MRC/CSO Social and Public Health Sciences Unit

Maternal and Child Health Network

Methods Briefing 1

Emma Stewart on behalf of the Maternal and Child Health Network

MRC/CSO Social and Public Health Sciences Unit, University of Glasgow

Acknowledgements

MatCHNet Network Management Group
Ruth Dundas – University of Glasgow
Sinead Brophy – Swansea University
Richard Cookson – University of York
Ruth Gilbert – University College London
Joanne Given – Ulster University
Pia Hardelid – University College London
Katie Harron – University College London
Alastair Leyland – University of Glasgow
Anna Pearce – University of Glasgow
Emma Stewart – University of Glasgow
Rachael Wood – Public Health Scotland

Special thanks to our workshop presenters:
Andy Baxter, Ronan McCabe, Katie Harron, Richard Cookson, Peter Craig.

We are grateful to Network members who provided feedback on previous versions of this briefing.

Introduction

The Maternal and Child Health Network aims to harness cross-country administrative data to evaluate national policy impacts on maternal, infant and child health, and health inequalities across the 4 UK nations.

MatCHNet's reports and briefings provide baseline knowledge in the areas of policy, data, and methods relevant to early years policy evaluations.

MatCHNet's methods briefings aim to provide examples of how natural experiment methodologies can be used to evaluate policies in the early years. The briefings also showcase novel methods and approaches. The topics covered in this briefing include:

1. Interrupted time series
2. Synthetic control methods
3. Propensity score matching methods
4. Modelling the long-term impacts of childhood interventions
5. Revised natural experiment guidance

In addition to this briefing, short video presentations and slides are available on our website.

See how to apply these methods to early years policy evaluations in our bitesize policy webinar series.

1. Interrupted time series

- Interrupted time series (ITS) is a quasi-experimental method widely used to evaluate population-level health interventions.
- ITS is used to understand how an outcome may have changed after a population-level intervention or policy was implemented at one specific point in time (Bernal et al 2017).
- Longitudinal data about an outcome is necessary to track the period before and after the intervention point.
- *Key considerations*: continuous variables are preferable; the outcome should be 'immediately' affected by the intervention.
- *Pros*: ITS is good for controlling for baseline trends and for independent effects.
- *Cons*: consider whether the comparators are truly 'unexposed'; seasonal data may need more complex handling.

Key steps
- Define the exposure (intervention) to identify the exposed and unexposed periods
- Choose a measurement of outcome at regular time periods
- Create impact models to determine the expected impact of the exposure on the outcome
- Fit a linear model and check whether coefficients indicate an effect

Using ITS to evaluate early years policies

Case study 1: Impact of the Finnish Maternity Grant on infant mortality rates in the 20th century: a natural experimental study (McCabe et al 2023)
- ITS is used to evaluate two distinct interventions: 1. Maternity Grant introduction in 1938 and 2. Maternity Grant universalisation in 1949.
- The outcome was IMR per 1000 live births.
- National data (Human Mortality Database) was analysed for all infants born in Finland between 1922 and 1975, estimating step and trend changes in the outcome following the point of intervention.
- Changes were observed in IMRs associated with Maternity Grant introduction and universalisation but these changes cannot be disentangled from the impact of the Second World War or other relevant policy developments on infant mortality.

Table 1: Examples of using interrupted time series in early years evaluations

	Intervention	*Outcome*	*Data*
McCabe (2022)	Scotland's Baby Box Scheme	13 different measures related to hospital admissions, tobacco smoke exposure, breastfeeding, infant sleeping position, and infant immunisation uptake	SMR-01, SMR-02, CHSP-PS, SIRS[a] (Scotland)
Honkaniemi et al (2022)	1995 Father's quota – Swedish fathers leave policy	Swedish-born and migrant fathers' psychiatric hospitalisations	TPR, MGR, LISA, MBR, NPR, CRD (Sweden)[b]
Hill et al (2021)	Safe At Home: national home safety equipment scheme	Hospital admissions for unintentional injuries in children under 5	Hospital admission data (England)
Adams et al (2018) [c]	Health in Pregnancy Grant	Primary: mean gestational age at booking. Secondary: proportion of women booking by 10, 18 and 25 weeks' gestation; proportion of babies small for gestational age.	Maternity unit routine data (England)

