

Creating synthetic data using composites of similar individuals

COMPASS Colloquium
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THE UNIVERSITY OF AUCKLAND

Whare Wānanga o Tāmaki Makaurau

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1. **Approach and Methods** - how we created synthetic data using ‘composite clusters’
2. **Quality** – how well did our synthetic data reproduce the “real” data in Census 2006
3. **Confidentiality** – how well did our synthetic data resist attempts to reveal “real” individuals in Census 2006

Why synthetic data?



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- ❑ Need representative birth cohort for simulation model, and need it released (for wide use)
 - 2006 Census is representative and has many of the variables we use to get our model running
 - 2006 Census micro-data unable to be released, but what if we had something that looked like 2006 Census micro-data but didn't contain any actual individual....
- ❑ Achievable if create 'synthetic birth cohort'
 - Usual approaches are perturbation or multiple imputation, but we're trying something different

Composite clusters

- ❑ Creating a synthetic base file of composite individuals





- Subset 2006 Census to include just new-borns (0-year olds) and their parents
 - Randomly select 10,000 (Processing speed)
- Calculate distance between each of the 10,000, based on 2006 Census characteristics.
 - Done separately for two-parent families, single mum families and single dad families (for consistency)
- Choose the closest 2 ranks to form 10,000 clusters of 3 individuals



- ❑ Randomly choose, characteristic-by-characteristic, which member of the cluster's characteristics contributes to the synthetic individual
- ❑ Voilà! A synthetic basefile of 10,000 composite individuals

Questions?



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Quality





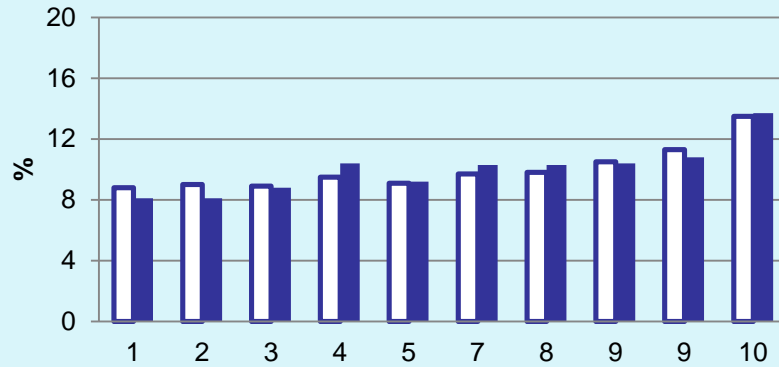
- ❑ Synthetic data should faithfully represent distributions and inter-relations of real data

- ❑ Distributions
 - ❑ Proportions in groups
 - ❑ Mean, SD & shape of continuous variables

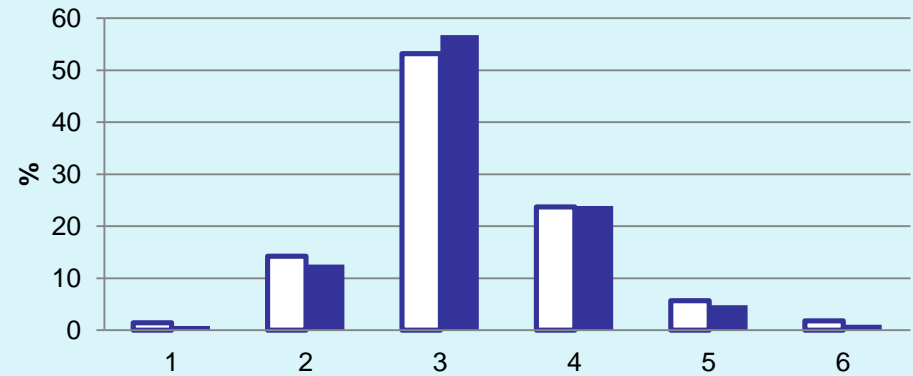
- ❑ Inter-relations
 - ❑ Variables strongly correlated in the real data should also be strongly correlated in the synthetic data

