "Full" (e.g., only observable in surveys): "basic" + citizenship + English ability + interview mode + migration in the last year + educational attainment + marital status + disability status + region + urban/rural indicator



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  - 2. *Linked:* Target sample restricted to linked respondents
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- Propensity scores from a logistic regression of W-2 linkage on a "typical" set of predictors
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Private-sector and government wage earners (ACS)





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#### PIK-induced bias in wage income by race/ethnicity



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#### Linkage-induced bias in wage income

Private-sector and government wage earners (ACS)





# Linkage-induced bias in wage income

Private-sector and government wage earners (ACS)





# Linkage-induced bias in wage income by race/ethnicity



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#### Discussion

Evidence of linkage-induced biases, even in settings with relatively high PIK rates

IPW tends to reduce linkage-induced bias, but does not necessarily eliminate it

- Underspecified models can fail to adjust for complex forms of selection into PIK assignment
  - The "basic" IPW specification accentuates linkage-induced bias for Hispanic workers
- Some evidence of instability



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Evidence of linkage-induced biases, even in settings with relatively high PIK rates

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#### Next steps

- 1. Incorporate additional correction techniques
  - Entropy balancing (Hainmueller, 2012; Bee et al., 2023)
  - Gradient-boosted IPW (McCaffrey, Ridgeway, and Morral, 2004; Cefalu et al., 2024)
  - Worst-case bounds for binary outcomes (Horowitz and Manski, 1995)
- 2. Extend analysis to the Current Population Survey (CPS)



# Thank you!

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# Appendix





















#### Black Asian AIAN SOR NHPI TOMR 2022 linkage rate = 79.62% \$5,000 \*+ + ++, ++, **∳**†\_ + **++**, . ♦♦. **₩ IPW** (basic) ++\_\_ **∳**∳⊥ Linked Bias (2022 dollars) \$0 IPW (full) -\$5,000 -\$10,000 2006 2010 2014 2018 2022 States

# Linkage-induced bias in wage income by race/ethnicity (other non-Hispanic groups)

DRB Clearance Numbers CBDRB-FY24-CES027-002 and CBDRB-FY24-CES027-006

#### Black Asian SOR NHPI TOMR AIAN 2022 linkage rate = 76.31% \$5,000 Linked IPW (basic) IPW (full) Bias (2022 dollars) \$0 -\$5,000 -\$10,000 2010 2006 2014 2018 2022 ted States<sup>®</sup>

#### Linkage-induced bias in wage income by race/ethnicity (other non-Hispanic groups)

#### Black NHPI Asian TOMR AIAN SOR 2022 linkage rate = 80.56% \$5,000 Linked **IPW** (basic) **IPW (full)** Bias (2022 dollars) \$0 -\$5,000 -\$10,000 2006 2010 2014 2018 2022 ted States<sup>®</sup>

#### Linkage-induced bias in wage income by race/ethnicity (other non-Hispanic groups)