[a] SMR-01: Scottish Morbidity Record 01, SMR-02: Scottish Morbidity Record, CHSP-PS: Child Health Surveillance Programme – Pre-School, SIRS: Scottish Immunisation & Recall System; [b] Total Population Register (TPR), Multigenerational Register (MGR); Longitudinal Integration Database for Health Insurance and Labour Market Studies (LISA); Medical Birth Register (MBR), National Patient Register (NPR) and Cause of Death Register (CDR); [c] Also see Leyland et al 2017 for Health in Pregnancy Grant in Scotland.

2. Synthetic control methods

- Synthetic control methodology (SCM), a relatively new addition to the natural experiment toolbox (Abadie et al 2010), is used to evaluate population level interventions.
- It provides an estimate of what would have happened to the exposed group if the intervention had not occurred (counterfactual).
- SCM involves the construction of a weighted combination of groups used as controls, to which the exposed group is compared.
- *Key requirements*: an exposure of interest, sequential measures of outcome of interest, clear theory of change, data for exposed/non exposed populations.
- *Pros*: avoids potential confounding, does not require a post-exposure link.
- *Cons*: difficult to meet data requirements, finding suitable control units.

Key steps (Bouttell et al 2018)
- Understand the theory behind the intervention – to identify independent variables and possible confounding variables
- Identify potential control units – includes subjective/objective assessment
- Develop the synthetic control
- Run outcome analysis and present results
- Run robustness checks
- Compare SCM-based estimates to effect estimates using other methods

Using synthetic control methods to evaluate early years policies

Case study 2: How effective was England's teenage pregnancy strategy? A comparative analysis of high-income countries (Baxter et al 2021)
- This paper uses synthetic control methods (SCM) to compare under-18 birth rates and under-20 pregnancy rates in England with 15 different European and English-speaking high-income countries.
- SCM are used to construct a comparison unit from a weighted average of other countries' rates, fitted to pre-intervention England and Wales observations.
- Results showed that under-18 birth rates were very similar in England and the synthetic control. Under-20 pregnancy rates were marginally higher in England than the control group.
- This raises doubts about the effectiveness of the teenage pregnancy strategy and has implications for future public health interventions in this area.

Table 2: Examples of using synthetic control methods in early years evaluations

	Exposure/Policy	*Outcome*	*Exposed unit*	*Donor pool*
Rado et al (2022) [d]	Smoke-free legislation	Neonatal mortality, infant mortality	Exposed middle-income countries	Unexposed middle-income countries
Chung et al (2016) [e]	Alaska Permanent Fund Dividend (APFD) - money transfer	Birth weights	Alaska	Unexposed US states
Oloomi (2016) [e]	Paid Family Leave	Delayed childbearing, infant health outcomes	California	Untreated US states
Pieters et al (2016)	Political transition	Child mortality	Countries that became democratic	Countries that remained autocratic
Wang et al (2014) [e]	Pasteurisation of milk	Child mortality	Treated US cities	Untreated US cities

[d] *Also see Rado et al 2020;* [e] *Examples taken from Bouttell et al (2018).*

3. Propensity score matching methods

- Propensity score analysis (PSA) can be used to evaluate policies when randomised trials are not feasible or ethical.
- This is a statistical matching technique employed to estimate the effect of a policy or intervention by accounting for the covariates that predict being exposed.
- The propensity score is the probability of exposure conditional on observed baseline characteristics (Austin 2011).
- *Key considerations*: *No interference* - exposure of one individual does not affect the potential outcomes of another individual; *Positivity* - every individual in the population must have a non-zero probability of having either treatment option; *Consistency* - no multiple versions of treatment; *No unmeasured confounding* (conditional exchangeability).
- *Pros*: ability to mimic characteristics of an RCT in the context of an observational study.
- *Cons*: potential selection bias due to unmeasured covariates.