Quality - Distributions

NZDep2006 Deciles

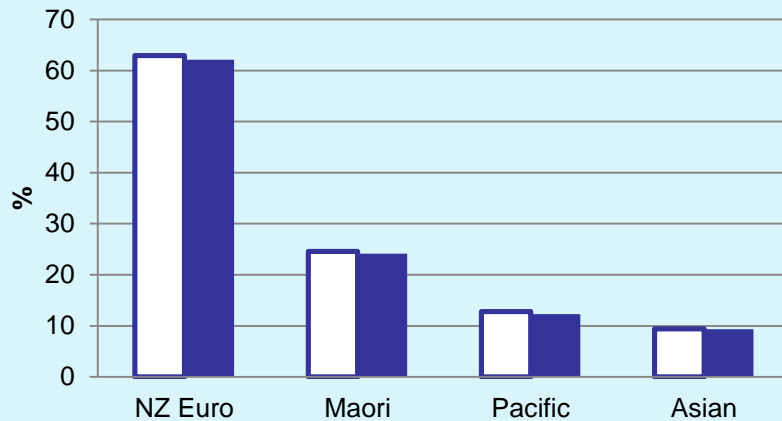


Number of bedrooms

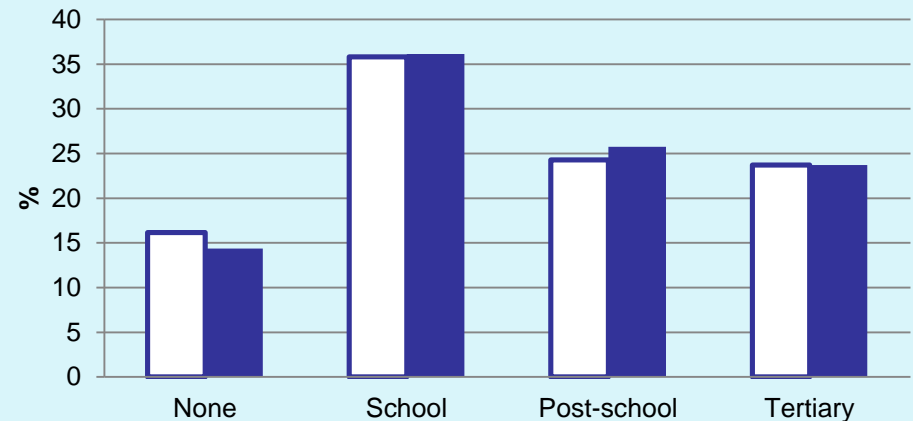


□ CENSUS
 ■ SYNTHETIC

Child ethnicity



Mother's highest education



Quality - Distributions



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		Mean	SD	Percentiles				
				10	25	50	75	90
Mum's age	Census	30.7	6.7	22	26	31	35	38
	Synth	30.5	6.2	22	26	31	34	37
Dad's age	Census	33.9	7.0	25	30	34	38	42
	Synth	33.6	6.2	26	30	34	37	41
Years at address	Census	2.96	4.40	0	0	2	4	7
	Synth	2.74	3.85	0	0	2	4	6

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Quality - Inter-relations



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		Var1	Var 2	Var 3	Var 4	Var n
Var 1	Census	1	.12	-.23	.3445
Var 2	Census		1	.02	-.1324
Var 3	Census			1	.42	-.01
Var 4	Census				117
.	Census					1
.							
Var n	Census						1

New Zealand

The University of Auckland

Quality - Inter-relations



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		Var1	Var 2	Var 3	Var 4	Var n
Var 1	Census Synthetic	1 1	.12 .05	-.23 -.29	.34 .2145 .51
Var 2	Census Synthetic		1 1	.02 -.04	-.13 -.2124 .19
Var 3	Census Synthetic			1 1	.42 .35	-.01 .06
Var 4	Census Synthetic				1 117 .05
.	Census Synthetic					1 1
Var n	Census Synthetic						1 1

