

How Well Does Automated Linking Perform (in Historical Samples)? Lessons for Modern Practice

MARTHA BAILEY, UNIVERSITY OF MICHIGAN AND NBER

JOINT WORK WITH CONNOR COLE, MORGAN HENDERSON, AND CATHERINE MASSEY



Dynamic Questions

How has the human experience evolved and why?

What factors—environmental or human made—have interacted to improve well being or hold back economic development?

What have been the long-run effects of policies, innovations, environmental factors, and public health efforts?



Need for Dynamic Data

Dynamic questions relate to lives and experiences vary *across time*

Until recently, most U.S. data spanning the late 19th and 20th centuries were cross-sectional—individuals *at one point in time*

Need for Dynamic Data

Dynamic questions relate to lives and experiences vary *across time*

Until recently, most U.S. data spanning the late 19th and 20th centuries were cross-sectional—individuals *at one point in time*

New data include

- 1940 full-count census
- 1850-1930 IPUMS Linked Historical Samples (linked to 1880)
- Possible links of historical to modern data with ALIRA, CLIP, AoS
- LIFE-M links from vital records to 1880-1940 (coming 2020)

New Data Require New Tools

Management of (very) large and complex data

Tools to link data

Theoretical and econometric tools to *use* linked data *wisely*



Outline of Talk

Overview of historical linking methods

Summarize method performance in four datasets

Case study: IGE estimates for the 1940s

Suggestions for modern practice

Measuring intergenerational mobility c. 1940

$$\log (y_1) = \pi \log (y_0) + \varepsilon$$

π is interpreted as the intergenerational earnings elasticity

The larger π , the more persistent social class
and the less equal economic opportunity
($1-\pi$ is interpreted as the intergenerational mobility)

US Record Linkage (Early 20th Century)

STATE OF NEW YORK
 CERTIFICATE AND RECORD OF BIRTH
 No. of Certificate, 9529
 Name of child, Mary Elizabeth Reinble
 Signature, Mary Elizabeth Reinble
 Residence, 294 W. 116th St. N.Y.C.

Name, Mary Elizabeth Reinble
 Sex, Female
 Color, White
 Date of Birth, Feb 16th 1895
 Place of Birth, 294 W. 116th St. N.Y.C.
 Father's Name, John H. Reinble
 Residence, 294 W. 116th St. N.Y.C.
 Birthplace, Sweden
 Age, 35 1/2 yrs
 Occupation, Lawyer
 Mother's Name, Sabrina Reinble
 Residence, 294 W. 116th St. N.Y.C.
 Birthplace, Norway
 Age, 35 1/2 yrs
 How long in New York, 10 yrs
 Date of Birth, Feb 16th 1895



Date	LOCATION		HOUSEHOLD DATA				NAME	RELATION	PERSONAL DESCRIPTION			EDUCATION		PLACE OF BIRTH	
	Street, avenue, etc.	House number (or other address)	Number of household in care of	Married (M) or single (S)	Value of house, if owned, or monthly rent, if rented	Does this household pay as a household?			Sex	Color or race	Age at last birthday	Married, single, or widowed (M, S, W)	Highest grade of school completed	Country	State
1			2800	4200	no		Grof Ernst G	head	M	W	47	11	no	7	New Jersey
2							Leathams @	wife	F	W	47	11	no	7	New Jersey
3							Ernst Jr	son	M	W	21	8	no	44	New Jersey
4							Thelma K	daughter	F	W	18	8	no	44	New Jersey
5							Giacomo Antonello	father-in-law	M	W	77	12	no	6	Italy
6			2810	6200	no	yes	Hernandez Paul E	head	M	W	54	10	no	8	Switzerland
7							Erna E	daughter	F	W	19	8	no	4	New Jersey
8			220	3000	no		Threlfal Thomas	head	M	W	54	11	no	8	New Jersey
9							Maria @	wife	F	W	44	11	no	6	New Jersey
10							Ruth	daughter	F	W	31	8	no	12	New Jersey
11							Fanny	daughter	F	W	26	8	no	14	New Jersey
12							Maria	daughter	F	W	18	8	no	14	New Jersey

US Record Linkage (Early 20th Century)

Problems

1. Misreports by individual
2. Errors in enumeration
3. Errors in transcription

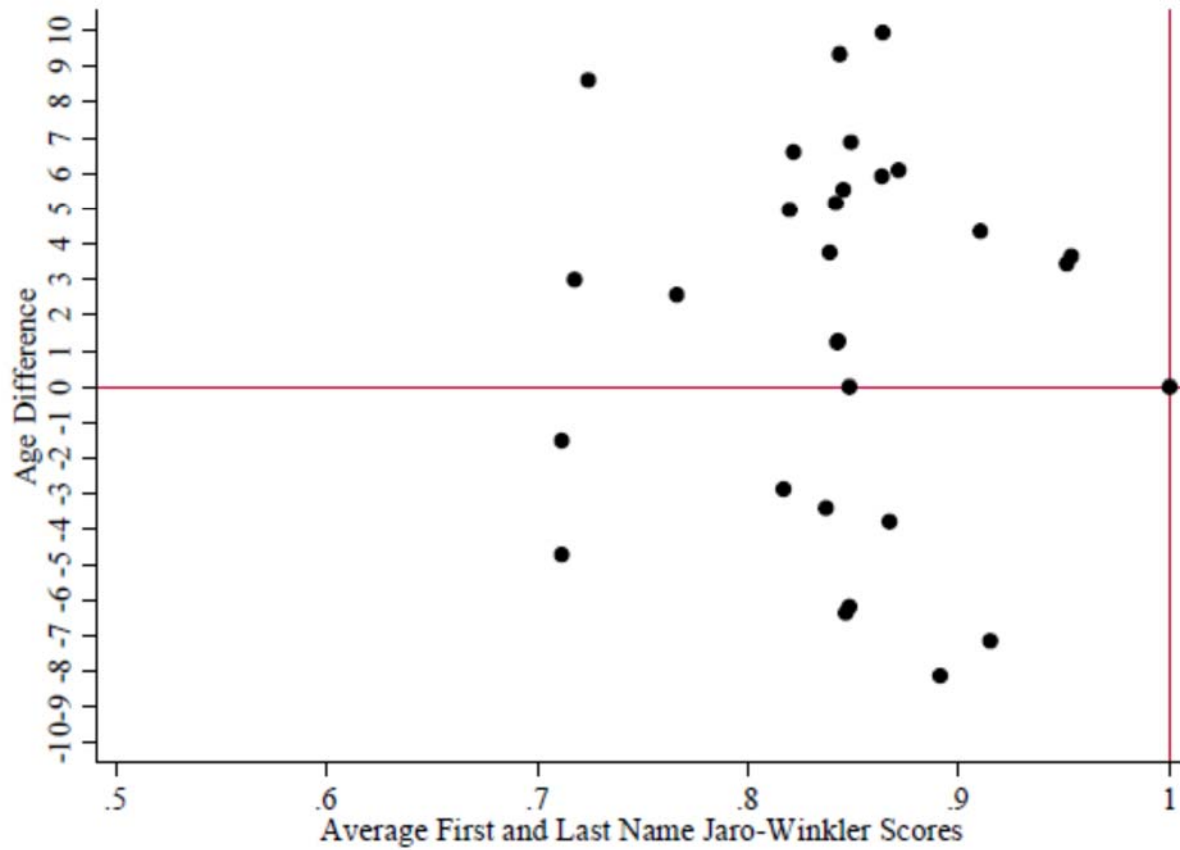
Table No.	LOCATION		HOUSEHOLD DATA				NAME	RELATION	PERSONAL DESCRIPTION					EDUCATION	PLACE OF BIRTH	
	Street, avenue, etc.	House number (or other address)	Number of household in care of	Household (O) or room (R)	Value of house, if owned, or monthly rent, if rented	Does this household pay to a "board" (Yes or No)			Sex-Male (M), Female (F)	Color or race	Age at last birthday	Married, never-married, widowed, divorced, separated (M, F, S, D, W, S, D, W)	Always in school or college, or the last school attended (Year or Month and Year)		Highest grade of school completed	CODE (Leave blank)
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
1			2800	4200	no	Grof. Ernest G	head	M	W	47	M	no	7	2	New Jersey	
2						Leathams @	wife	F	W	47	M	no	7	2	New Jersey	
3						Ernest Jr	son	M	W	21	S	no	H4	2	New Jersey	
4						Thelma K	daughter	F	W	18	S	no	H4	2	New Jersey	
5						Giacomo Antonello	father-in-law	M	W	77	W2	no	6	6	Italy	
6			281 D	5 20	no	Hernandez Paul E	head	M	W	54	W1	no	8	7	Switzerland	
7						Erna E	daughter	F	W	19	S	no	H4	2	New Jersey	
8			22 D	3000	no	Threlfal Thomas	head	M	W	54	M	no	8	7	New Jersey	
9						Maria @	wife	F	W	44	M	no	6	7	New Jersey	
10						Ruth	daughter	F	W	31	S	no	H2	7	New Jersey	
11						Fanny	daughter	F	W	26	S	no	H4	7	New Jersey	
12						Maria	daughter	F	W	18	S	no	H4	7	New Jersey	

What Record Linking Algorithms Do

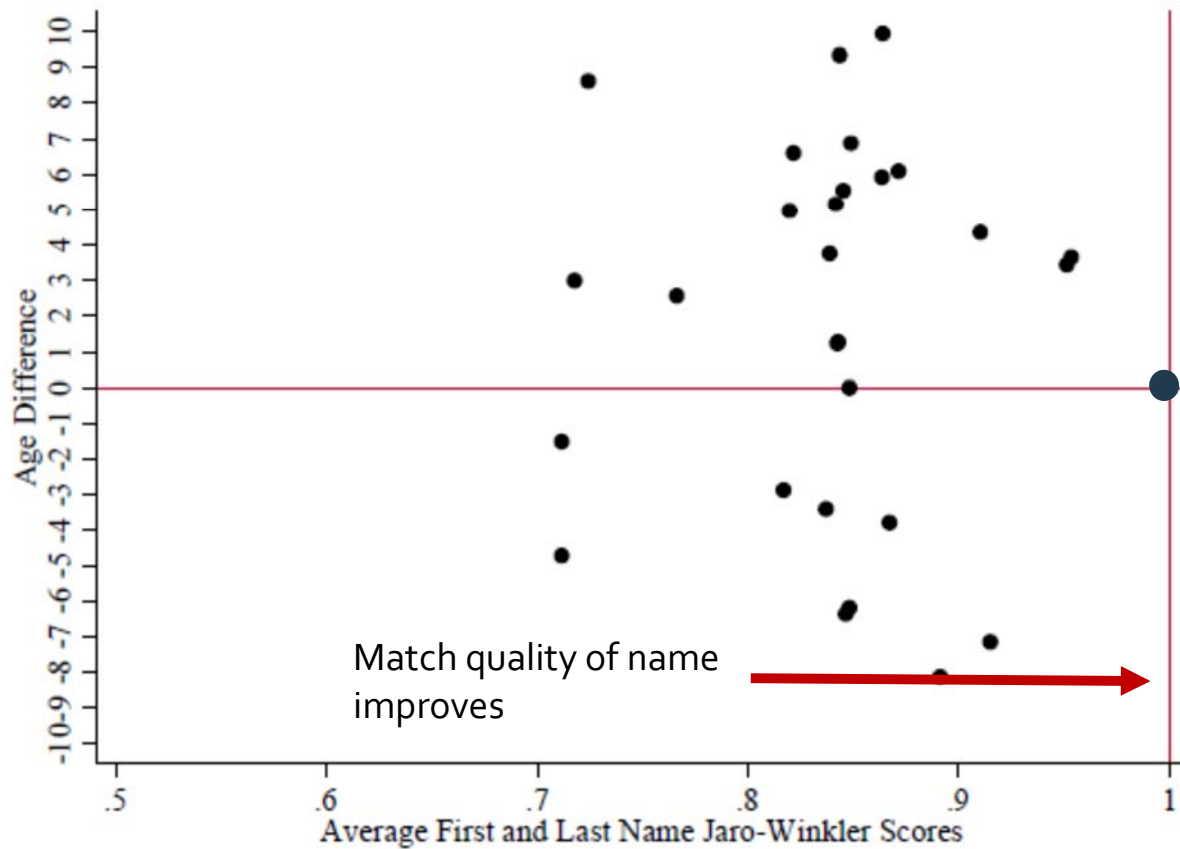
LINKING TO US CENSUS DATA



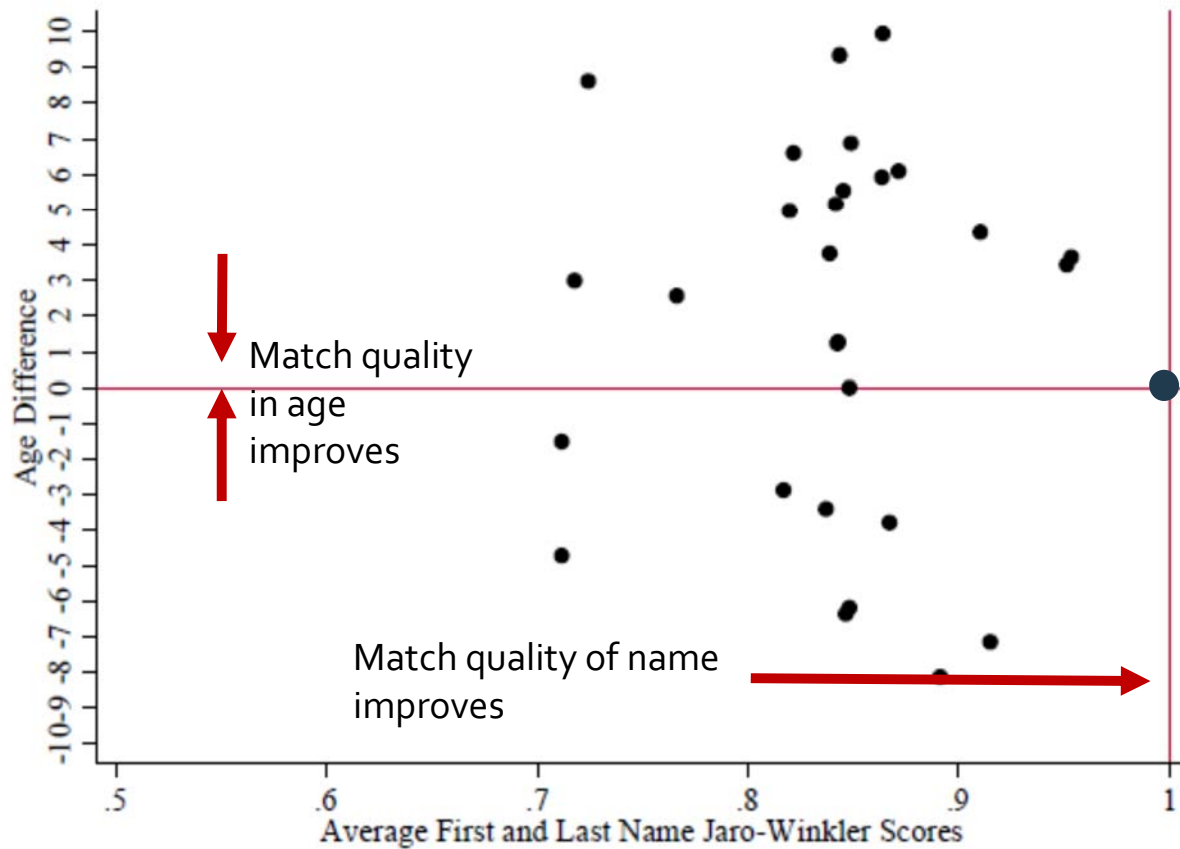
Example Matching Problem



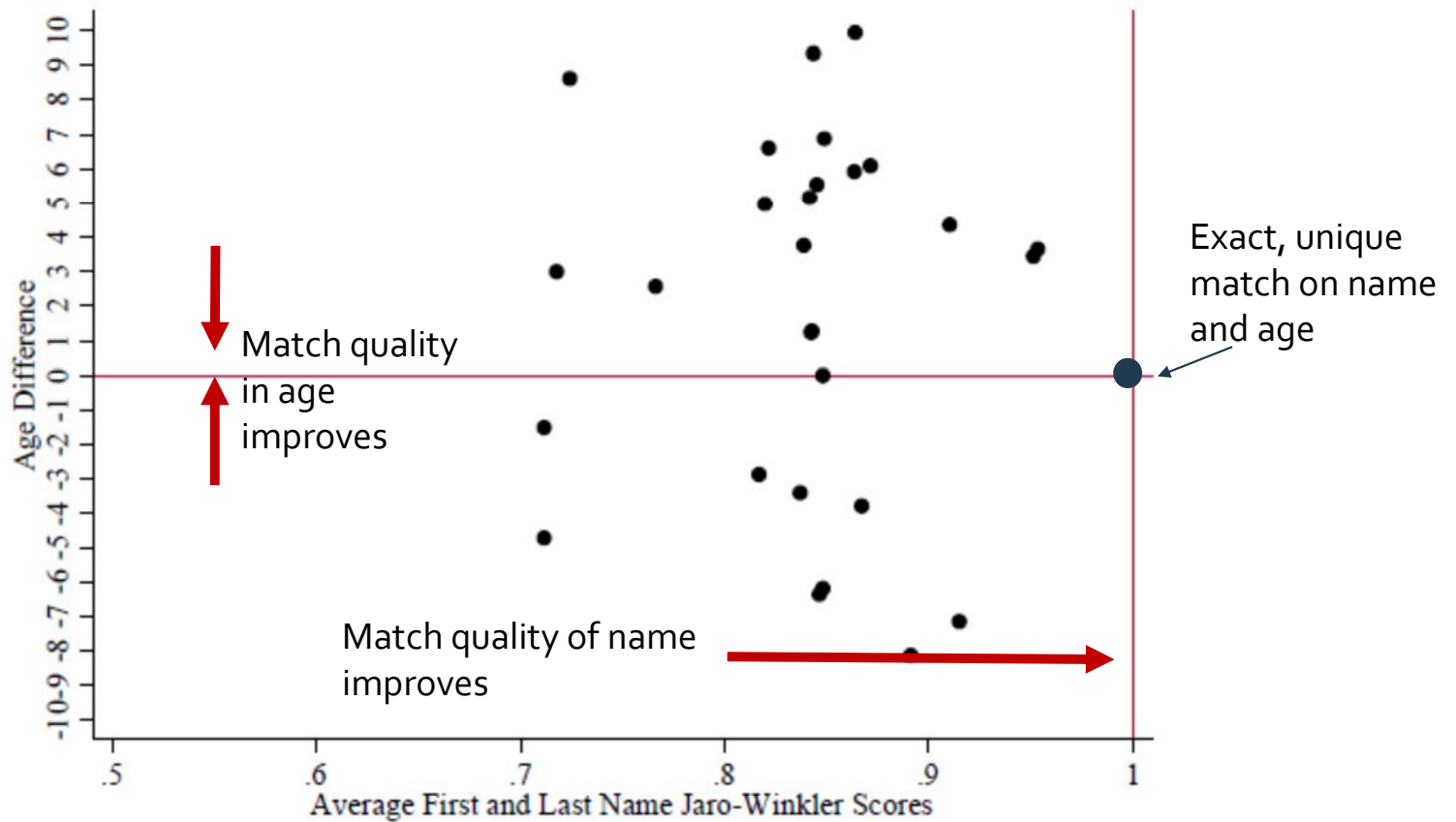
Example Matching Problem



Example Matching Problem



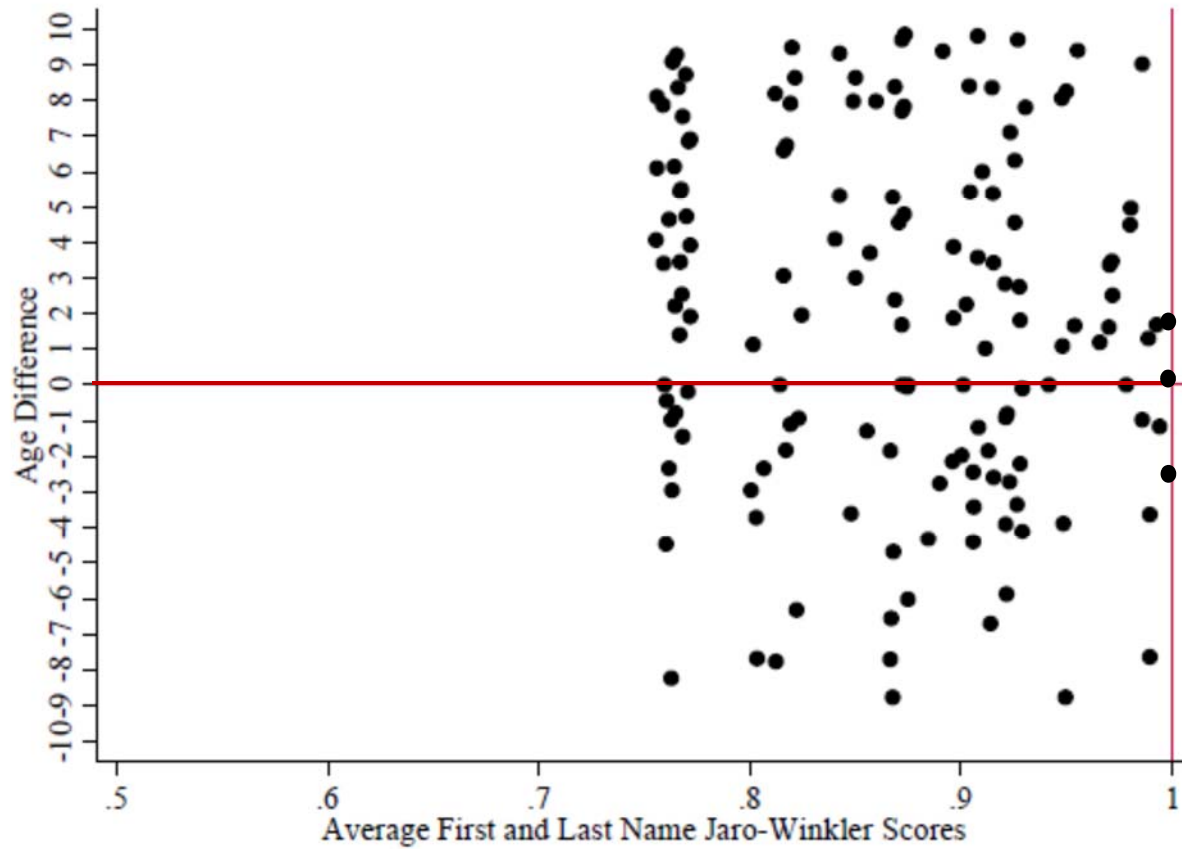
Example Matching Problem



Ferrie (1996)

