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Using Independent Cross-Sectional Survey Data to Approximate Post-Migration Health Trajectories among Refugees

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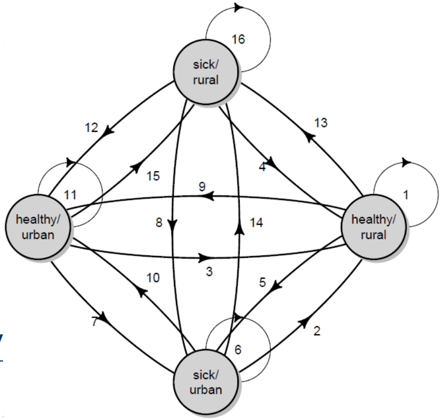
Background and Objective

- Collection of longitudinal data is resource-intensive
- Extrapolate a pseudo-panel of independent cross-sectional data (data of T_0 and T_1) to approximate a longitudinal health trajectory ($T_0 - T_1$)
- Study contextual effects (rural/urban) on health (good/bad) among refugees by calculating
  1. transition probability with associated
  2. variance



Data and Handling of Missing Information

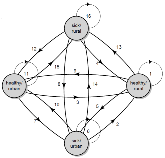
Two large-scale cross-sectional health surveys among randomly selected refugee samples in reception centers (T_0) and accommodation centers (T_1) located in Baden-Württemberg (data of 560 refugees, RESPOND study, Biddle et al. (2019)).

0. handling of missing data by multiple imputations:
Fully Conditional Specification (Van Buuren et al., 2006), Predictive Mean Matching (Rubin, 1986; Little, 1988)

Calculate Transition Probability and Variance

1. For each imputed data set transition probabilities were calculated based on

   a) Probabilistic Discrete Event Systems with Moore-Penrose generalized inverse matrix (PDES) (Chen and Wilson, 2015)



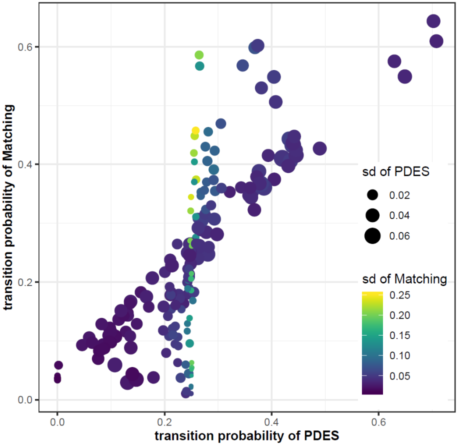
   b) Propensity score matching (Rosenbaum and Rubin, 1983).

$T_0 \leftarrow$ Matching $\rightarrow T_1$

2. By application of sampling approaches, exploiting the fact that status membership is multinomially distributed, results of both methods were pooled by Rubin's Rule (Rubin, 2004), accounting for within and between imputation variance.

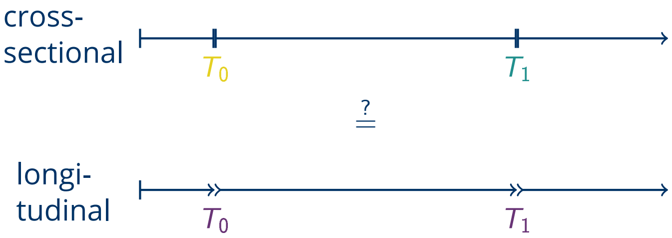
Comparison of Results

Results are comparable between both methods. (!!) They handle sparse cells differently: either assigning an average value for the transition probability for all states with high certainty (PDES), or assigning a more extreme value for the transition probability with large variance estimate (Matching).



Conclusion

Further research on the potential to extrapolate the results of cross-sectional data is needed.
$\Rightarrow$ Results of this analysis will be compared to results of prospective natural experiment study with longitudinal data collection of contextual and individual factors.



References

Biddle, L., Menold, N., Bentner, M., Noest, S., Jahn, R., Ziegler, S., and Bozorgmehr, K. (2019). Health monitoring among asylum seekers and refugees: a state-wide, cross-sectional, population-based study in germany. *Emerging themes in epidemiology*, 16(1):3.

Chen, D.-G. and Wilson, J. (2015). *Innovative Statistical Methods for Public Health Data*. Springer.

Little, R. J. (1988). Missing-data adjustments in large surveys. *Journal of Business & Economic Statistics*, 6(3):287–296.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rubin, D. B. (1986). Statistical matching using file concatenation with adjusted weights and multiple imputations. *Journal of Business & Economic Statistics*, 4(1):87–94.

Rubin, D. B. (2004). *Multiple imputation for nonresponse in surveys*, volume 81. John Wiley & Sons.

Van Buuren, S., Brand, J. P., Groothuis-Oudshoorn, C. G., and Rubin, D. B. (2006). Fully conditional specification in multivariate imputation. *Journal of statistical computation and simulation*, 76(12):1049–1064.