Quality - Inter-relations



		Var1	Var 2	Var 3	Var 4	Var n
Var 1	Census Synthetic	1 1	.12 .05	-.23 -.29	.34 .2145 .51
Var 2	Census Synthetic		1 1	.02 -.04	-.13 -.2124 .19
Var 3	Census Synthetic			1 1	.42 .35	-.01 .06
Var 4	Census Synthetic				1 117 .05
.	Census Synthetic					1 1
Var n	Census Synthetic						1 1

Quality - Inter-relations

- ❑ Correlation between
 - two-way correlations among Census variables
 - two-way correlations among Synthetic variables
 - **$r=0.66$** (n=1596 pairwise correlations for 57 vars)
- ❑ Moreover, associations aren't dampened. Mean magnitude of correlations
 - CENSUS: $r = .097$
 - SYNTHETIC: $r = .102$
- ❑ Correlations in Census tend to be replicated in synthetic file
 - Suggests inter-relations have been maintained

Confidentiality



- ❑ 'Hacker scenarios'
- ❑ Could a 'hacker' gaining access to our synthetic file learn anything 'new' about a real individual (about whom they had some basic information).
- ❑ Process
 - Find 'uniques' in the synthetic data using 'strongly identifying' information (ethnicity [M/F/C], age [M/F], sex [C])
 - Are there individuals with the same characteristics in the 2006 Census? If so, can we learn 'sensitive' information about these real individuals based on their synthetic data?