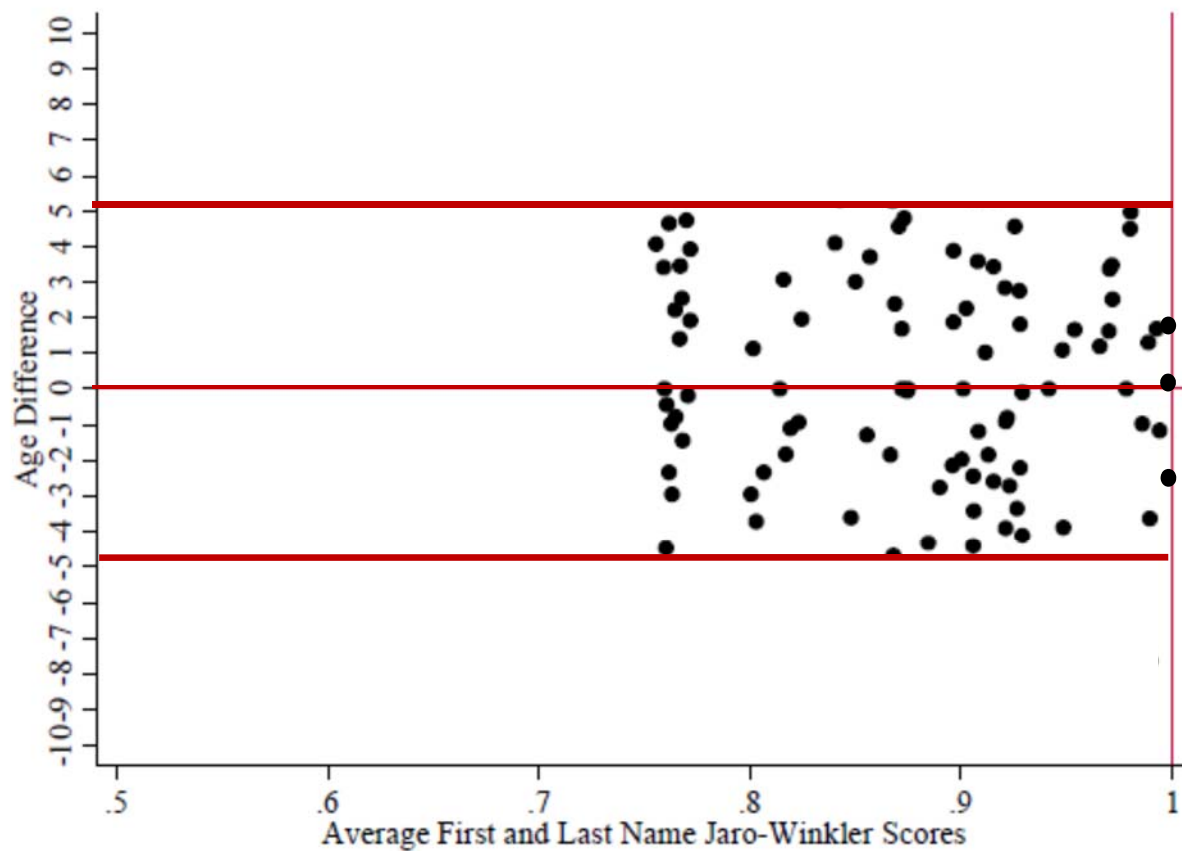


Ferrie (1996)



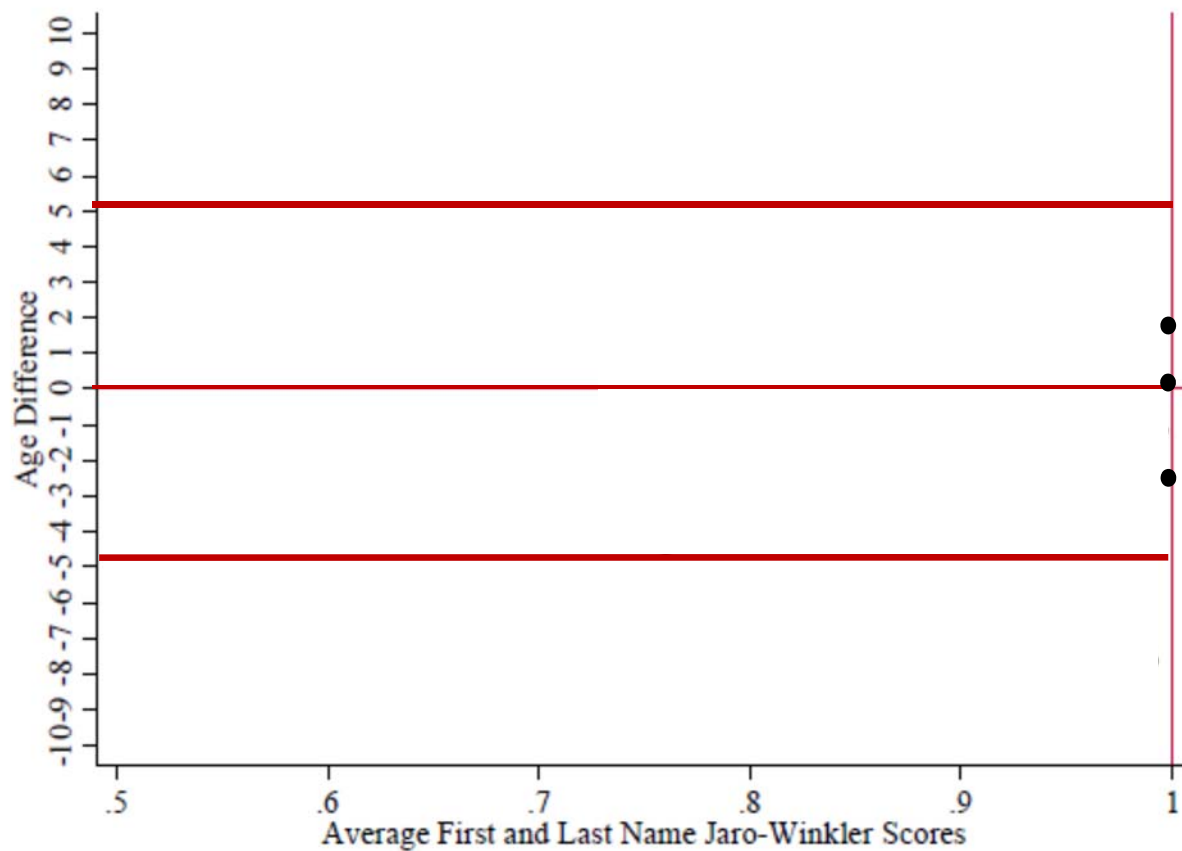
1. Uses uncommon name sample

Ferrie (1996)



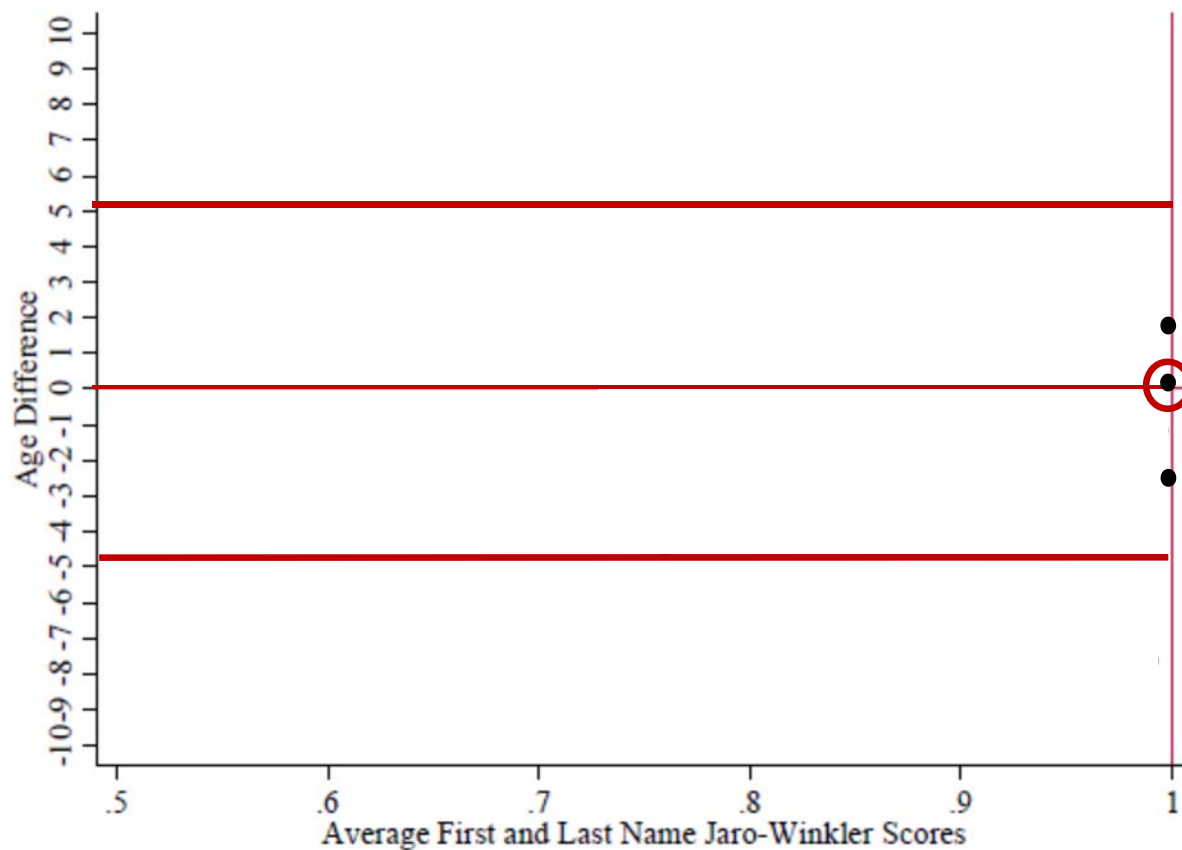
1. Uses uncommon name sample
2. Restricts age difference to be +/-5

Ferrie (1996)



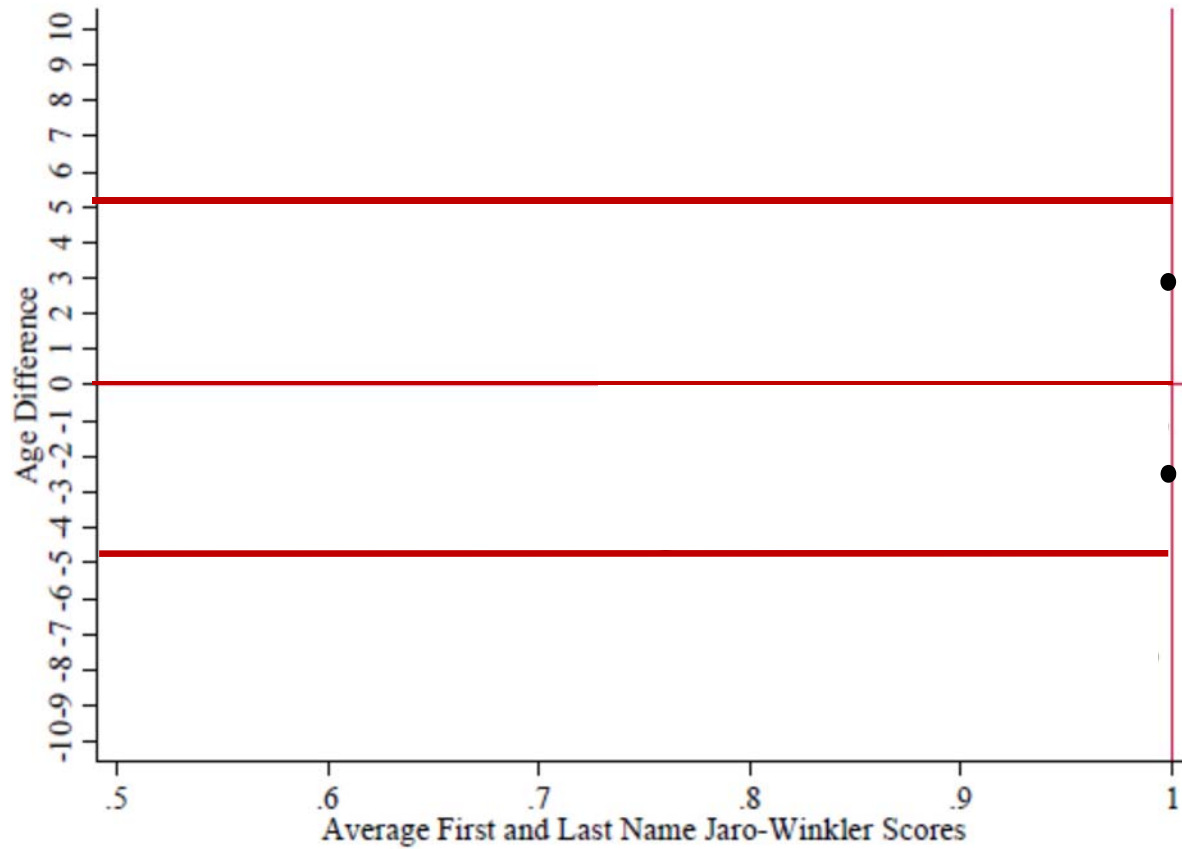
1. Uses uncommon name sample
2. Restricts age difference to be +/-5
3. Finds exact name matches

Ferrie (1996)



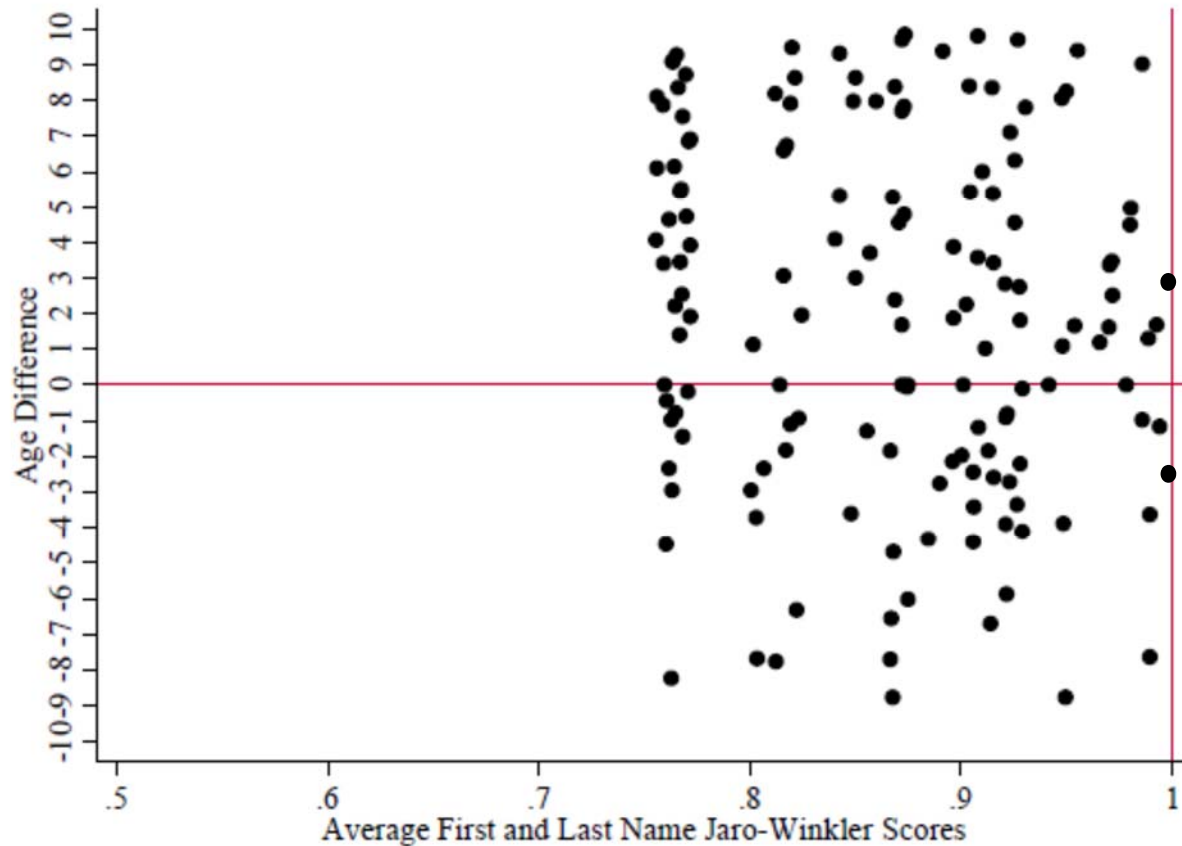
1. Uses uncommon name sample
2. Restricts age difference to be +/-5
3. Finds exact name matches
4. Minimizes age difference

Ferrie (1996)



5. No match chosen when ties

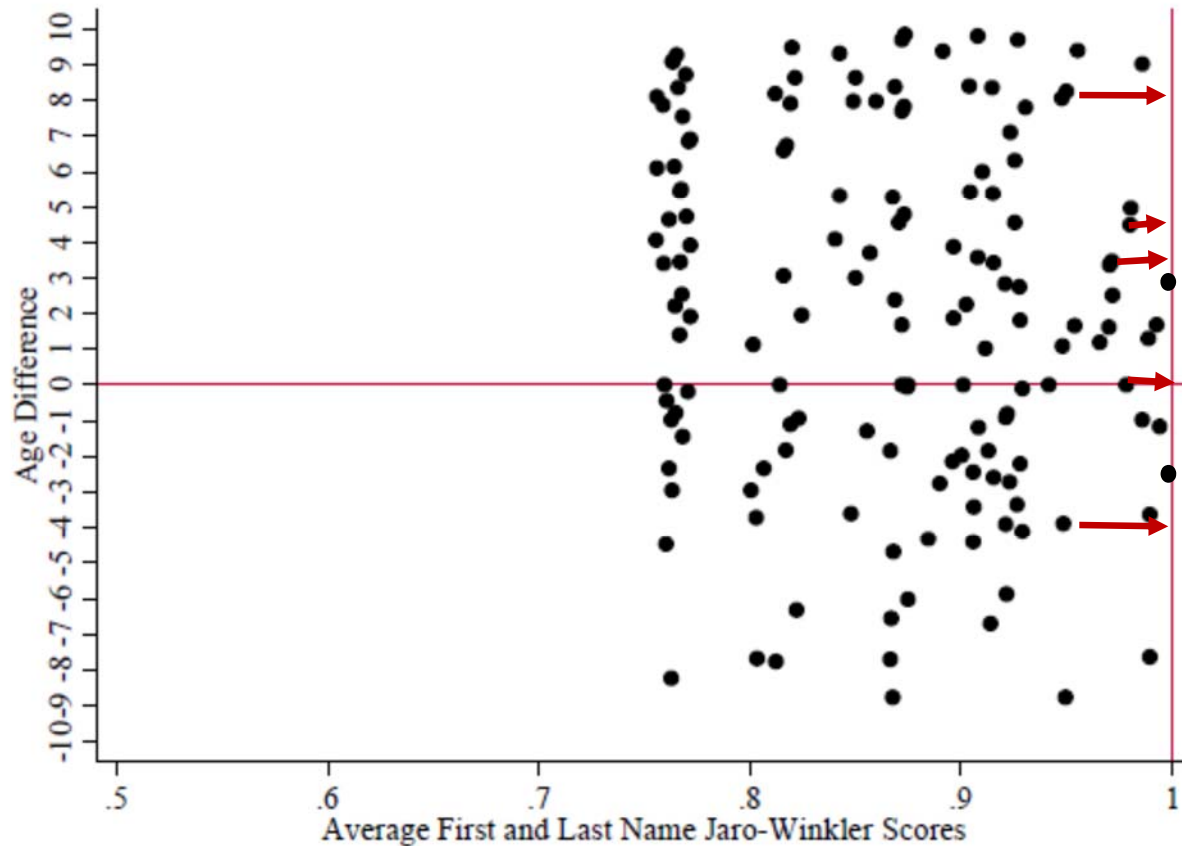
Phonetic Name Cleaning



Soundex and NYSIIS

- Soundex: "Smith," "Smyth" and "Smythe" to the same code (S530)
- NYSIIS: "Wilhem" and "William" to WALAN