Key steps

- Construct a regression model
- Use model to predict each individual's probability of being exposed (propensity score)
- Select matched controls for participants with similar propensity score
- Perform matched analysis on sub-sample of matched participants and controls

Using propensity score matching to evaluate early years policies

Case study 3: Evaluation of the real-world implementation of the Family Nurse Partnership in England: an observational cohort study using linked data from health, education, and children's social care (Cavallaro et al 2022)

- Propensity score matching is employed to evaluate the Family Nurse Partnership in England.
- Linked administrative data from hospital admissions (Hospital Episode Statistics) and education and social care (National Pupil Database) was used to construct a cohort of all mothers in England.
- Several outcomes were evaluated: child maltreatment, child health & development and maternal outcomes.
- The study found little benefit for measured child maltreatment and maternal outcomes, but some evidence of benefit for school readiness.

Table 3: Examples of using propensity score analysis in early years evaluations

	Exposure/Intervention	*Outcome*	*Type of analysis*[f]
Martín-de-Las-Heras et al (2022)	Psychological intimate partner violence	Pre-term birth	Weighting by inverse probability
Falconi et al (2022)	Doula care (US)	Mode of delivery, maternal health	Matching
Barlow et al (2017)	A Better Start – area-based intervention (England)	Nutrition, socioemotional development, speech, language and learning	Matching
Ruzek et al (2014)	Pre-school childcare	Cognitive skills	Covariate adjustment
Wen et al (2012)	Head Start Program (early educational intervention)	Academic and social outcomes	Matching
Jiang et al (2011)	Breastfeeding initiation and duration	Child cognitive development	Matching
Hong & Yu (2008)	Kindergarten retention	Children's social-emotional development	Stratification

[f] Propensity score analysis can include matching, stratification, inverse probability of treatment weighting, and covariate adjustment (Austin 2011).

4. Modelling the long-term impacts of childhood interventions

- Lifecourse simulation is useful to understand the long-term impacts of childhood interventions for health, wellbeing and public cost, and how they vary for different children in different circumstances.
- Simulation modelling can facilitate childhood policy co-ordination by comparing the value for money and equity impacts of childhood interventions in different sectors (e.g., education, social care, welfare).

Key steps
- Review evidence on short-term effects
- Map short-term effects
- Predict long-term effects using computer model

Applying microsimulation models in the early years

- *LifeSim Childhood*: poverty in early childhood and adverse health outcomes (Villadsen et al 2022)
- *LifeSim Adulthood*: Incredible Years Parenting Programme for Preschoolers (Skarda et al 2022)

5. Revised natural experiment guidance

- Natural experiment (NE) approaches are useful for evaluating population health interventions that are not amenable to experiment manipulation.
- The NE guidance is being updated due to:
    - continued debate surrounding key concepts and definitions
    - emergence of new methods
    - developments in the design and conduct of natural experiment evaluations
- The new guidance will provide a single, integrated, up-to-date guide to the conduct and use of natural experiment evaluations.

Key steps
- Identify a candidate intervention
- Assess feasibility of evaluation design (e.g., data availability)
- Develop/refine a theory of how the intervention achieves its effects
- Engage stakeholders
- Identify the effect of the intervention and how effects achieved, using quantitative and qualitative methods

Table 4: Examples of natural experiment evaluations in the early years

	Intervention	*Outcome*	*Data*
Bennett et al (2021)	Children's Services prevention spend per child under 5	Annual rates of children entering care aged 1-4	Panel data from 150 English LAs (2011-2019)
Mason et al (2021)	Local authority expenditure on Sure Start Children's Centres	Childhood obesity	National Child Measurement Programme data and Department for Education data (England)
Laverty et al (2020)	Ban on smoking in cars with children present	Child-reported exposure to tobacco smoke in cars	Smoking, Drinking and Drug Use (SDDU) Survey (England) and Scottish Health Surveys
Katikireddi et al (2018)	Lone parent obligations (LPOs)	Mental health of lone mothers	Understanding Society Survey

Further reading/resources

1. Interrupted time series

Bernal, J. L., et al. (2017). "Interrupted time series regression for the evaluation of public health interventions: a tutorial." Int J Epidemiol 46(1): 348-355.