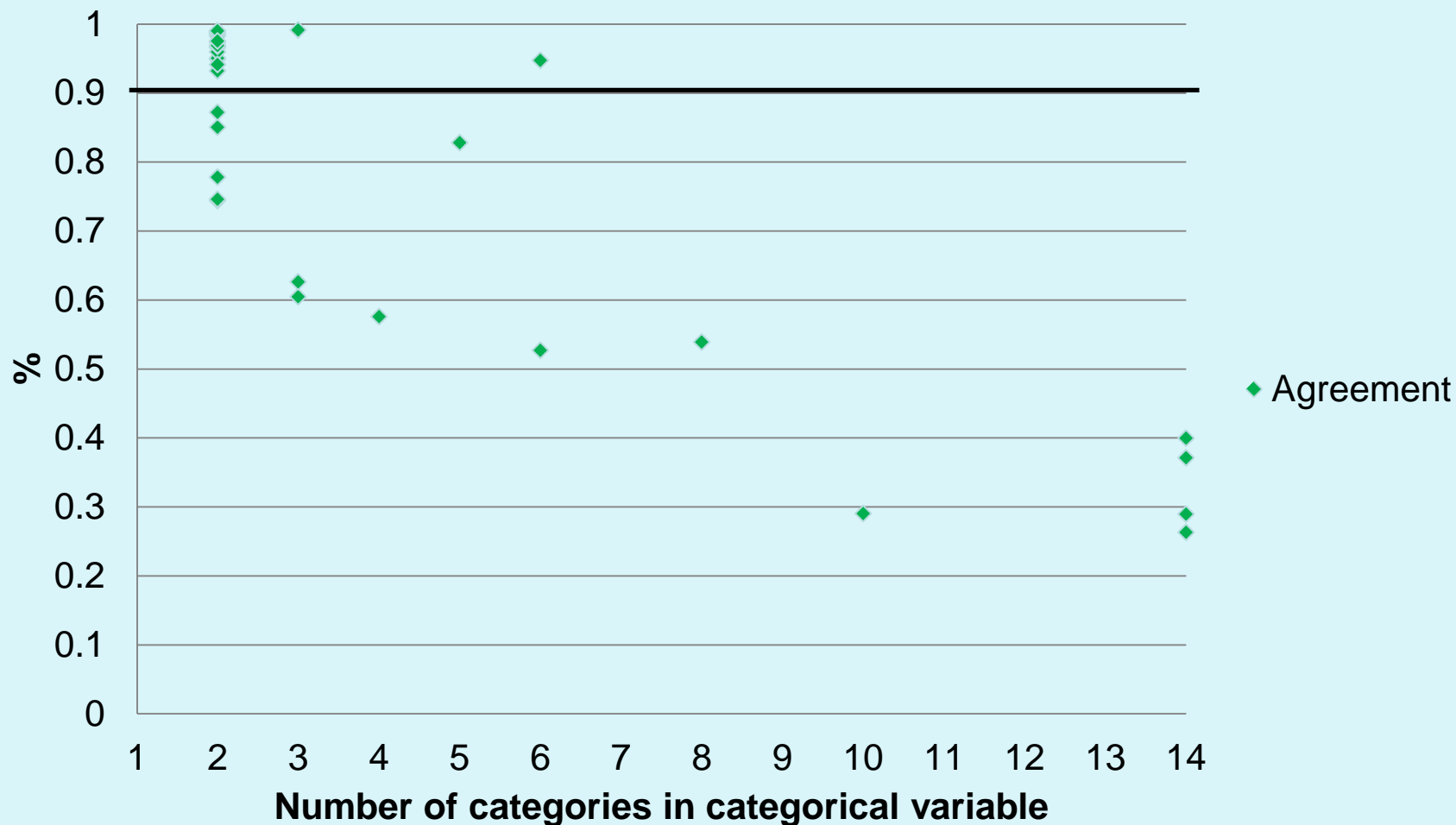
Confidentiality - Uniques

- ❑ Of synthetic individuals with ‘unique’ characteristics (C sex, M, F & C ethnicity, M & F age; 48.6%)
 - 62.5% don’t exist in the Census
 - 13.3% are unique in the Census
 - 24.1% are shared by 2+ people in the Census
- ❑ What is the level of agreement for non-identifying characteristics?
 - Synthetic uniques vs. unique counterpart in Census
 - Synthetic uniques vs. non-unique counterparts in Census
 - Not allowed to exceed 90%