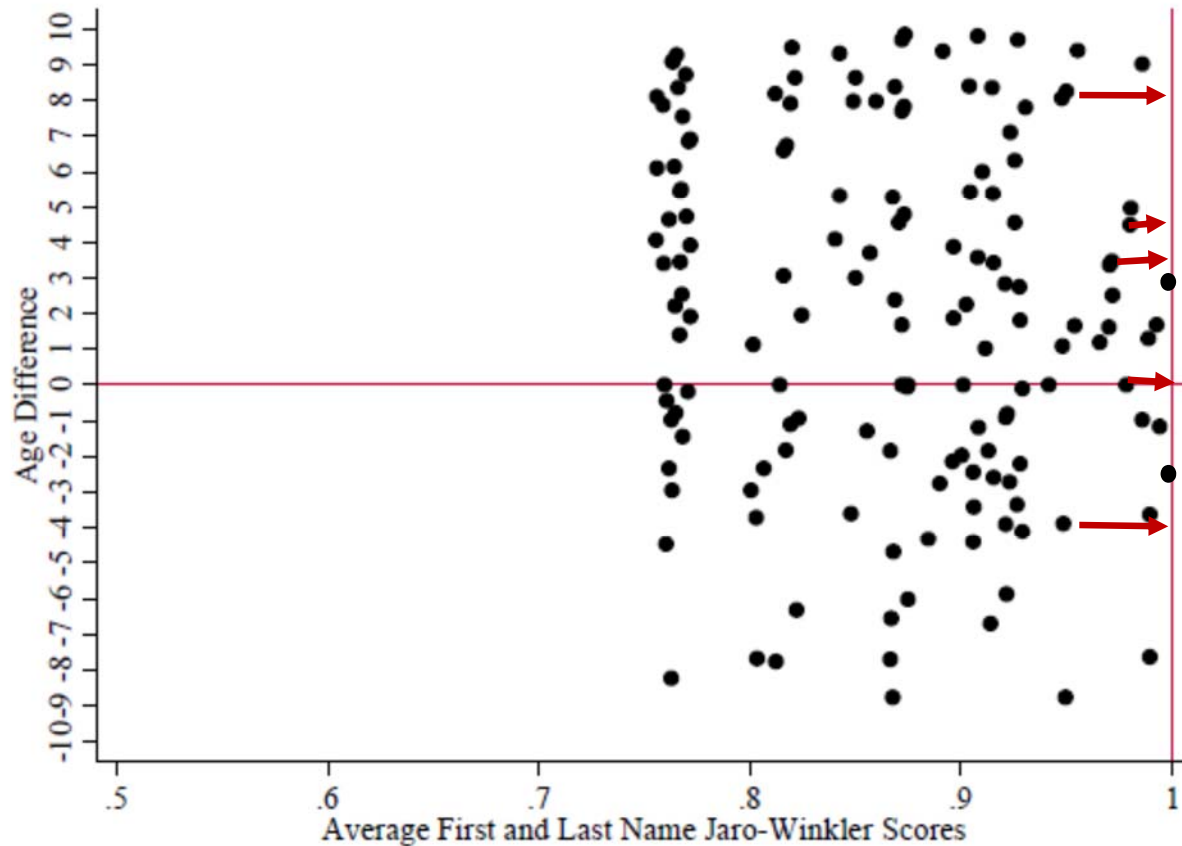
Phonetic Name Cleaning



Soundex and NYSIIS

- Soundex: "Smith," "Smyth" and "Smythe" to the same code (S530)
- NYSIIS: "Wilhem" and "William" to WALAN

Phonetic Name Cleaning

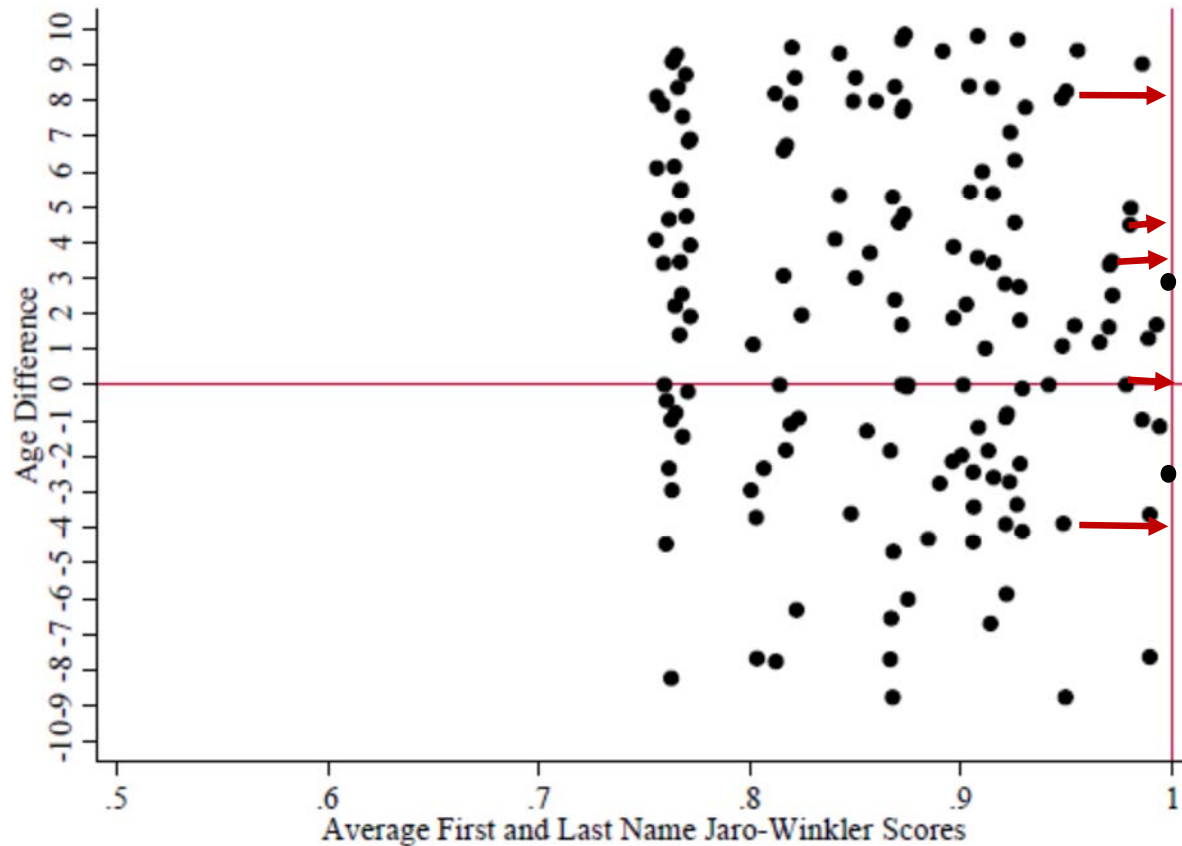


Soundex and NYSIIS

- Soundex: "Smith," "Smyth" and "Smythe" to the same code (S530)
- NYSIIS: "Wilhem" and "William" to WALAN

Ferrie (1996) uses NYSIIS

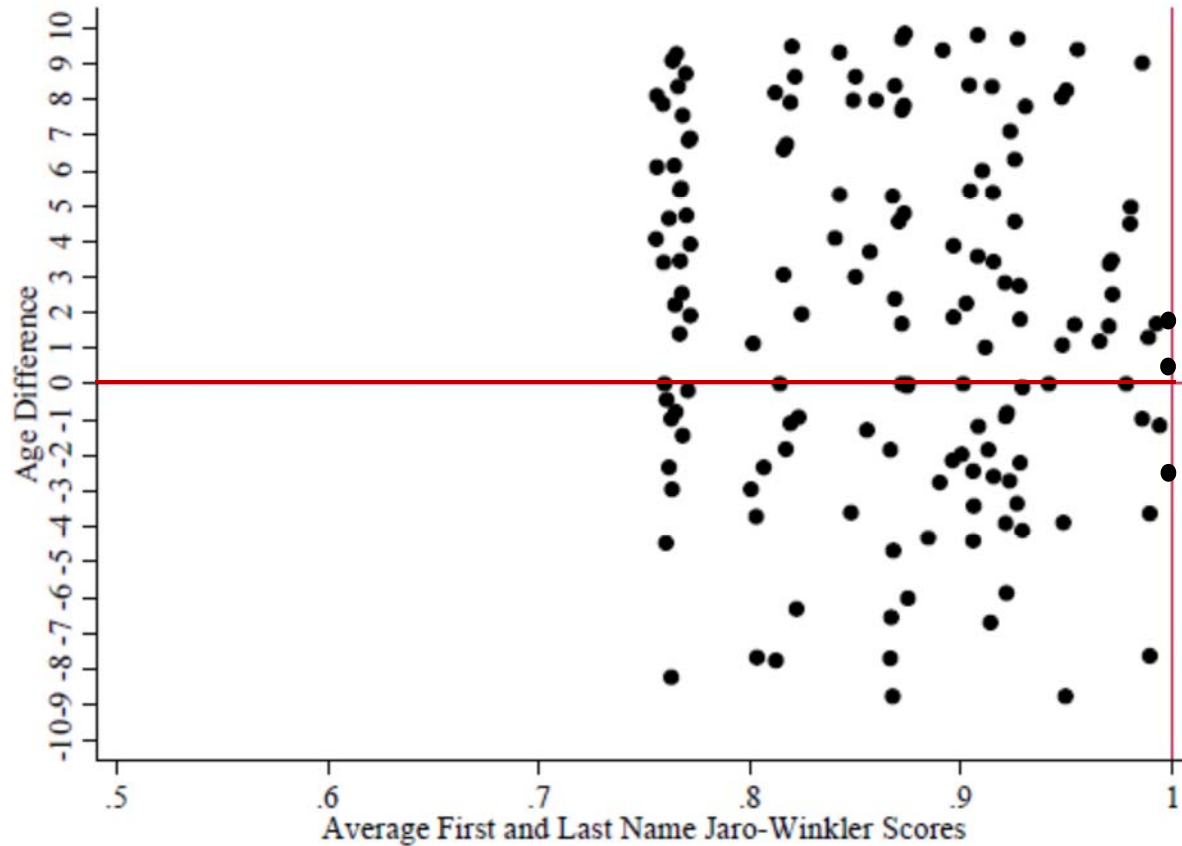
Phonetic Name Cleaning



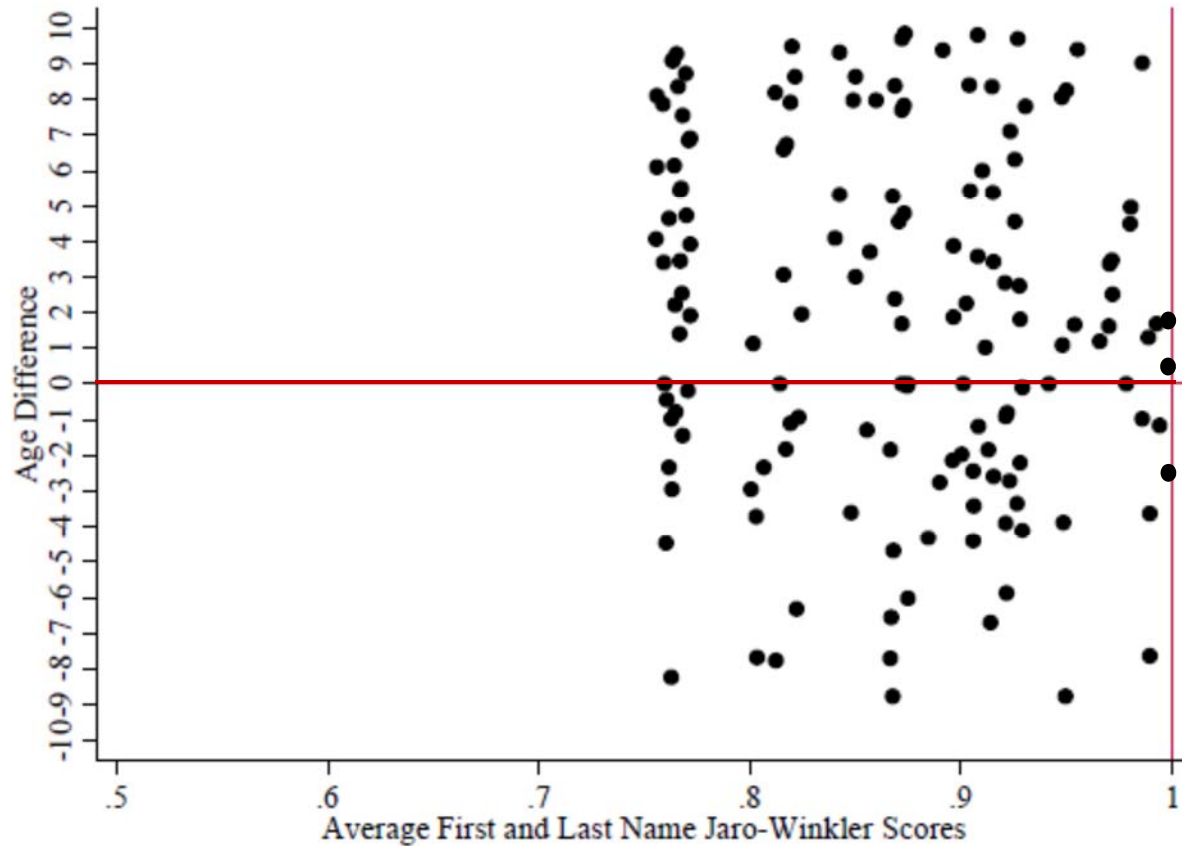
Soundex and NYSIIS

- may increase the number match candidates
- may worsen name matching
- may increase problems with match ties

Abramitzky, Boustan, and Erickson (2012)

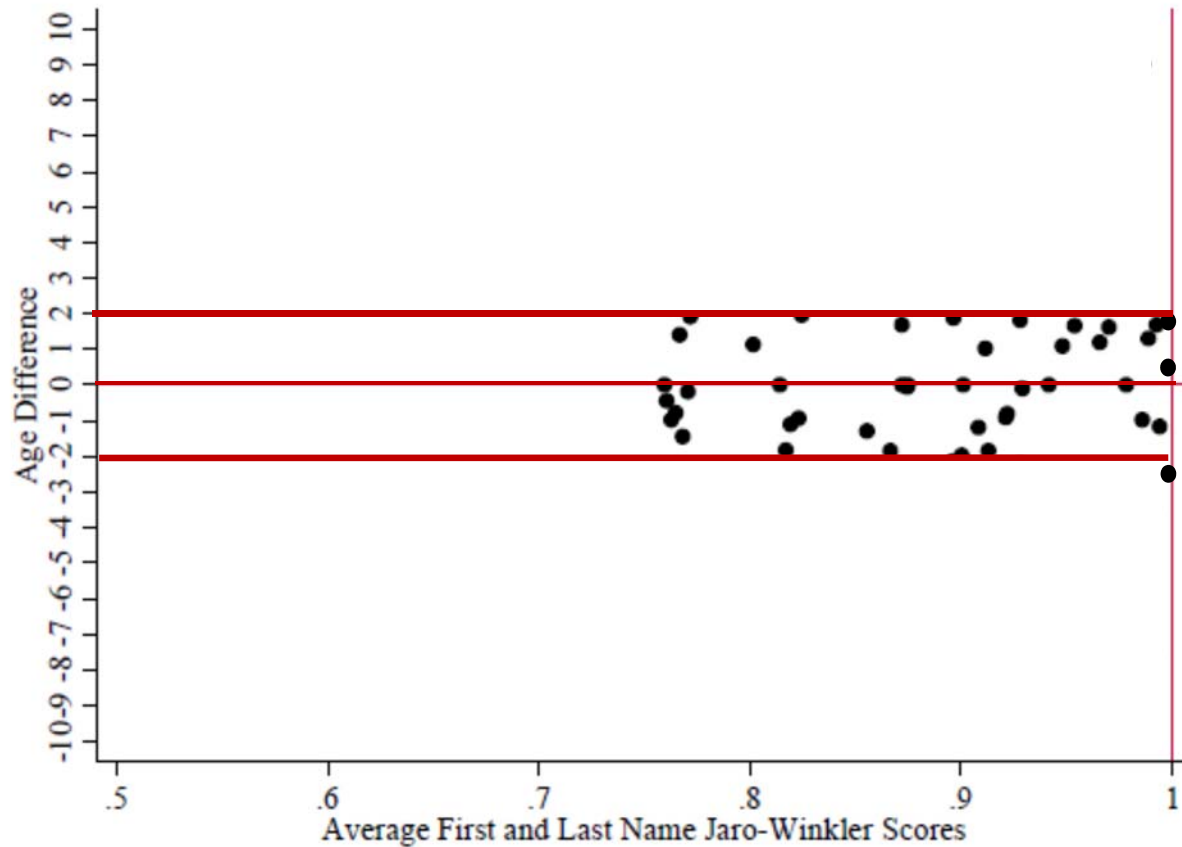


Abramitzky, Boustan, and Erickson (2012)



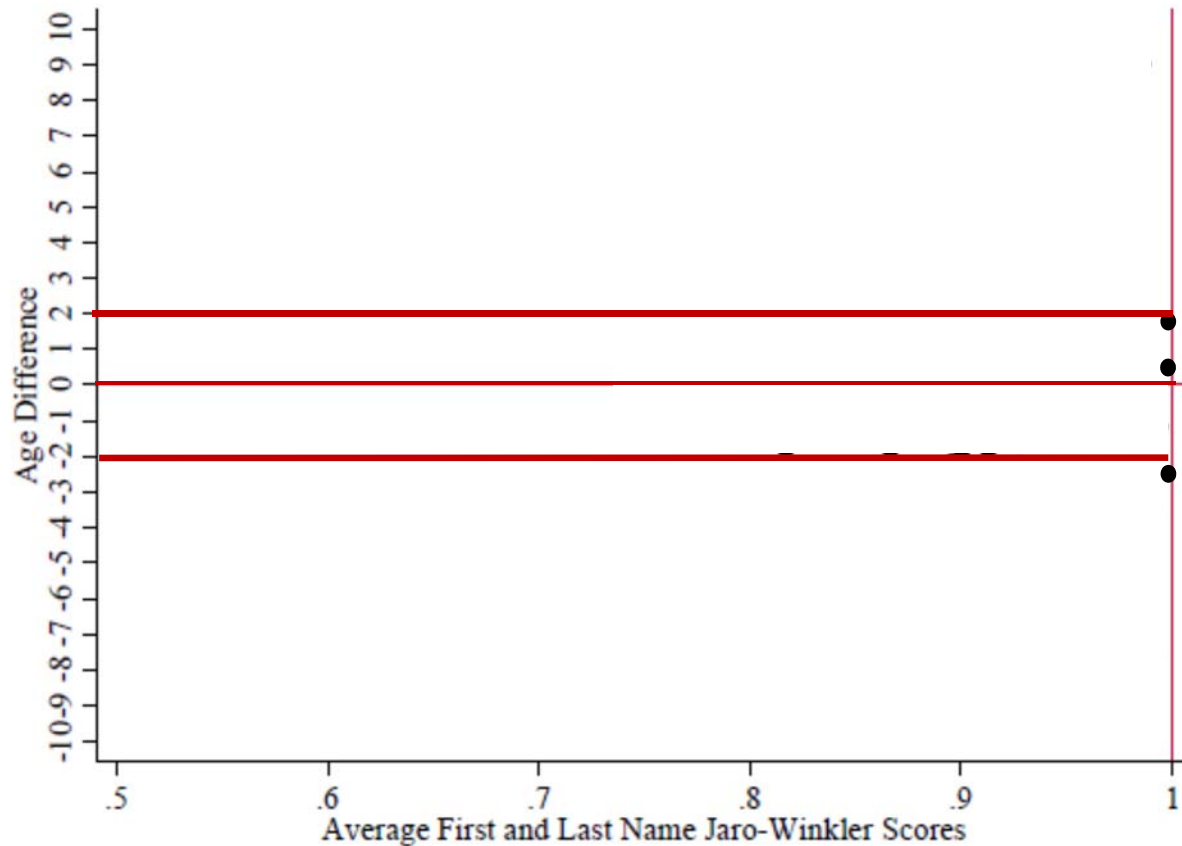
1. Keeps common names

Abramitzky, Boustan, and Erickson (2012)



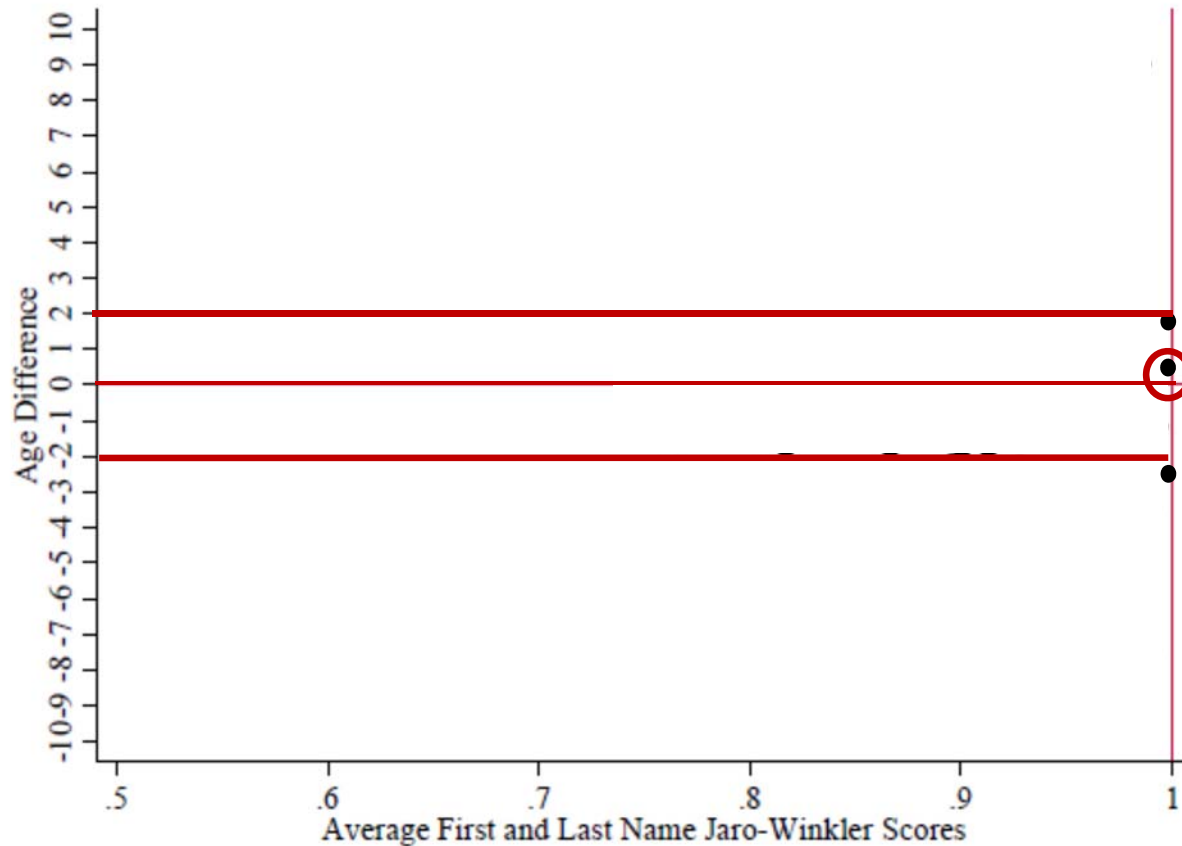
1. Keeps common names
2. Restricts age difference to be +/-2

