Understanding nonresponse behaviour on the European Social Survey: The role of survey paradata vs. external auxiliary data

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The problem

- Declining survey response rates
- Research into causes and correlates of nonresponse
  - Improve fieldwork efficiency (e.g. responsive design)
  - Post-hoc analysis and adjustments
- Requires data that is
  - available for respondents and nonrespondents
  - predictive of response behaviour <u>and</u> substantive survey responses

The solution?

Use multi-level multi-source auxiliary data (Smith and Kim, 2011)

- Sample frame
- Survey paradata
  - Call records
  - Interviewer characteristics
  - Interviewer observations
- External data sources
  - Small area admin data e.g. census
  - Commercial data bases

The solution?

Multi-level multi-source auxiliary data (Smith, 2011)

- Sample frame
- Survey paradata
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  - Interviewer characteristics
  - Interviewer observations
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Which is most useful for predicting survey nonresponse?

Where should surveys invest resources?

Comparing data sources

	Paradata	Small-area data	Commercial data
Timeliness	✓		
Completeness	✓		
Unit of analysis	✓		
Accuracy	?		
Cross-national comparability	✓		
Cost	~		

Comparing data sources

	Paradata	Small-area data	Commercial data
Timeliness	✓	~	✓
Completeness	✓	✓	x
Unit of analysis	✓	x	✓
Accuracy	?	✓	?
Cross-national comparability	✓	x	x
Cost	~	✓	x

ADDResponse

- Auxiliary Data Driven nonResponse bias analysis (ADDResponse)
- European Social Survey Round 6 (2012/13)
  - 54% response rate (34% refusal, 7% non contact)
  - Clustered PAF sample of 4,520 addresses in 220 PSUs
- Append geocoded auxiliary data
  - Small area data (census, DCLG, HO, DfE, DWP etc.)
  - Commercial data
  - OS Points of Interest data
  - Interviewer observations

ADDResponse: Interviewer observations

- Five interviewer observations collected for all sampled addresses
  - Type of dwelling unit (1= multi-person occupancy 0=single occupancy)
  - Barriers to entry present (1= yes 0= no)
  - Physical condition of property (1 = very good 5 = very bad)
  - Litter (1=present 0 = not present)
  - Graffiti (1=present 0 = not present)

- Observations complete for 97 % addresses

- Interviewer observations correlate with census data - > none recorded in OAs where there are no flats

ADDResponse: Commercial data

- Data purchased from two “value added resellers”
  - Consumer segmentation variables: ACORN, MOSAIC etc.
  - Specific variables e.g. length of residency, tenure, house price, age, employment status, children present, marital status
  - Consumer preferences data (very patchy)
- Data from 2015 but ESS fieldwork completed 2013
- Missing data
  - Company 1: 10% Company 2: 20 -50%
- Differences between two commercial databases
  - N of adults = 54% match Tenure =75%
- Discrepancies compared with ESS data
  - N of adults = 71% match Married = 77% match Retired = 87% match

Modelling and methods

- Logistic regression: response vs. not
- Controlling for clustering at PSU level
- Nested models
  - Coefficients
  - Model fit

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- Logistic regression: response vs. not
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- Nested models
  - Coefficients
  - Model fit
- Models
  - Model 1: interviewer observations
  - Model 2: Model 1 + small area data
  - Model 3: Model 2 + commercial data (MOSAIC)
  - Model 3 a : Model 2 + commercial data (separate variables)

Results: Interviewer observations

	Response vs. not
Variable	Log odd
(Intercept)	0.608*** (0.024)
Access	-0.133*** (0.03)
Living in a flat	-0.032 (0.029)
Vandalism	0.052 (0.04)
Litter	-0.007 (0.025)
Physical condition	-0.029* (0.011)
R2	0.034
AIC	1025.34

Results: Interviewer observations

	Response vs. not	Contact vs. not
Variable	Log odd	Log odd
(Intercept)	0.608*** (0.024)	0.976*** (0.011)
Access	-0.133*** (0.03)	-0.086*** (0.026)
Living in a flat	-0.032 (0.029)	-0.080*** (0.022)
Vandalism	0.052 (0.04)	-0.008 (0.024)
Litter	-0.007 (0.025)	-0.019 (0.0151)
Physical condition	-0.029* (0.011)	-0.008 (0.006)
R2	0.034	0.086
AIC	1025.34	290.91

Results: Interviewer observations

	Response vs. not	Contact vs. not	Refusal vs. not
Variable	Log odd	Log odd	Log odd
(Intercept)	0.608*** (0.024)	0.976*** (0.011)	0.341*** (0.023)
Access	-0.133*** (0.03)	-0.086*** (0.026)	0.104** (0.034)
Living in a flat	-0.032 (0.029)	-0.080*** (0.022)	-0.037 (0.032)
Vandalism	0.052 (0.04)	-0.008 (0.024)	-0.044 (0.042)
Litter	-0.007 (0.025)	-0.019 (0.0151)	-0.012 (0.024)
Physical condition	-0.029* (0.011)	-0.008 (0.006)	0.026* (0.011)
R2	0.034	0.086	0.019
AIC	1025.34	290.91	866.88

Results: Including auxiliary data

	Deviance (Model 1 vs Model 2)	Deviance (Model 2 vs Model 3)	Deviance (Model 2 vs Model 3 a)	P - value
Model 2	6.438			0.3701
Model 3		48.401		0.0000
Model 3 a			29.505	0.0002

Results: Including auxiliary data

- Interviewer observations remain significant
- Other significant auxiliary variables
  - **Model 2**
    - None
  - **Model 3**
    - MOSAIC
  - **Model 3a**
    - Children present
    - Full-time employment
    - Missingness from commercial data
    - (single and recent movers, but only at 10% level)

Conclusions

- ESS interviewer observations helpful in predicting nonresponse
- Quality issues with commercial variables and minimal improvement in model fit
- No “silver bullet” for modelling survey nonresponse
- Further research needed into
  - Validating interviewer observations
  - Conditions under which observations are more/less accurate

Find out more

www.addresponse.org

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References

- Sinibaldi, J., Durrant, G.B. and Kreuter, F., 2013. Evaluating the measurement error of interviewer observed paradata. *Public Opinion Quarterly*, *77*(S1), pp.173-193.
- Sinibaldi, J., Trappmann, M. and Kreuter, F., 2014. Which is the better investment for nonresponse adjustment: purchasing commercial auxiliary data or collecting interviewer observations?. *Public Opinion Quarterly*
- Smith, T. W. (2011) “The Report on the International Workshop on Using Multi-level Data from Sample Frames, Auxiliary Databases, Paradata, and Related Sources to Detect and Adjust for Nonresponse Bias in Surveys,” International Journal of Public Opinion Research, 23, 389-402.
- Sturgis, P. and Brunton-Smith, I., 2012. An assessment of the potential utility of interviewer observation variables for reducing non-response error in the National Survey for Wales.
- Vercruyssen, A., Wuyts, C. and Loosveldt, G., 2016. Auxiliary data for the European Social Survey Belgium. A search for easily available and straightforwardly useable external data.
- West, B.T. and Kreuter, F., 2013. Factors affecting the accuracy of interviewer observations evidence from the National Survey of Family Growth. *Public opinion quarterly*, p.nft016.
- West, B.T., Wagner, J., Hubbard, F. and Gu, H., 2015. The Utility of Alternative Commercial Data Sources for Survey Operations and Estimation: Evidence from the National Survey of Family Growth. *Journal of Survey Statistics and Methodology*, p.smv004.