Confidentiality - Agreement with real data



Uniques vs Uniques



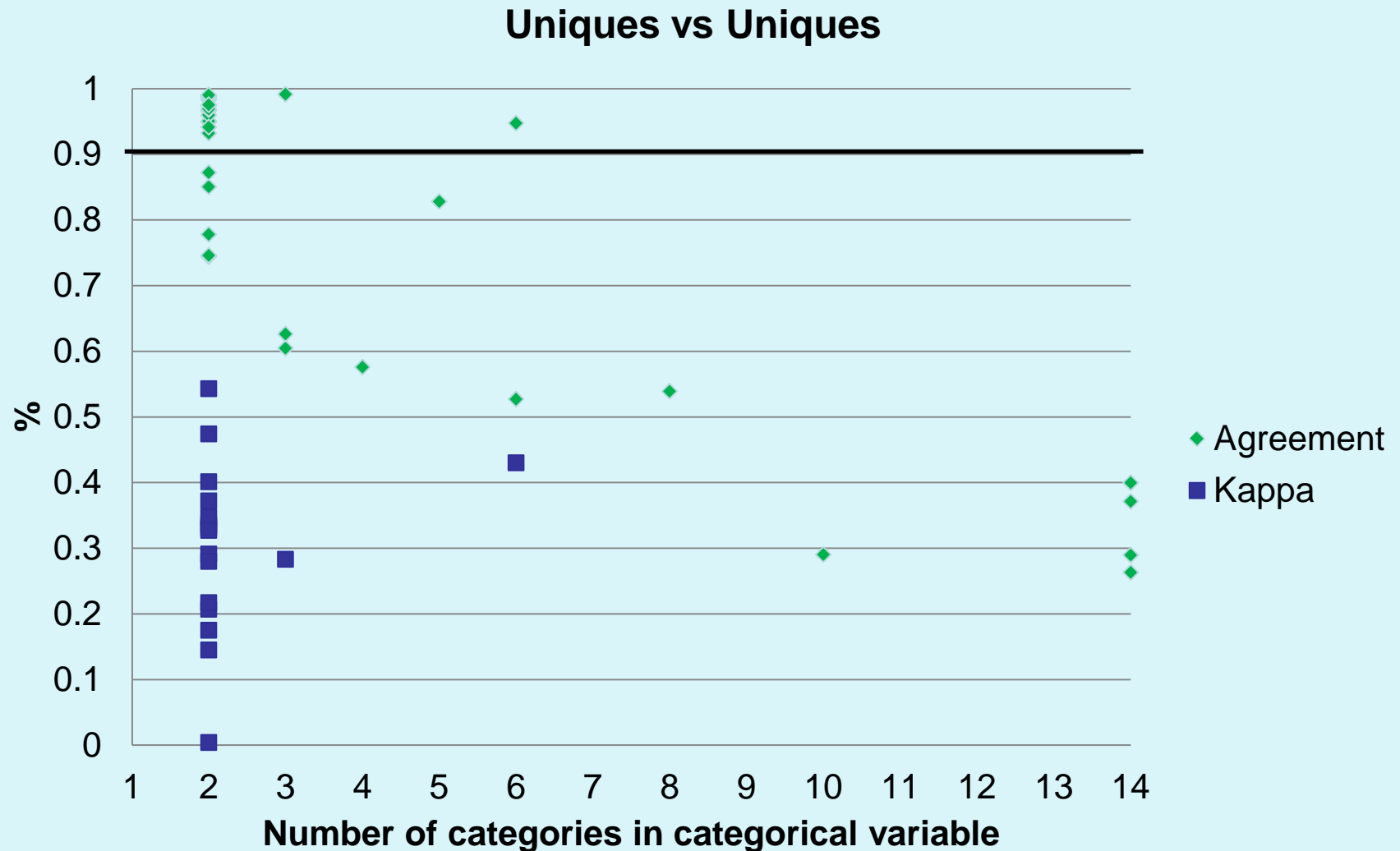
Confidentiality - Agreement with real data