Abramitzky, Boustan, and Erickson (2012)



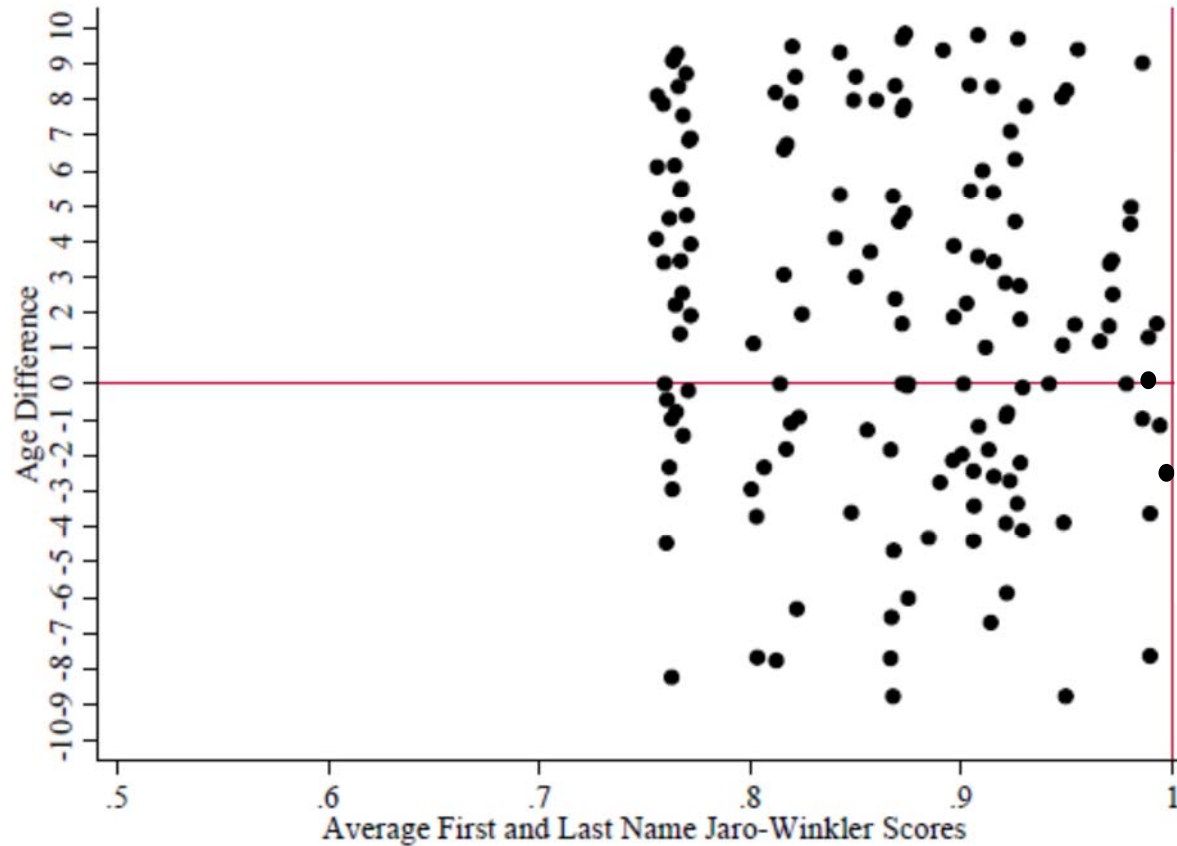
1. Keeps common names
2. Restricts age difference to be +/-2
3. Finds exact name matches (NYSIIS)

Abramitzky, Boustan, and Erickson (2012)



1. Keeps common names
2. Restricts age difference to be +/-2
3. Finds exact name matches (NYSIIS)
4. Searches iteratively +1, -1, +2, -2, etc. over age difference
5. No match chosen with multiples

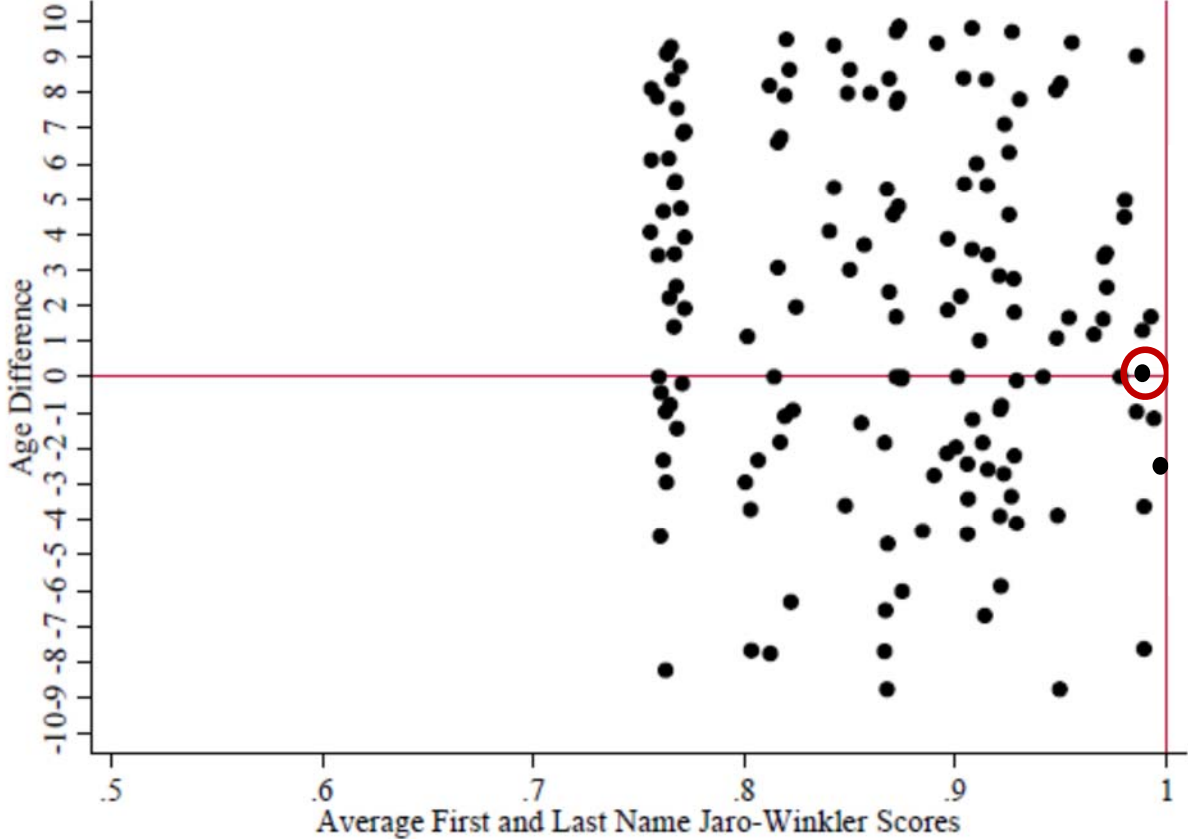
Trade-Offs: Age vs. Name Similarity?



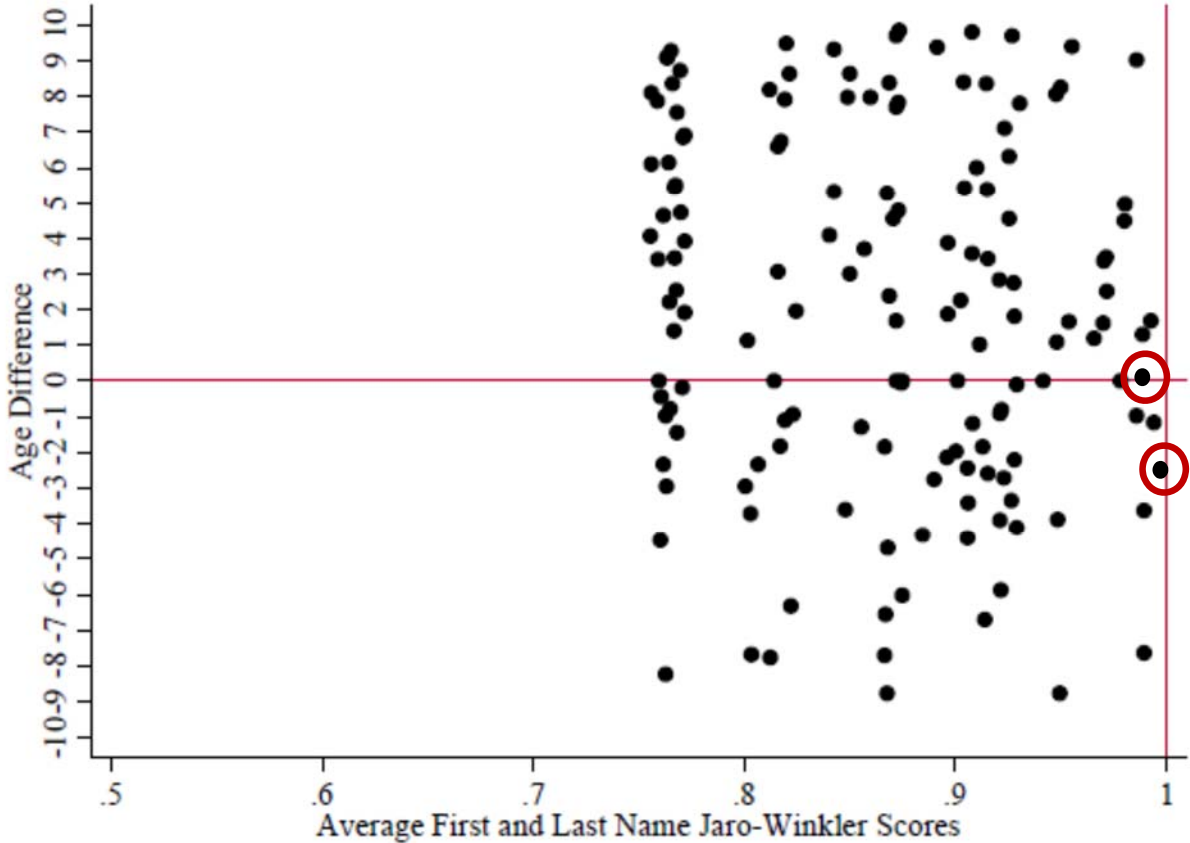
Trade-Offs: Age vs. Name Similarity?



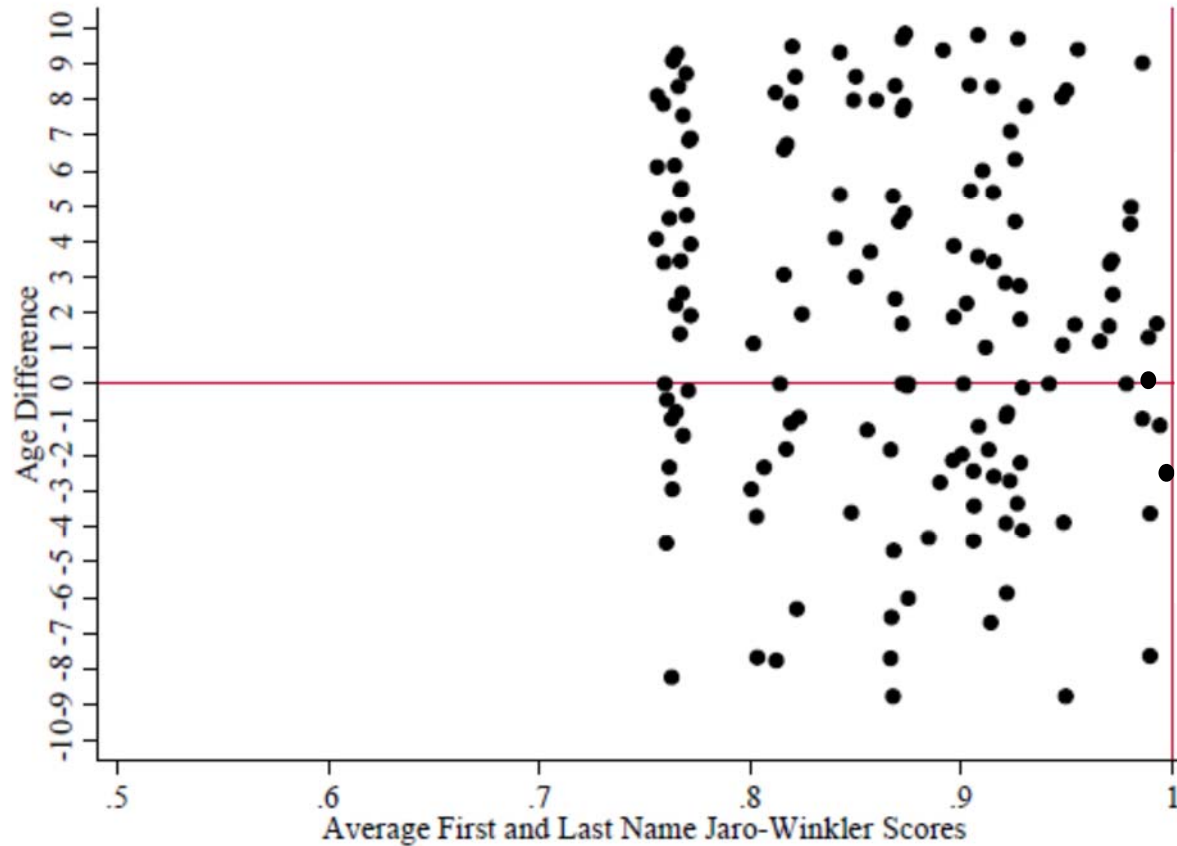
Trade-Offs: Age vs. Name Similarity?



Trade-Offs: Age vs. Name Similarity?



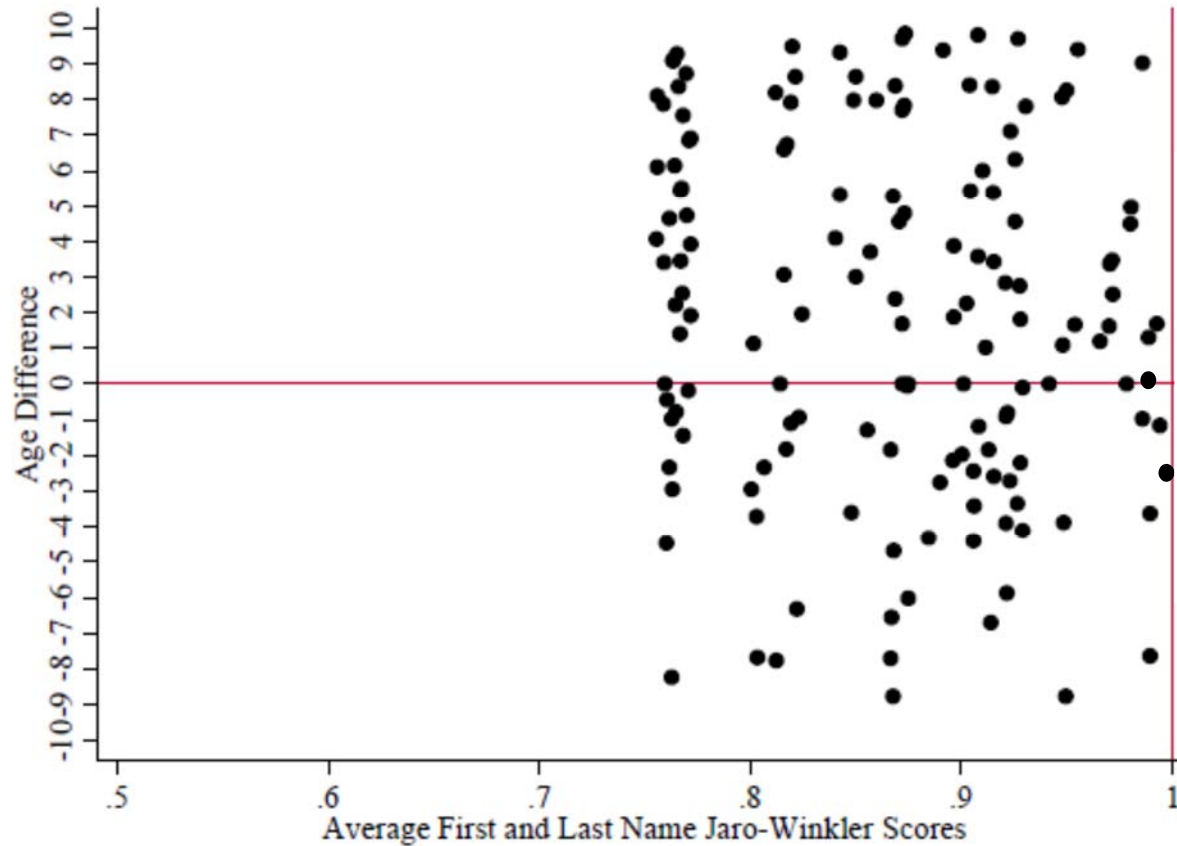
Trade-Offs: Age vs. Name Similarity?



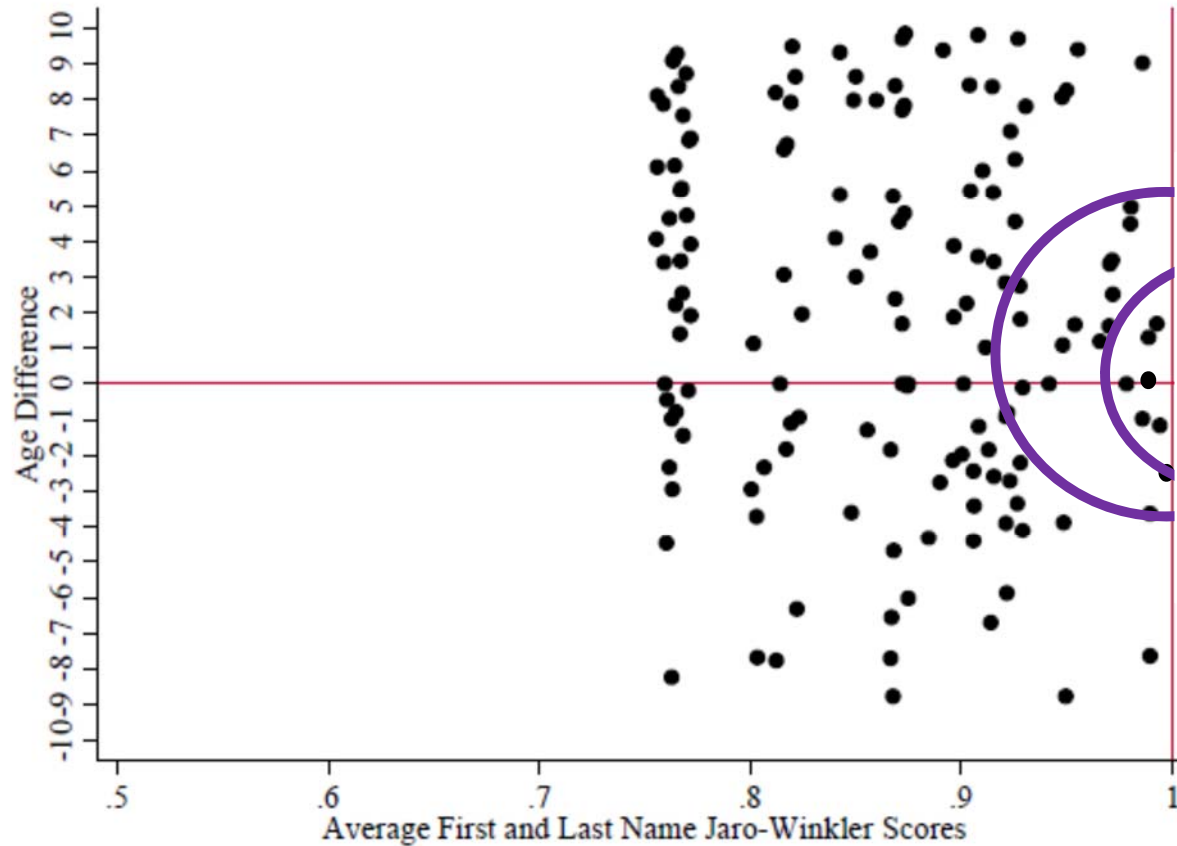
Trade-Offs: Age vs. Name Similarity?



Trade-Offs: Age vs. Name Similarity?



Trade-Offs: Age vs. Name Similarity?



Machine Learning

Key idea: use information in a “truth dataset” to “train” a model to classify links

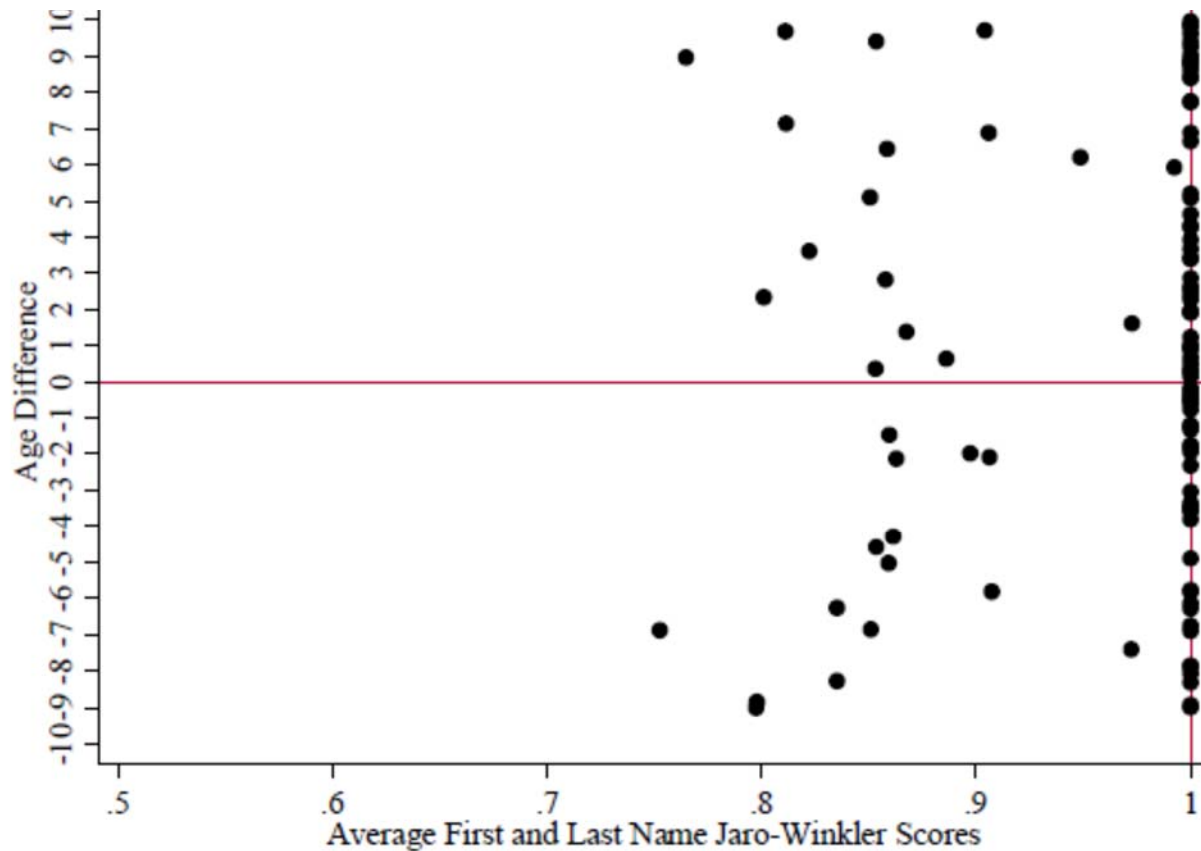
Machine Learning

Key idea: use information in a “truth dataset” to “train” a model to classify links

IPUMS Linked Historical samples uses a SVM to model trade-offs in multiple dimensions

Feigenbaum (2016) “regression-based” method to model trade-offs in multiple dimensions

Final Frontier: How to Choose Among Ties?



Choosing among (Exact) Ties

Exact ties in name-age: ~20 to 35 percent of U.S. samples; higher in some subsamples

Choosing among (Exact) Ties

Exact ties in name-age: ~20 to 35 percent of U.S. samples; higher in some subsamples

Statistics literature suggests probabilistic weighting:

- For exact ties, weight by $p=1/m$ (where m =number of ties)

Choosing among (Exact) Ties

Exact ties in name-age: ~20 to 35 percent of U.S. samples; higher in some subsamples

Statistics literature suggests probabilistic weighting:

- For exact ties, weight by $p=1/m$ (where m =number of ties)

Nix and Qian (2015) suggest random selection among ties

Choosing among (Exact) Ties

Exact ties in name-age: ~20 to 35 percent of U.S. samples; higher in some subsamples

Statistics literature suggests probabilistic weighting:

- For exact ties, weight by $p=1/m$ (where m =number of ties)

Nix and Qian (2015) suggest random selection among ties

➔ Assuming one of ties is correct, expected number of “wrong links” is the *same* for both methods

Method Performance

MATCH RATES AND REPRESENTATIVENESS



Method Performance

MATCH RATES AND REPRESENTATIVENESS

INCIDENCE OF TYPE I ERRORS



Method Performance

MATCH RATES AND REPRESENTATIVENESS

INCIDENCE OF TYPE I ERRORS

INCIDENCE OF TYPE II ERRORS



Ground Truth Samples

1. LIFE-M data
2. Synthetic data
3. Early Indicators data
4. IPUMS Historical Linked Censuses, 1850-1900

LIFE-M :

NC & Ohio Boys linked to 1940 Census

Births Records

1. Random samples of NC and Ohio birth certificates from 1909-20
2. Add in all siblings

N=45,442



1940 Census

birth place*, age*,
name*,
education, wages

LIFE-M Linking Process

1. Every link reviewed by two independent “data trainers”
2. Agreements assumed to be correct

LIFE-M Linking Process

1. Every link reviewed by two independent “data trainers”
2. Agreements assumed to be correct
3. Disagreements send records to *re*-review by an additional three individuals to resolve these discrepancies

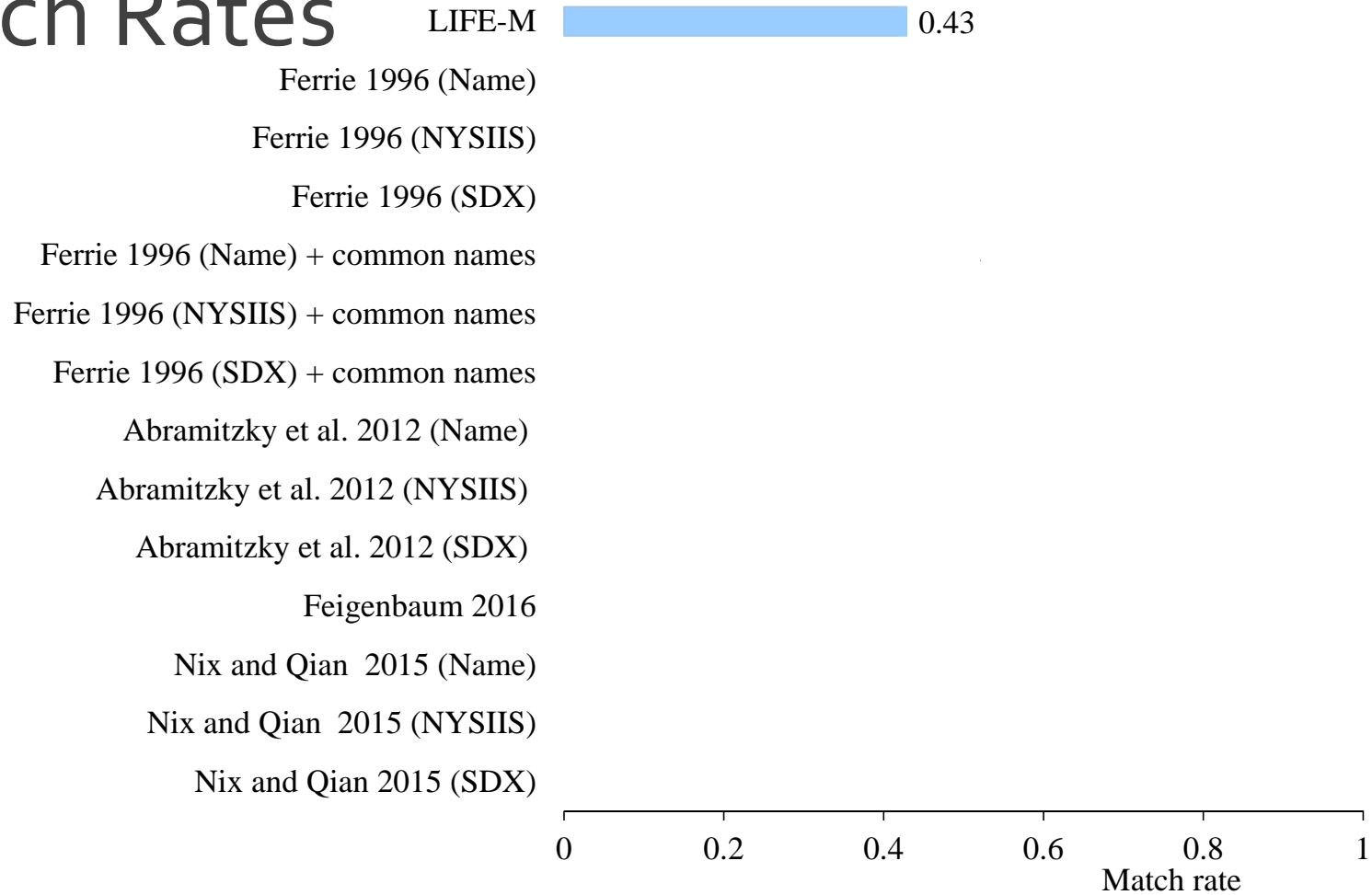
LIFE-M Linking Process

1. Every link reviewed by two independent “data trainers”
2. Agreements assumed to be correct
3. Disagreements send records to *re*-review by an additional three individuals to resolve these discrepancies
4. “Audit batches” and weekly meetings help maintain quality

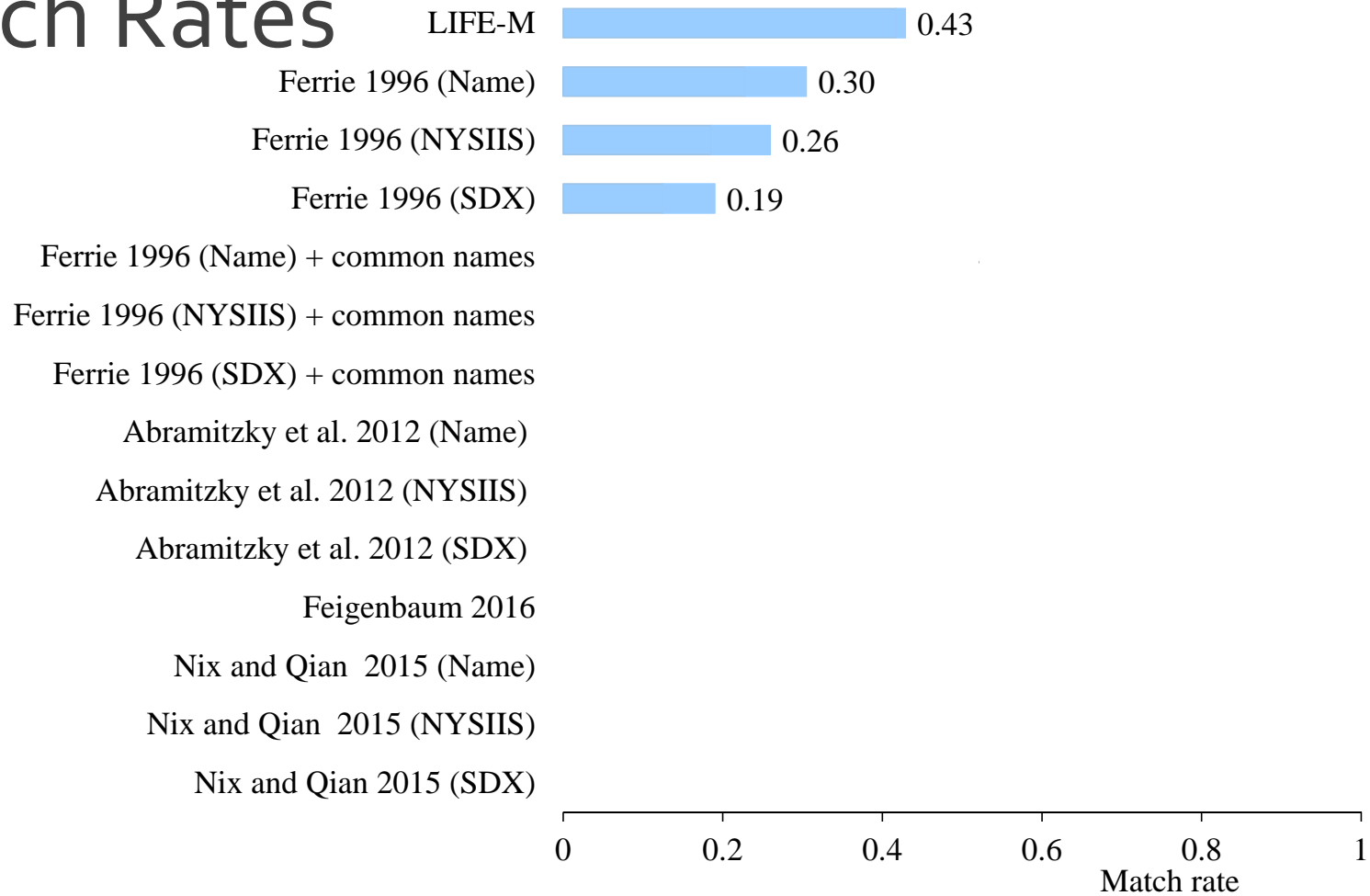
LIFE-M Linking Process

1. Every link reviewed by two independent “data trainers”
2. Agreements assumed to be correct
3. Disagreements send records to *re*-review by an additional three individuals to resolve these discrepancies
4. “Audit batches” and weekly meetings help maintain quality
5. Independent validation of links by BYU agrees 96% of the time