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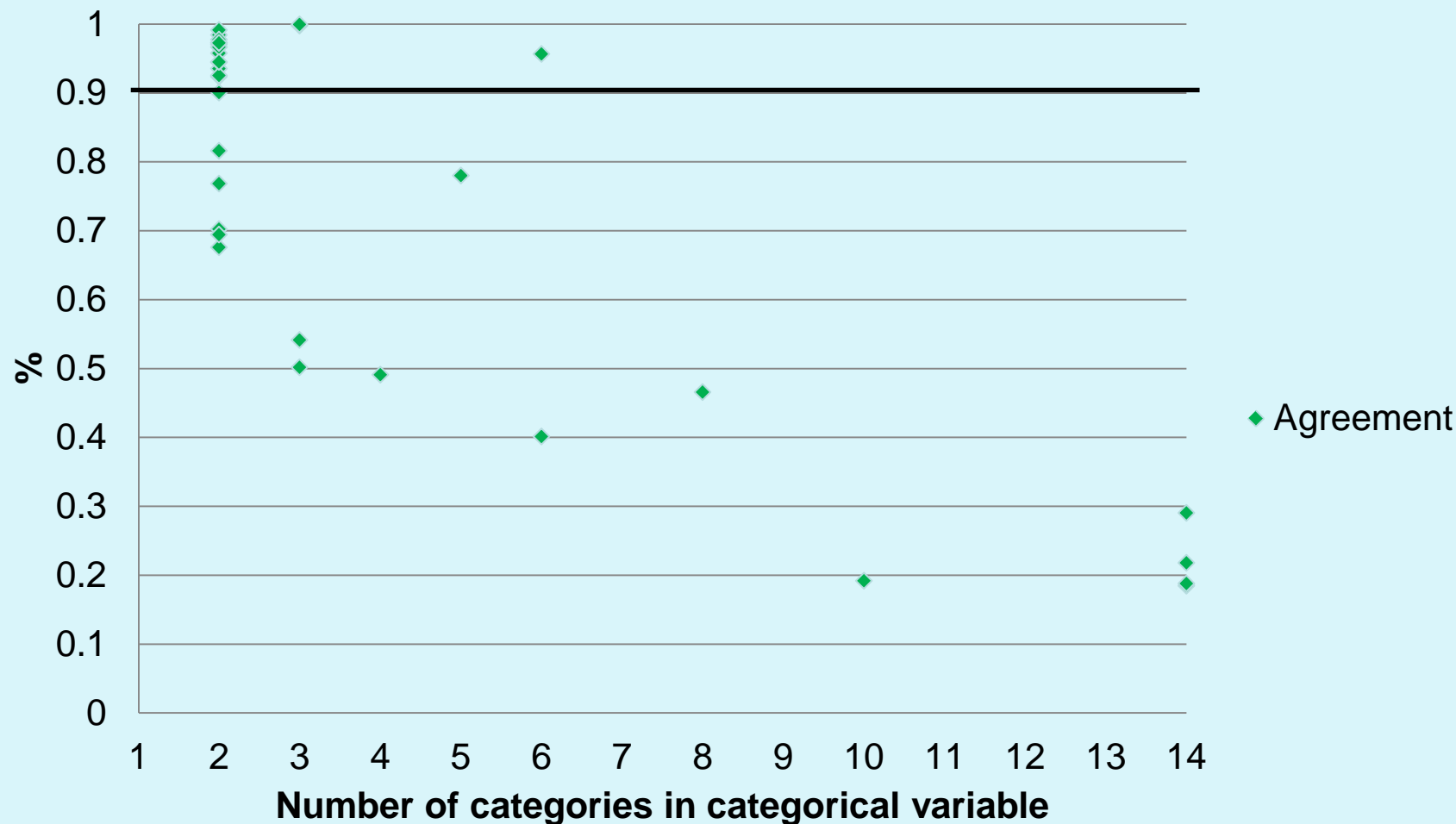
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Confidentiality - Agreement with real data