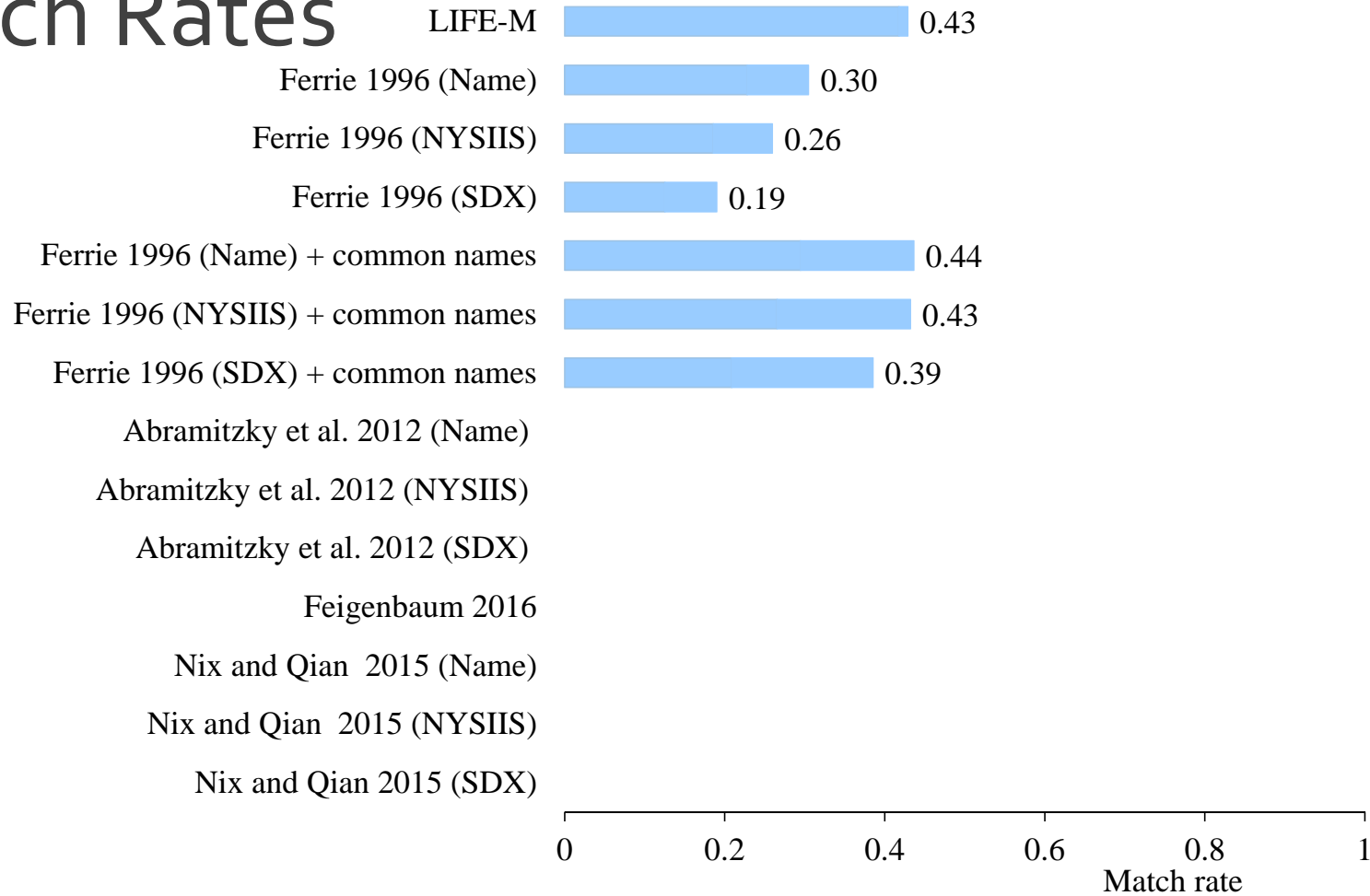
Match Rates



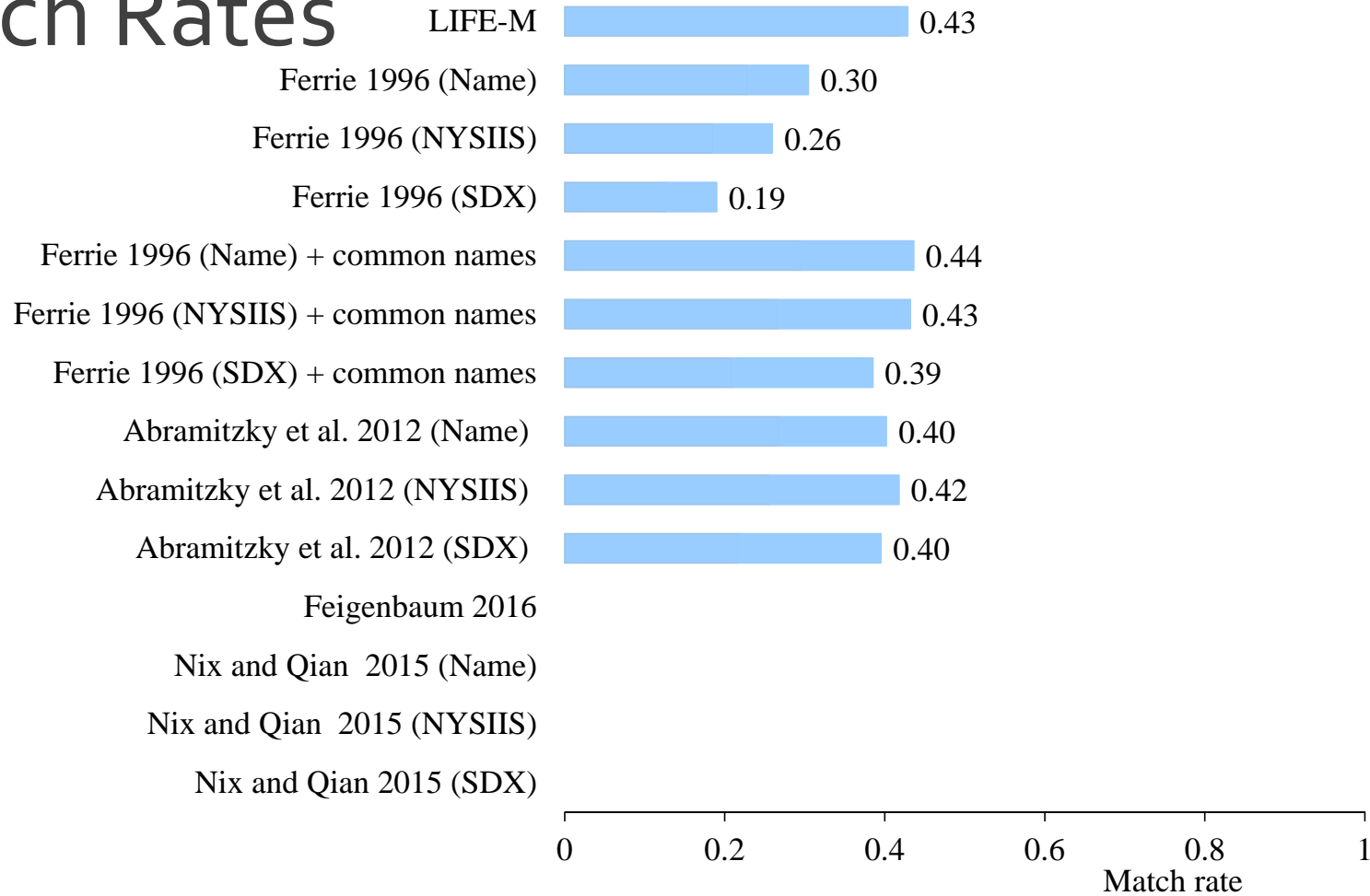
Match Rates



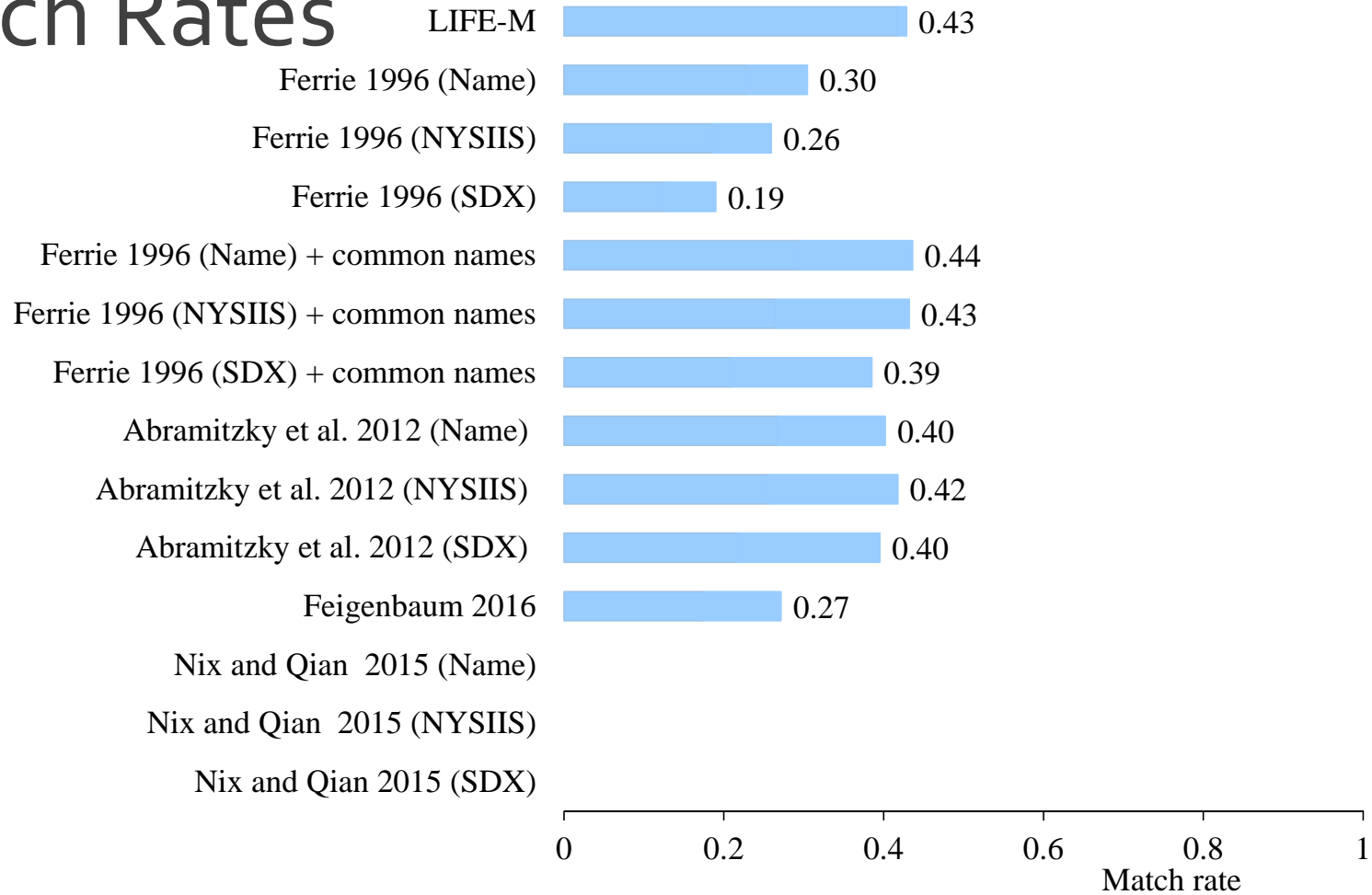
Match Rates



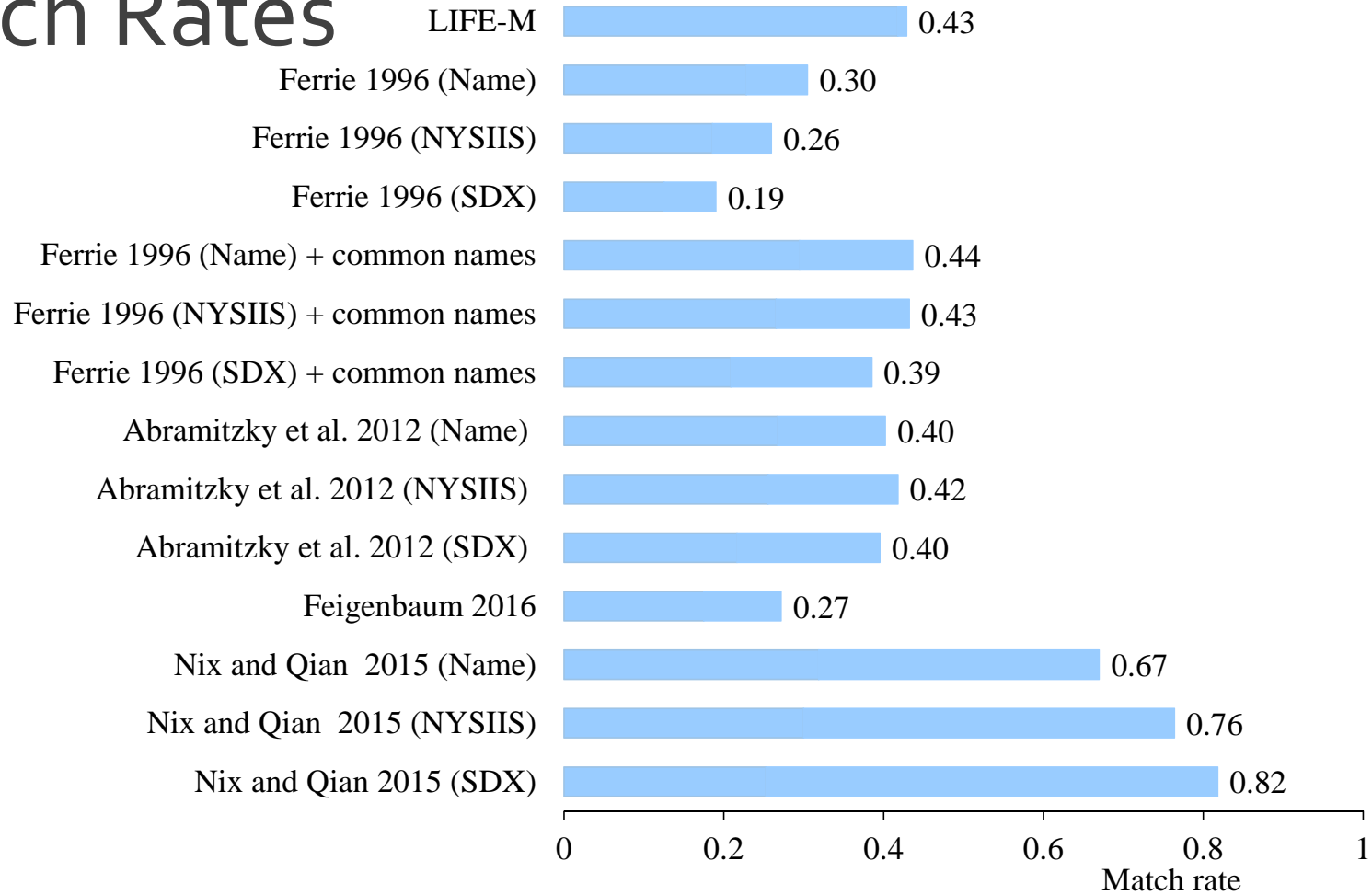
Match Rates



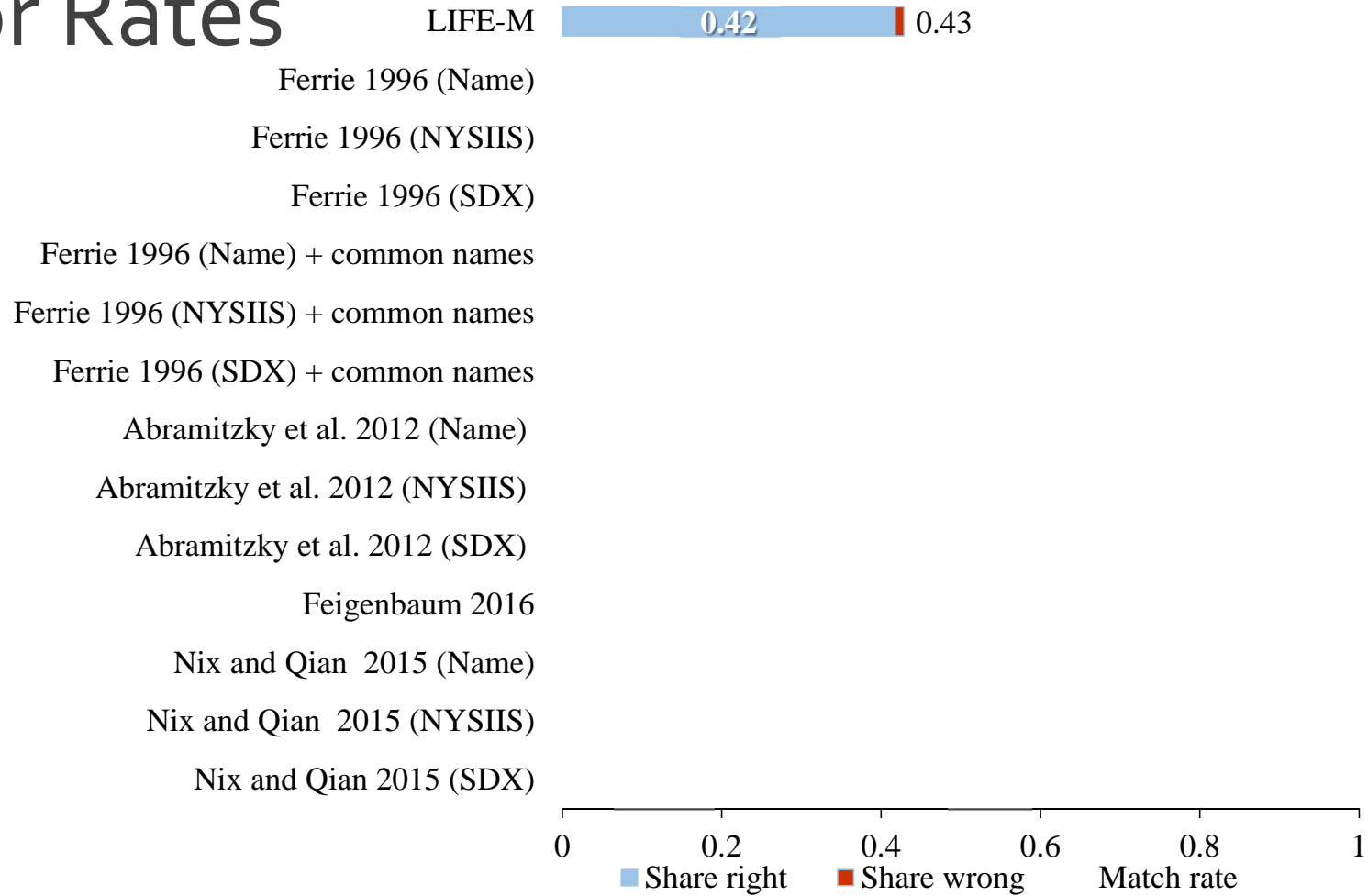
Match Rates



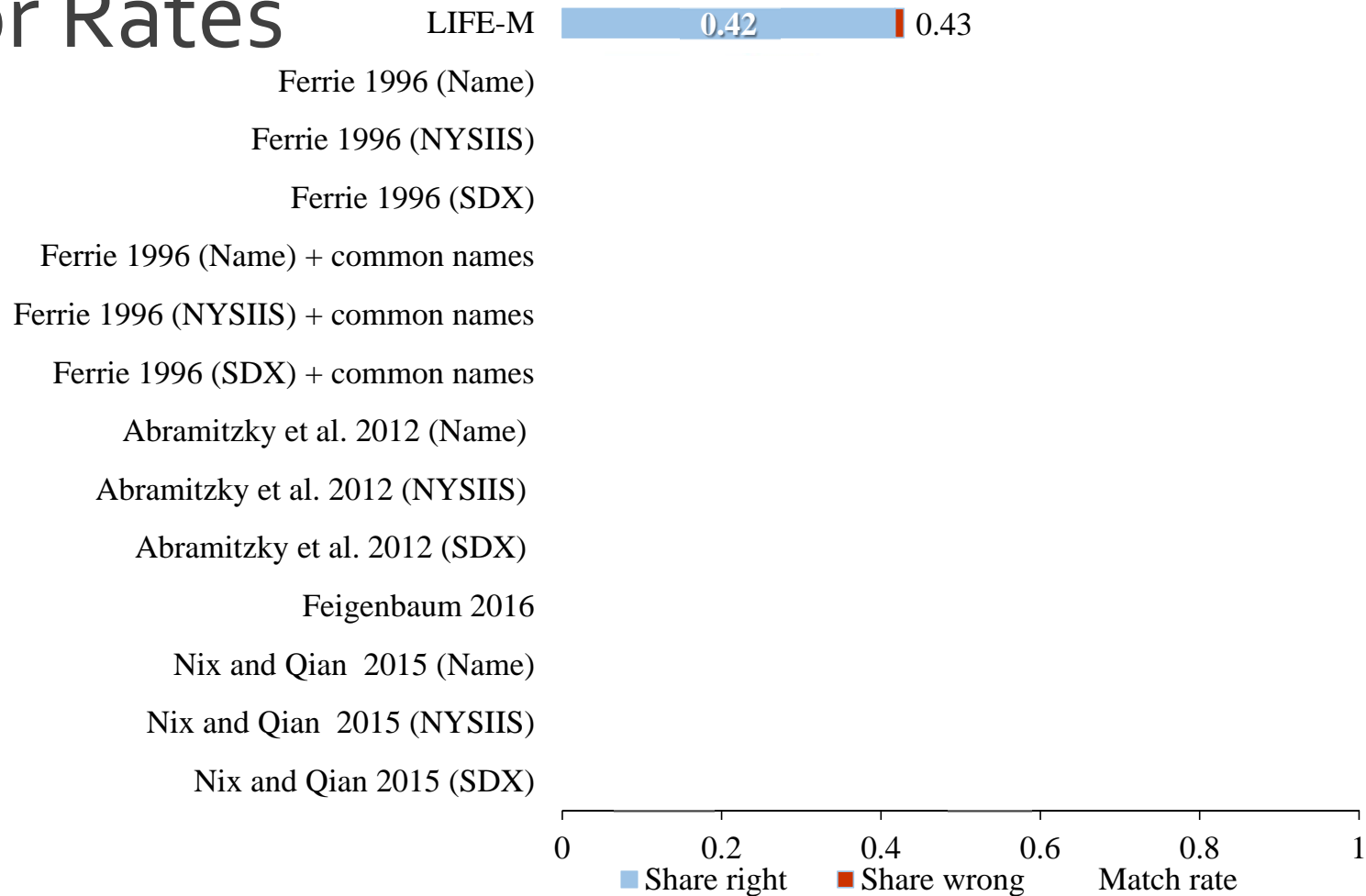
Match Rates



Error Rates



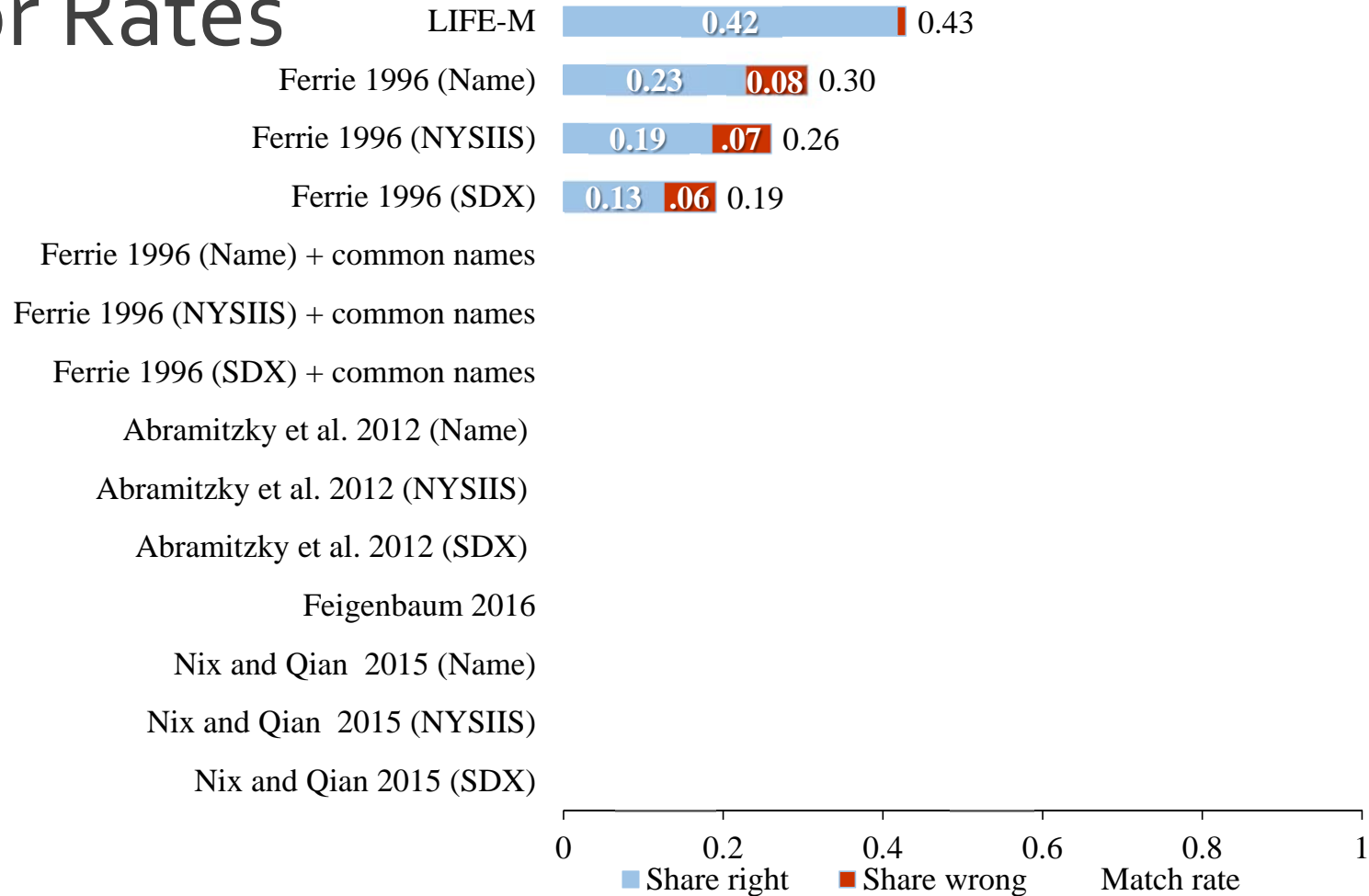
Error Rates



T1 Error Rate

0.02

Error Rates



T1 Error Rate

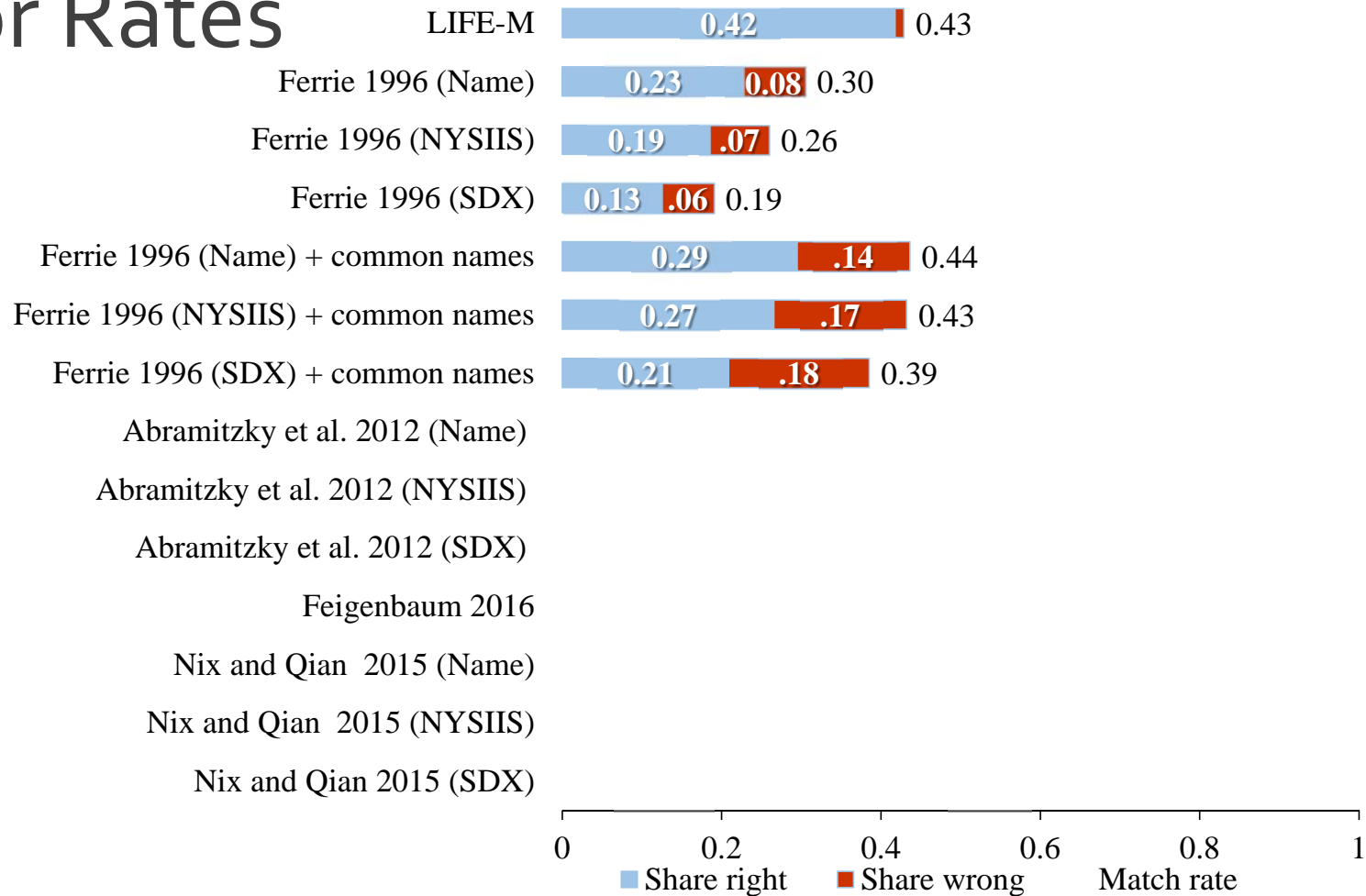
0.02

0.27

0.27

0.32

Error Rates



T1 Error Rate

0.02

0.27

0.27

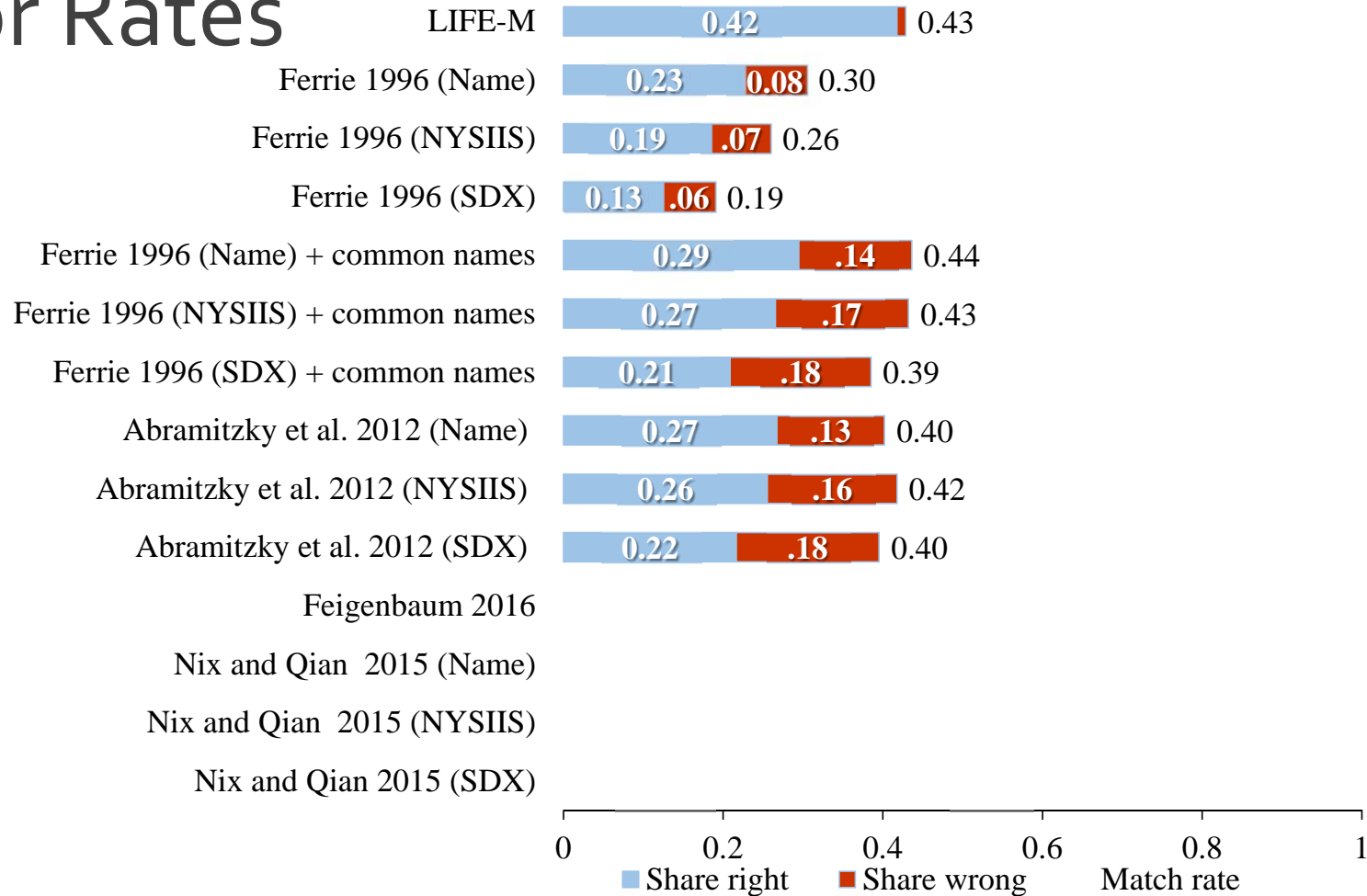
0.32

0.31

0.40

0.46

Error Rates



T1 Error Rate

0.02

0.27

0.27

0.32

0.31

0.40

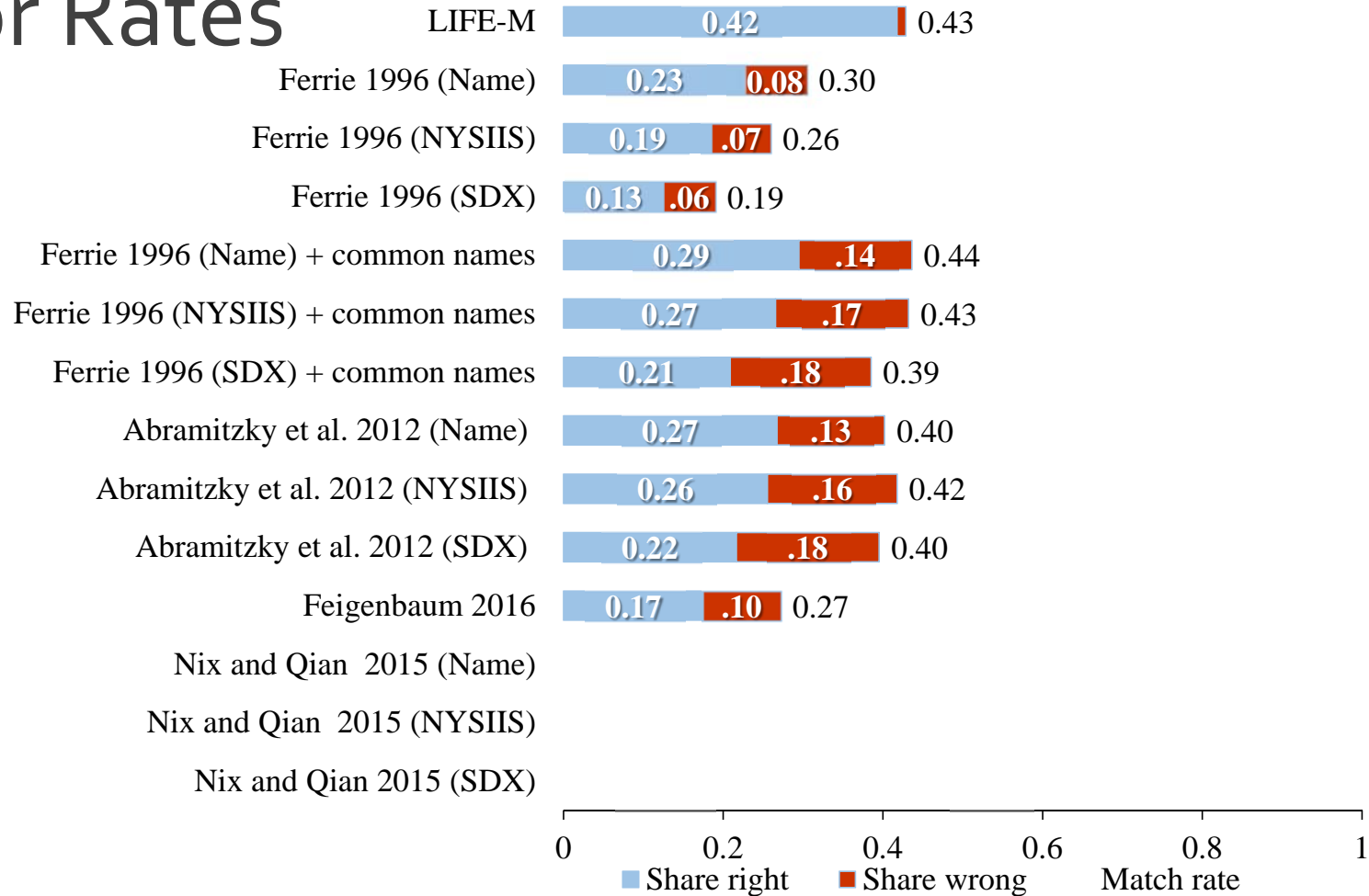
0.46

0.33

0.38

0.45

Error Rates



T1 Error Rate

0.02

0.27

0.27

0.32

0.31

0.40

0.46

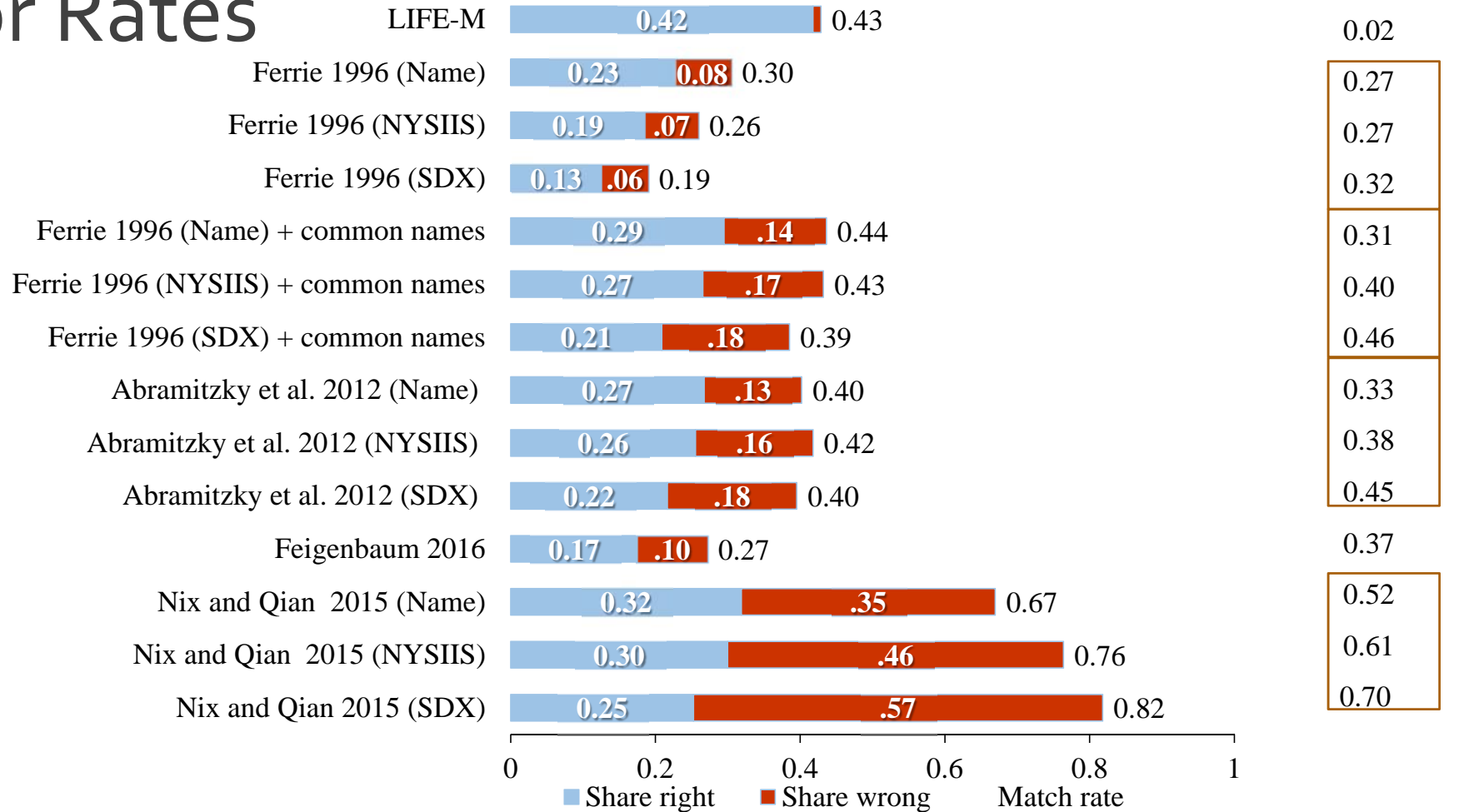
0.33

0.38

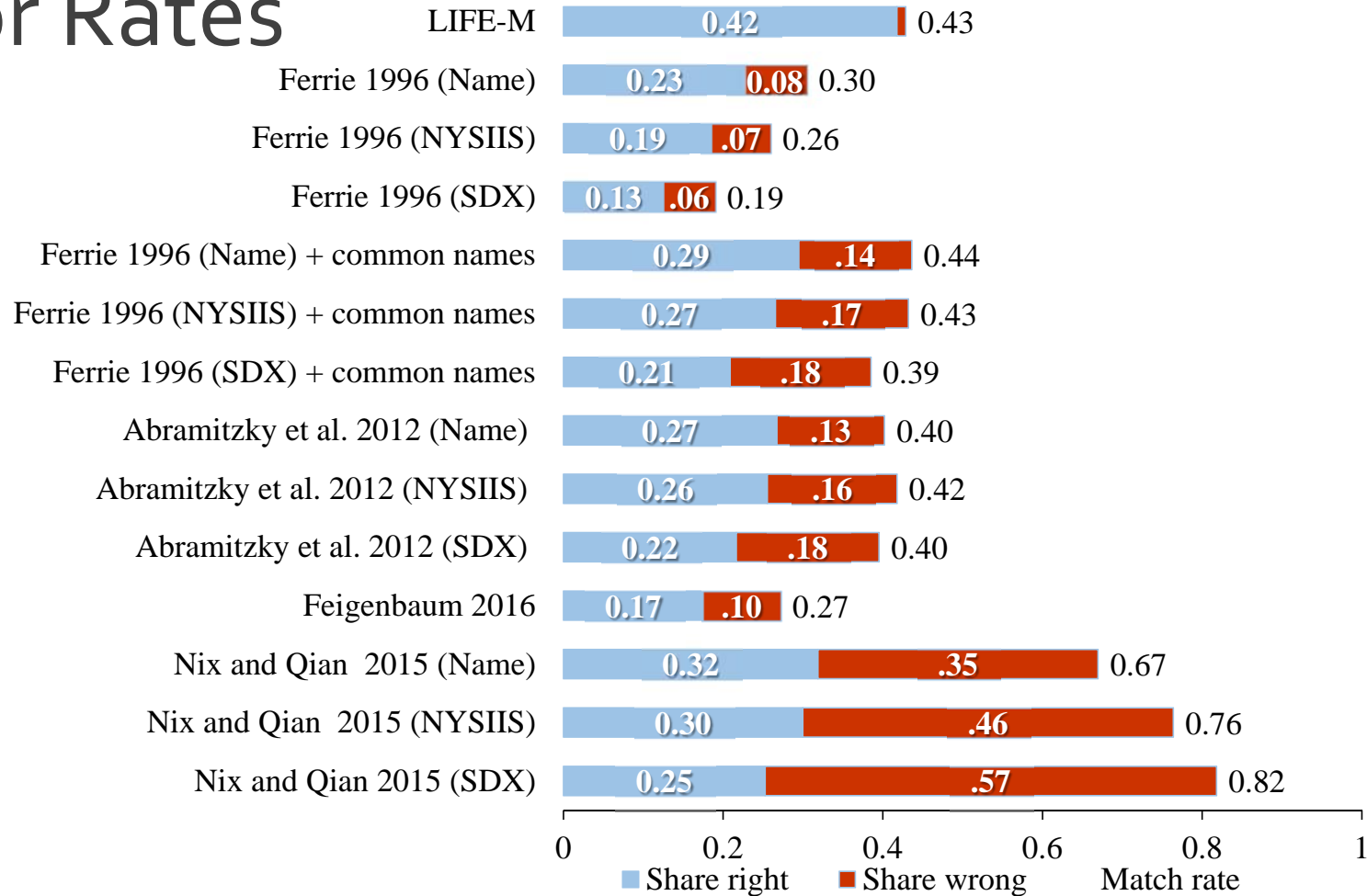
0.45

0.37

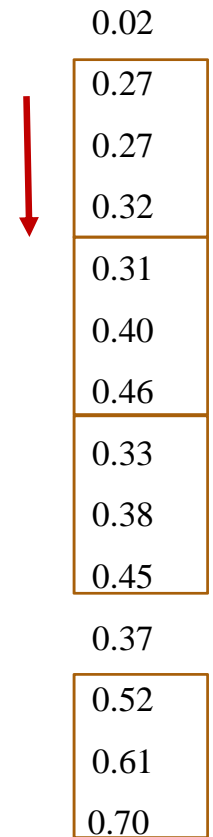
Error Rates



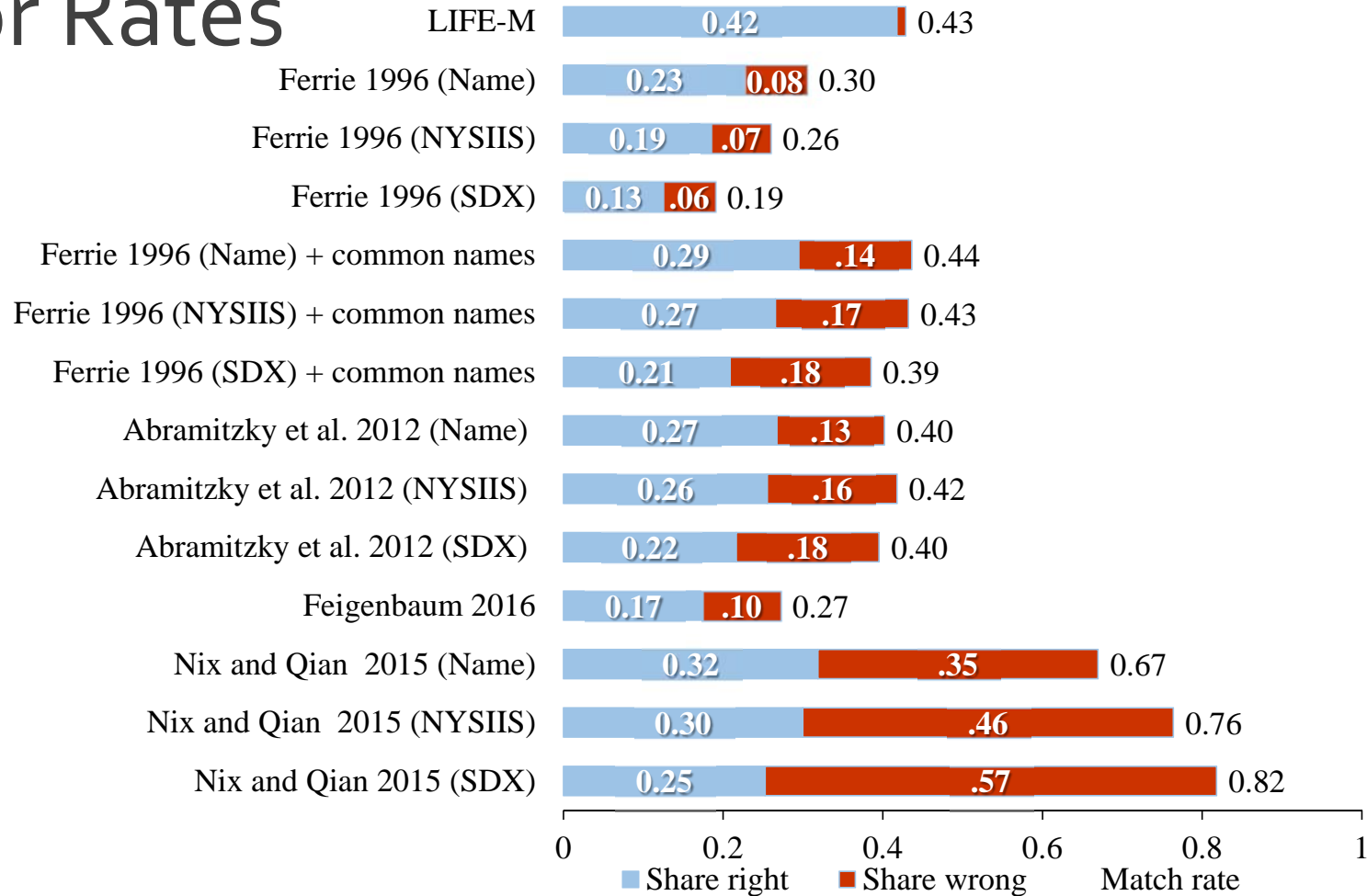
Error Rates



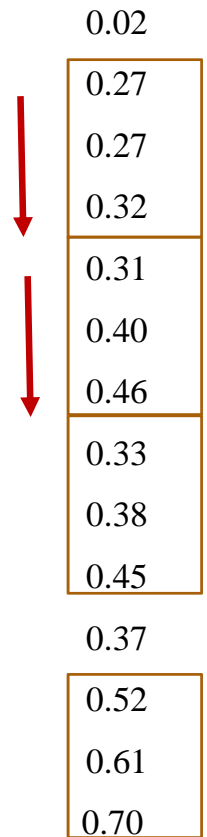
T1 Error Rate



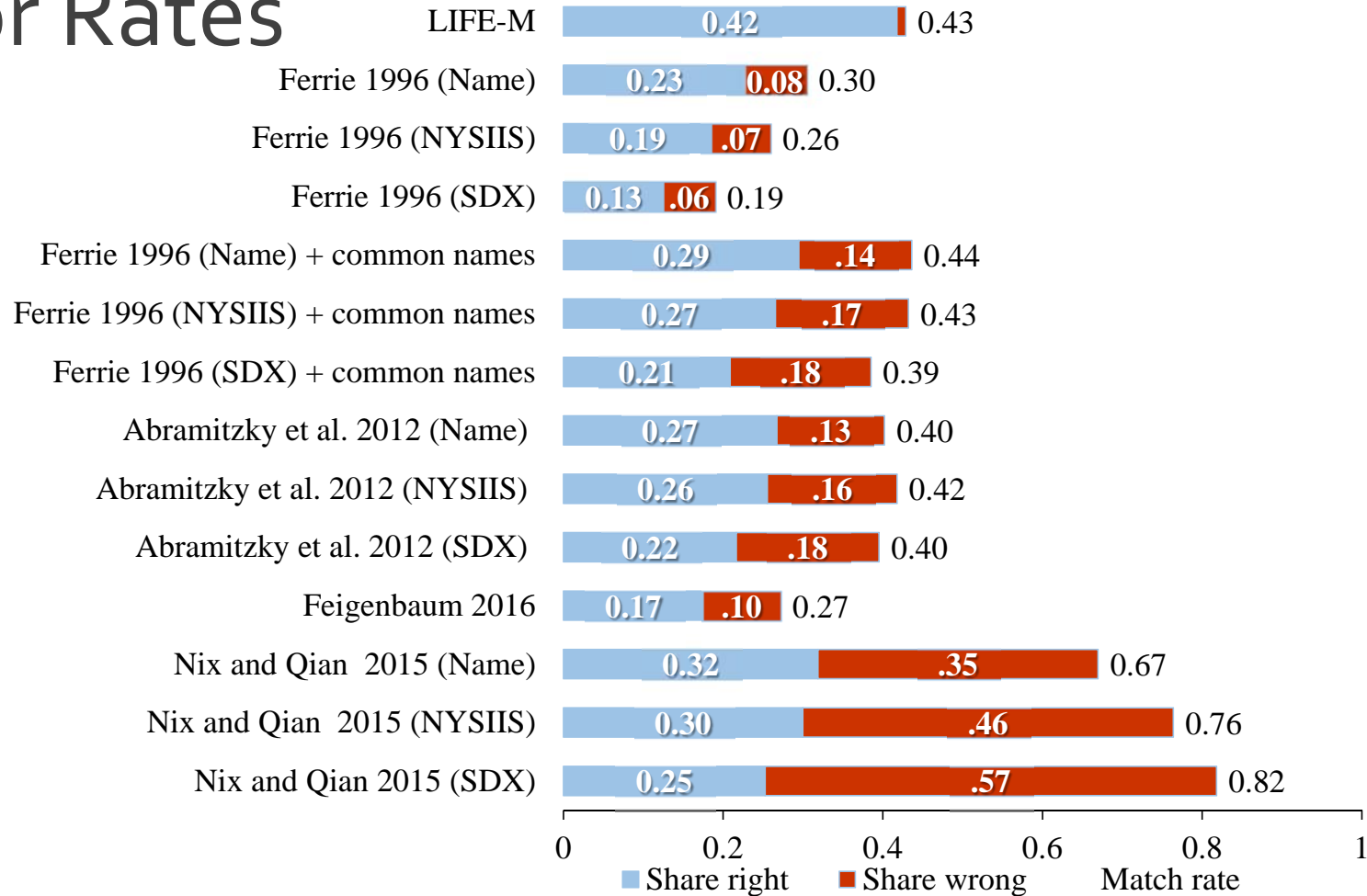
Error Rates



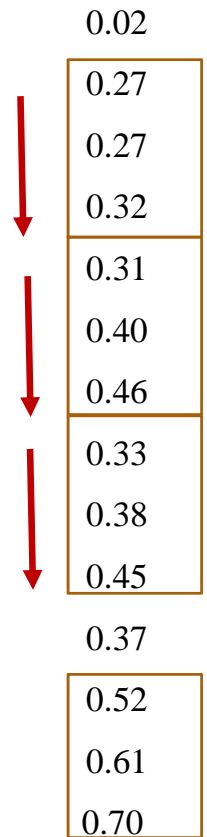
T1 Error Rate



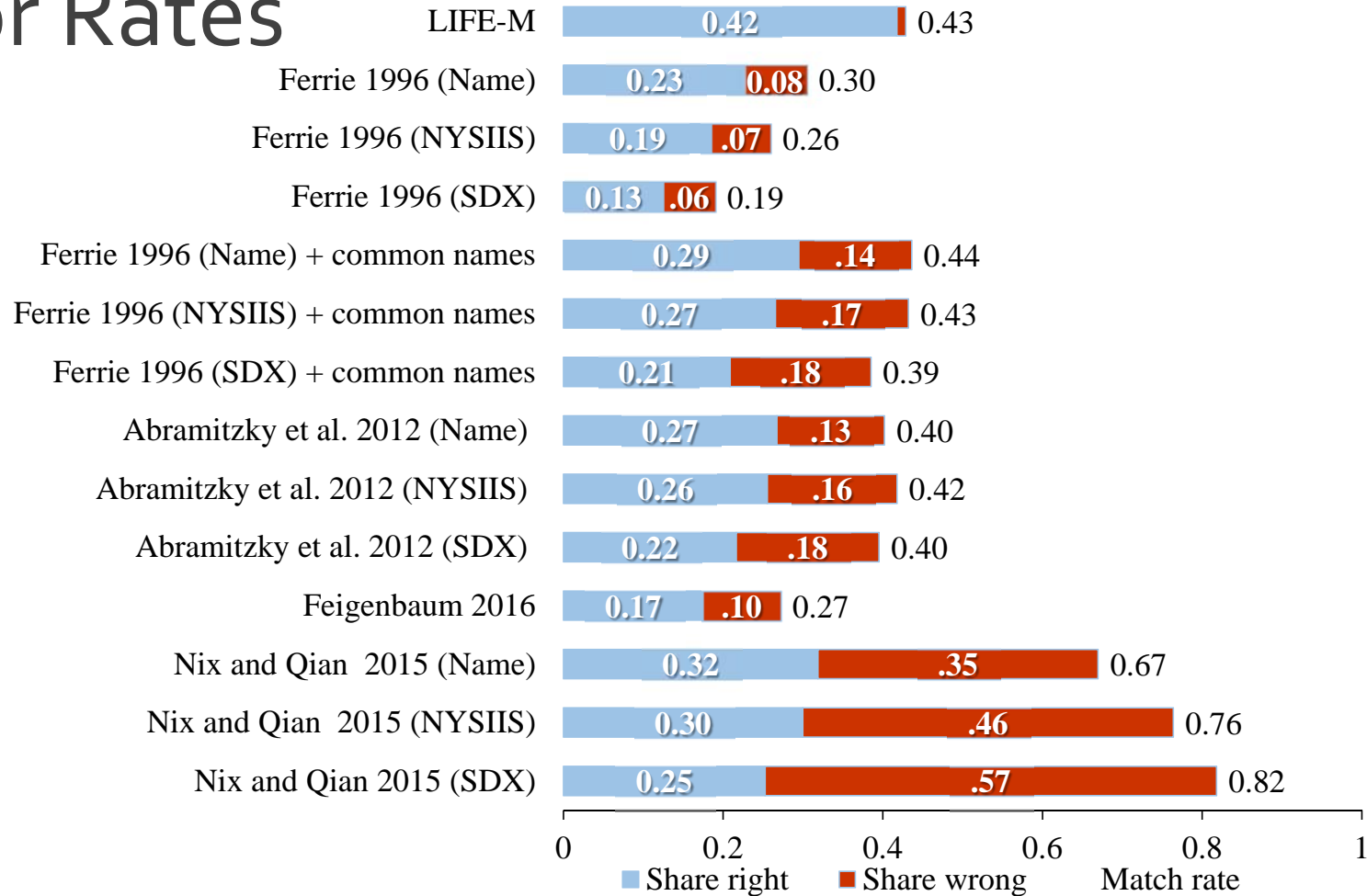