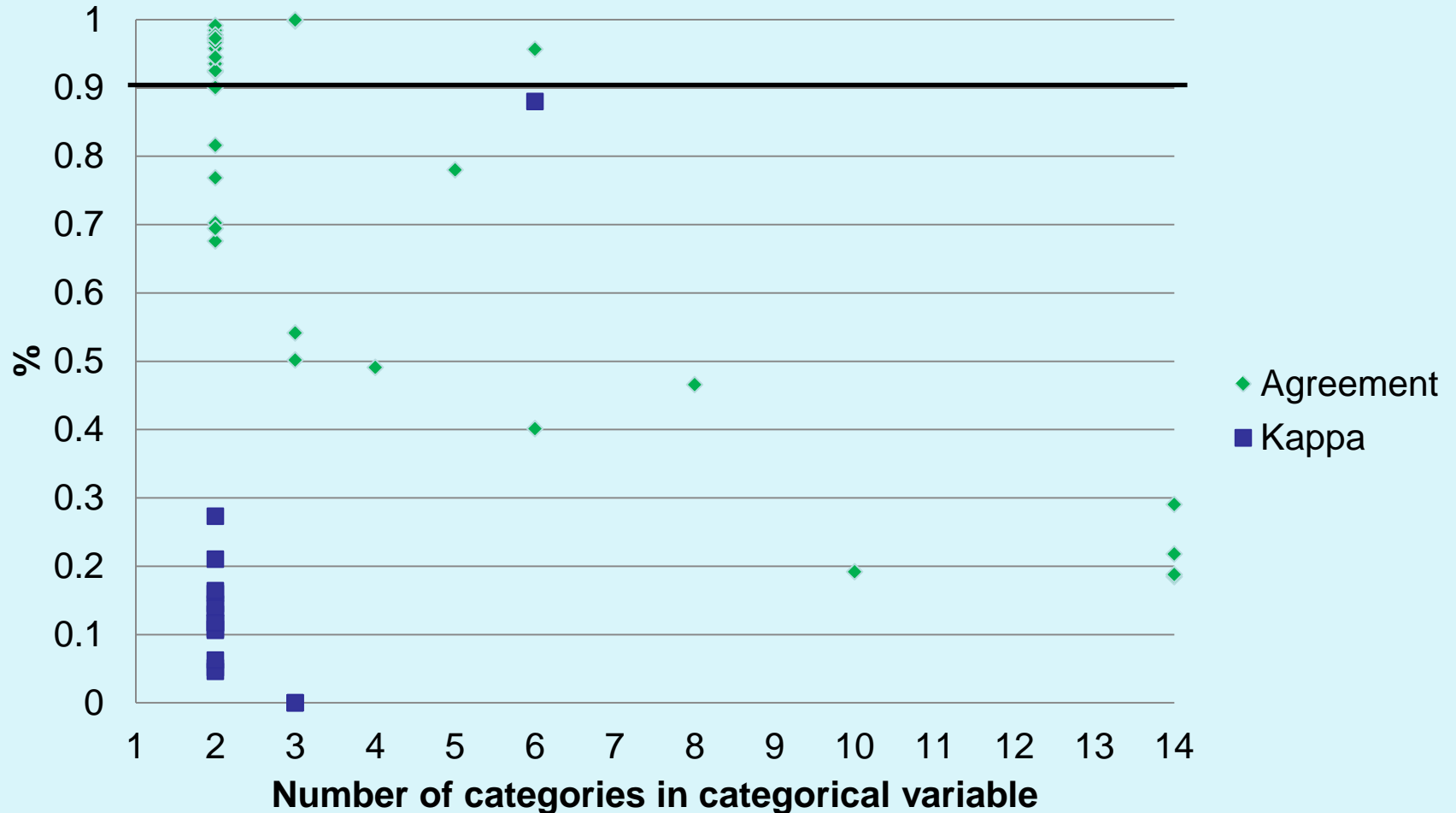


Uniques vs 2+



Confidentiality - Agreement with real data

Uniques vs 2+



Results - Confidentiality

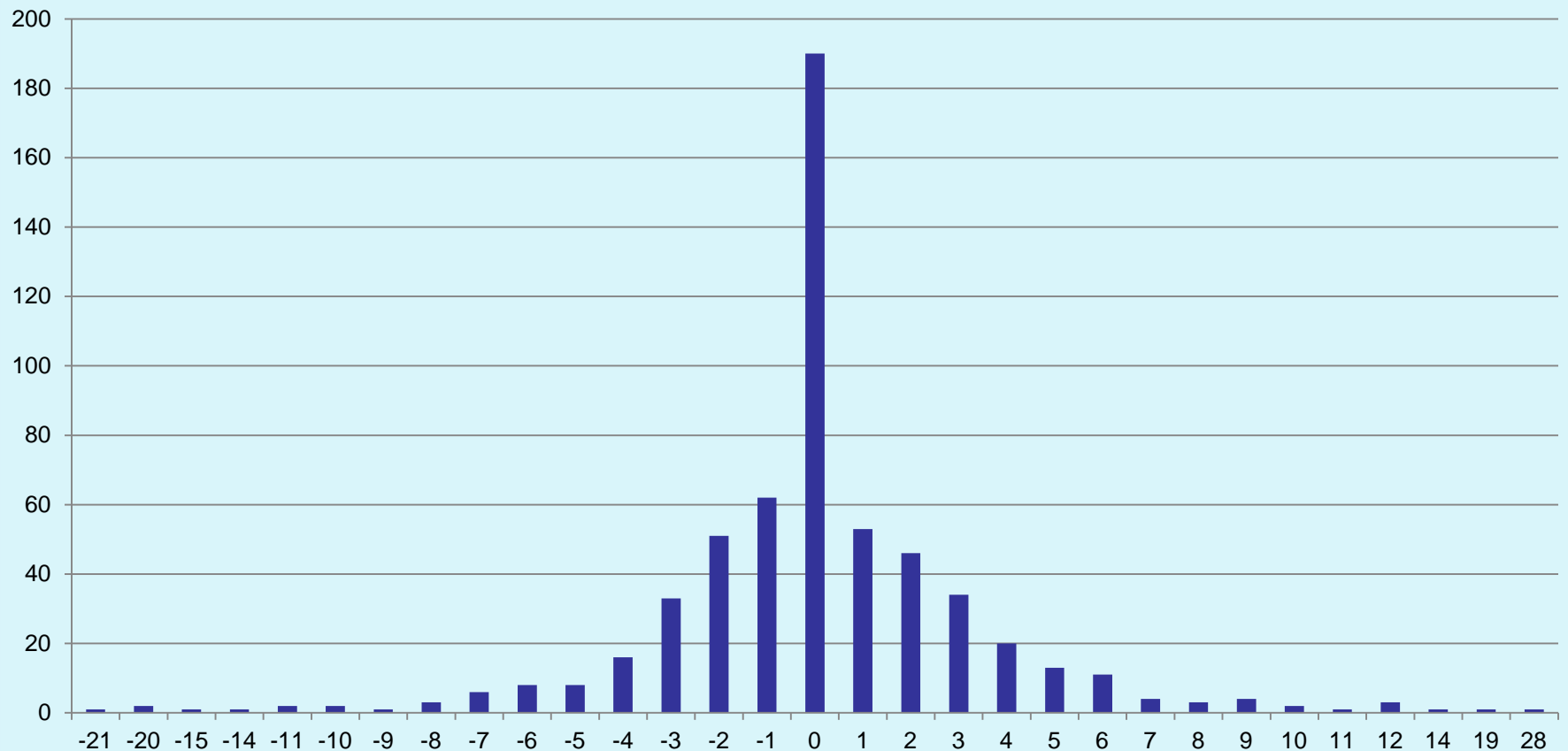


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▣ Years at address: 32% perfect agreement



Results - Confidentiality



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- ❑ 'On-diagonals' never exceed 90% EXCEPT for very low base rate characteristics
 - High probability of hitting on-diagonals by chance
- ❑ For most exceeding 90% kappa suggests far from perfect agreement, except
 - child_depend_family_type_code (6 categories)
 - Couple with dependent child
 - Couple with dependent child & adult
 - Couple with dependent child & unknown
 - One parent with dependent child
 - One parent with dependent child & adult
 - One parent with dependent child & unknown

Conclusions



1. Creating synthetic data using ‘composite clusters’ is achievable and (relatively) quick
2. Data is high quality
 - + Distributions closely match those of Census
 - + Inter-relations approximate those of Census (both in directionality & magnitude)
3. Data meets confidential requirements
 - + Small overlap between ‘uniques’ in synthetic file and ‘uniques’ in Census; and ‘uniques’ don’t reliably reveal anything factual about a ‘real’ individual

- ❑ How does it compare with multiple imputation?
 - Direct test is underway

- ❑ Composite approach potentially suitable to any synthetic data creation
 - Processing power may be issue

- ❑ Flexibility to adequately balance quality and confidentiality
 - Quality poor? Use fewer matches
 - Confidentiality compromised? Use more matches

Questions?



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