Error Rates



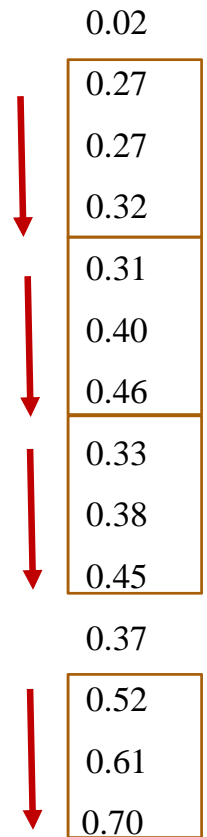
T1 Error Rate



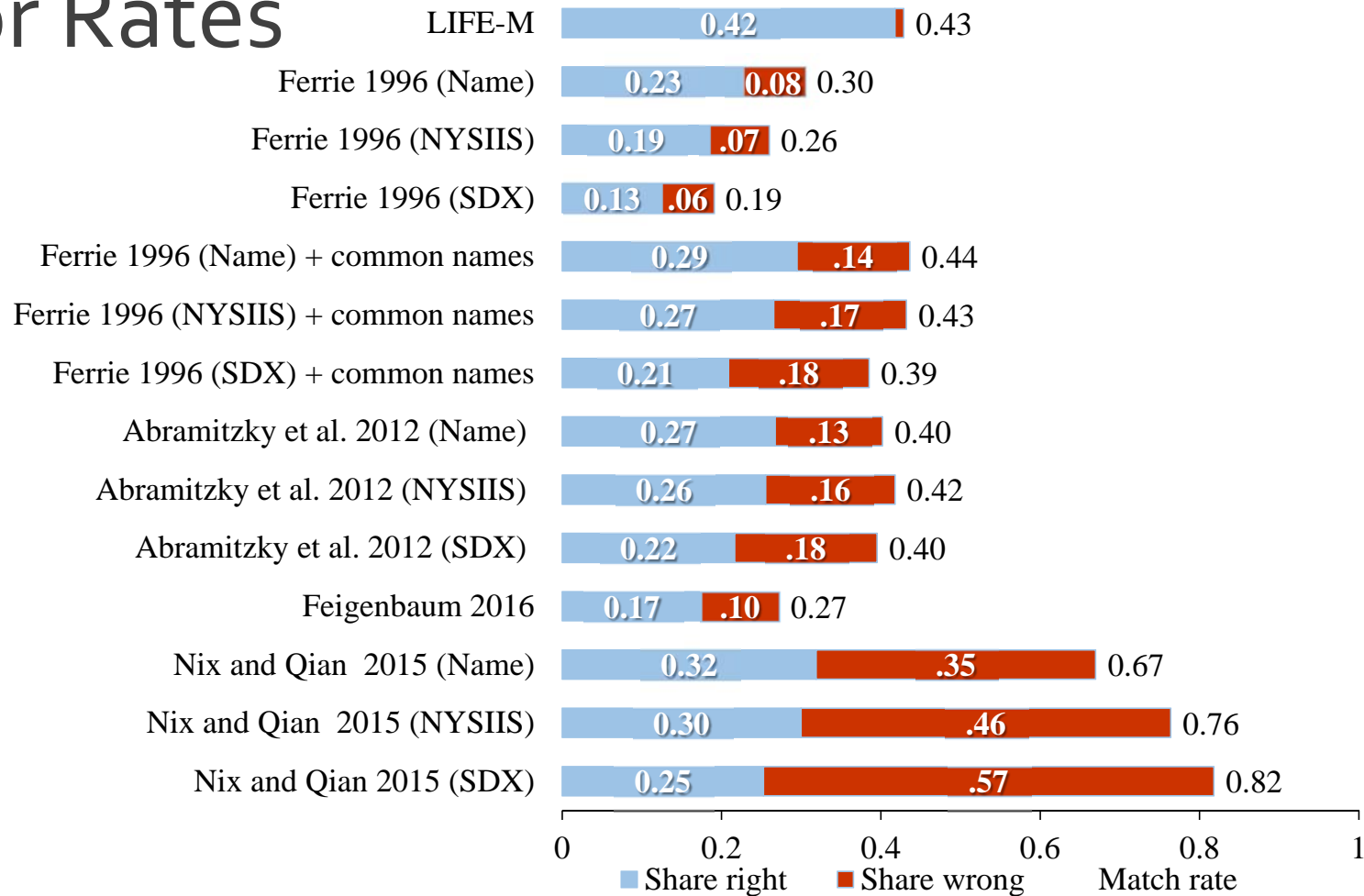
Error Rates



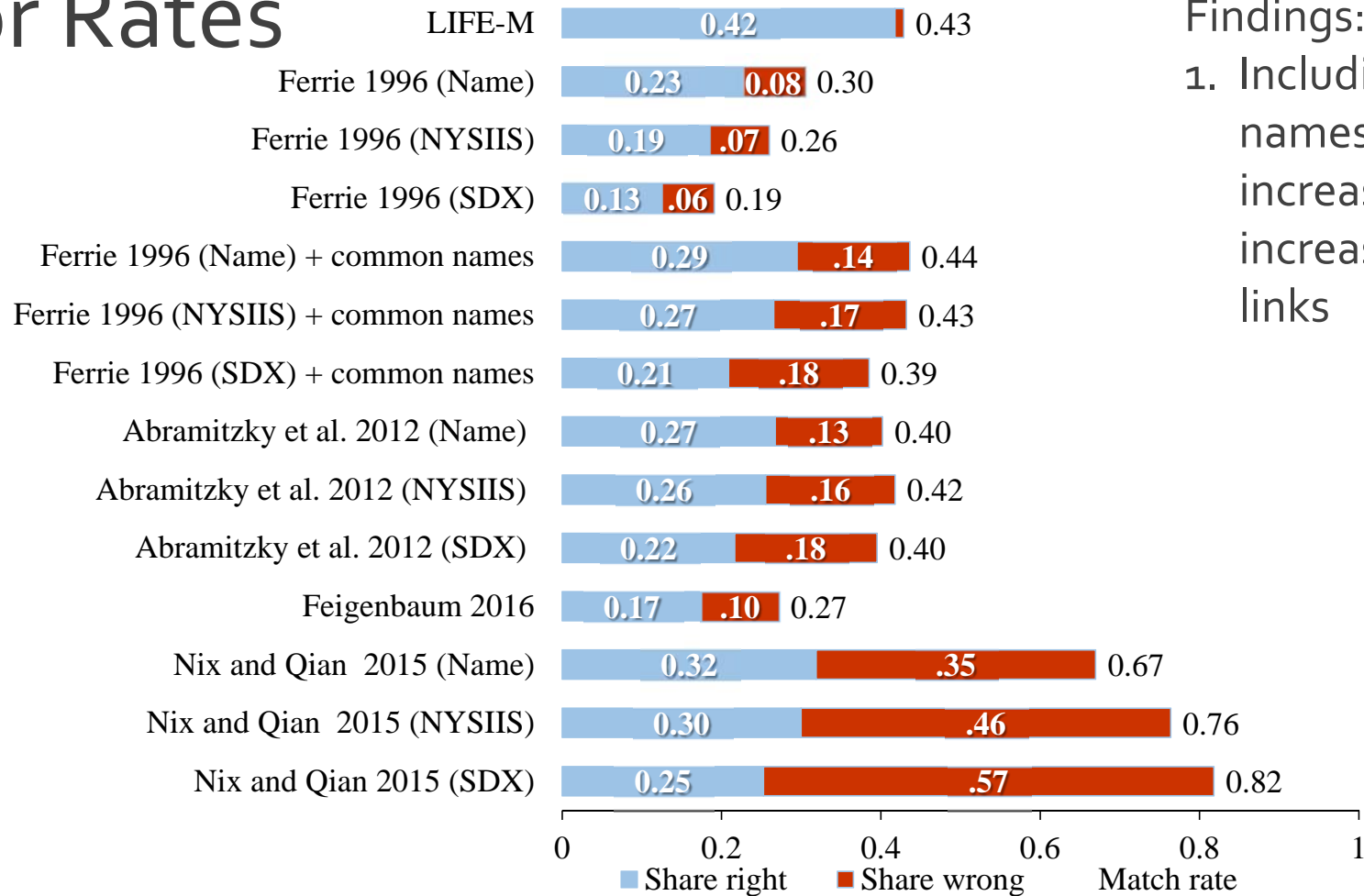
T1 Error Rate



Error Rates



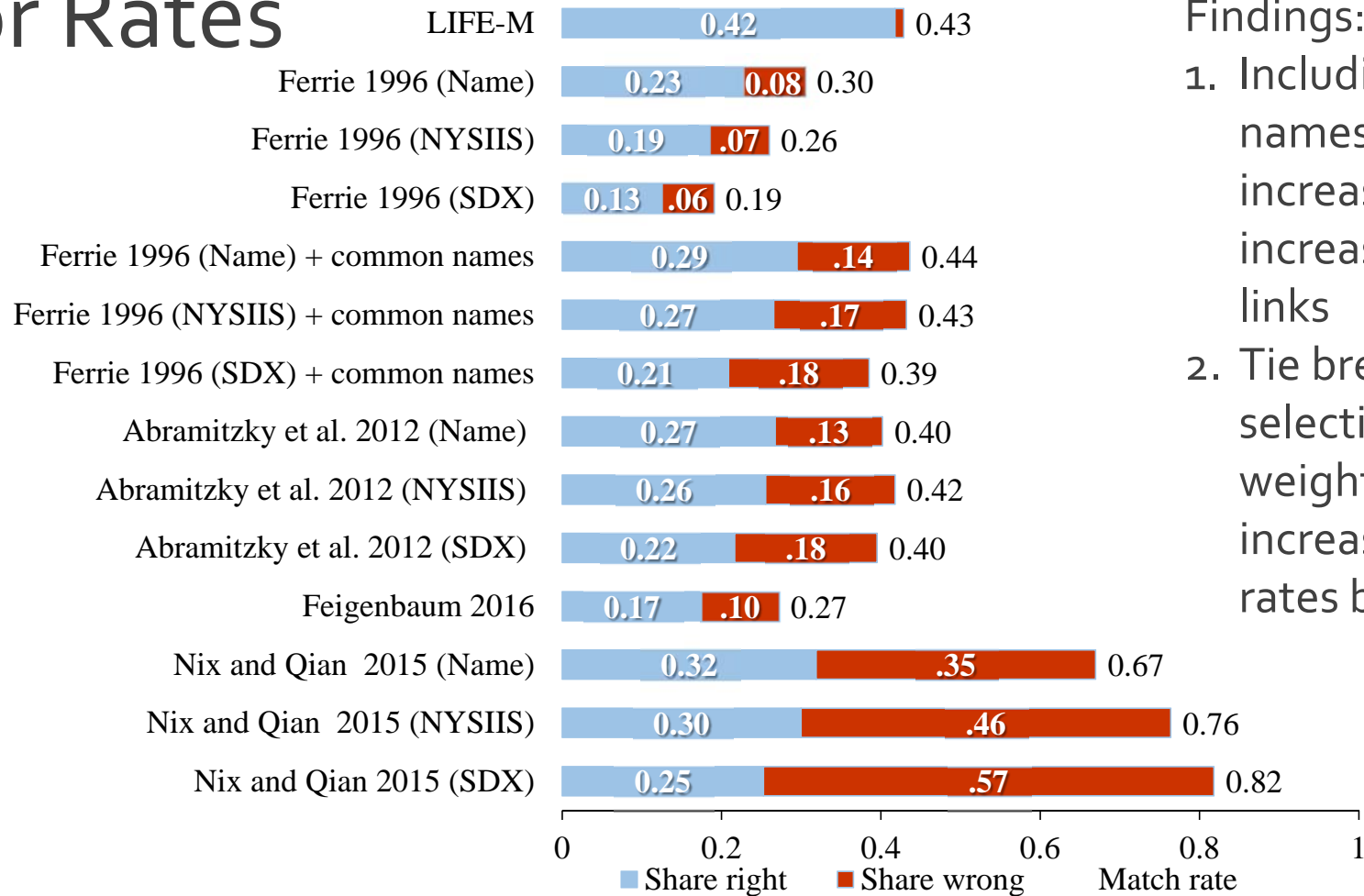
Error Rates



Findings:

1. Including common names sample increases errors but increases correct links

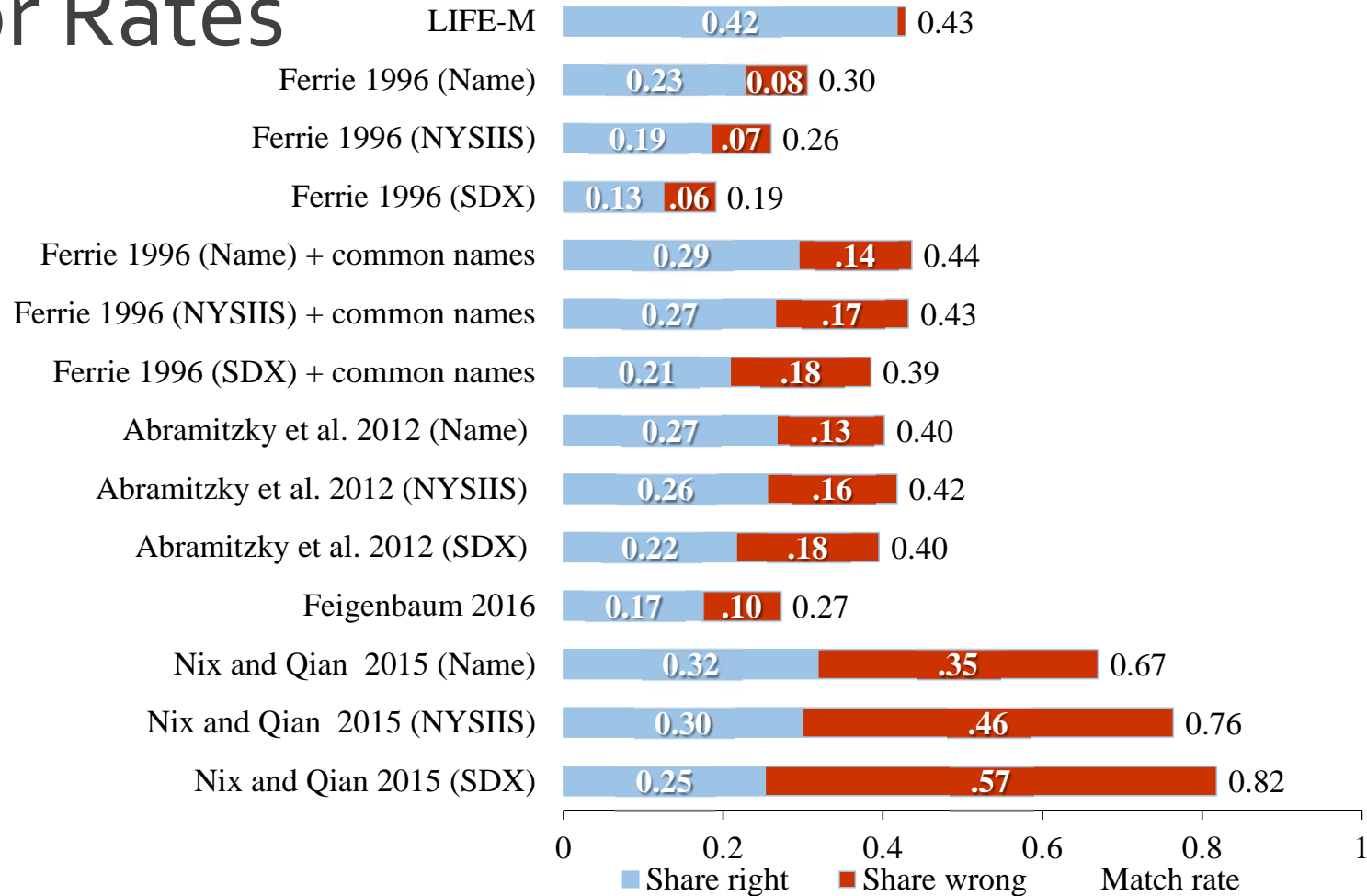
Error Rates



Findings:

1. Including common names sample increases errors but increases correct links
2. Tie breaks (random selection or $1/m$ weighting) increases match rates but also errors

Error Rates



T1 Error Rate