- Adams, J., et al. (2018). "Associations between introduction and withdrawal of a financial incentive and timing of attendance for antenatal care and incidence of small for gestational age: natural experimental evaluation using interrupted time series methods." BMJ Open 8(1): e017697.
- Hill, T., et al. (2021). "Impact of the national home safety equipment scheme 'Safe At Home' on hospital admissions for unintentional injury in children under 5: a controlled interrupted time series analysis." Journal of Epidemiology and Community Health: jech-2021-216613.
- Honkaniemi, H., et al. (2022). "Psychiatric consequences of a father's leave policy by nativity: a quasi-experimental study in Sweden." Journal of Epidemiology and Community Health 76(4): 367.
- Leyland, A. H., et al. (2017). "Evaluation of health in pregnancy grants in Scotland: a natural experiment using routine data." Public Health Research 5(6): doi: 10.3310/phr05060.
- McCabe, R. (2022). Scotland's Baby Box Scheme: A Mixed-Methods Public Health Evaluation. PhD Thesis. https://theses.gla.ac.uk/83142/1/2022mccabephd.pdf, University of Glasgow.
- McCabe, R., et al. (2023). "Impact of the Finnish Maternity Grant on infant mortality rates in the 20th century: a natural experimental study." Journal of Epidemiology and Community Health 77(1): 34.

2. Synthetic control methods

Bouttell, J., et al. (2018). "Synthetic control methodology as a tool for evaluating population-level health interventions." Journal of Epidemiology and Community Health 72(8): 673.

- Abadie, A. and J. Gardeazabal (2003). "The Economic Costs of Conflict: A Case Study of the Basque Country." American Economic Review 93(1): 113-132.
- Abadie, A., et al. (2010). "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." Journal of the American Statistical Association 105(490): 493-505.
- Abadie, A., et al. (2011). "Synth: An R Package for Synthetic Control Methods in Comparative Case Studies." Journal of Statistical Software 42(13): 1 - 17.
- Baxter, A. J., et al. (2021). "How effective was England's teenage pregnancy strategy? A comparative analysis of high-income countries." Social Science & Medicine 270: 113685.
- Chung, W., et al. (2016). "Money transfer and birth weight: evidence from the Alaska Permanent Fund Dividend." Economic Inquiry 54(1): 576-590.
- Oloomi, S. (2016). Impact of Paid Family Leave of California on Delayed Childbearing and on Infant Health Outcomes. https://www.lsu.edu/business/economics/files/workingpapers/pap16_08.pdf, Department of Economics Working Paper series Louisiana State University.
- Pieters, H., et al. (2016). "Effect of democratic reforms on child mortality: a synthetic control analysis." The Lancet Global Health 4(9): e627-e632.
- Radó, M. K., et al. (2022). "Effect of comprehensive smoke-free legislation on neonatal mortality and infant mortality across 106 middle-income countries: a synthetic control study." The Lancet Public Health 7(7): e616-e625.
- Radó, M. K., et al. (2020). "Investigating the effects of comprehensive smoke-free legislation on neonatal and infant mortality in Thailand using the synthetic control method." eClinicalMedicine 27.
- Wang, H., et al. (2014). The Public Health Effect of Mandatory and Voluntary Food Safety Measures: Generalized Synthetic Control Methods on Milk Pasteurization in the United States. https://ideas.repec.org/p/ags/aaea14/169775.html, Agricultural and Applied Economics Association.

Further reading/resources

3. Propensity score analysis
Austin, P. C. (2011). "An introduction to propensity score methods for reducing the effects of confounding in observational studies." Multivariate Behav Res 46(3): 399-424.

- Barlow, J., et al. (2017). "Initial protocol for a national evaluation of an area-based intervention programme (A Better Start) on early-life outcomes: a longitudinal cohort study with comparison (control) cohort samples." BMJ Open 7(8): e015086.
- Cavallaro, F., et al. (2022). "Evaluation of the real-world implementation of the Family Nurse Partnership in England: an observational cohort study using linked data from health, education, and children's social care." The Lancet 400: S29.
- Falconi, A. M., et al. (2022). "Doula care across the maternity care continuum and impact on maternal health: Evaluation of doula programs across three states using propensity score matching." eClinicalMedicine 50.
- Hong, G. and B. Yu (2008). " Effects of kindergarten retention on children's social-emotional development: An application of propensity score method to multivariate, multilevel data." Developmental Psychology 44(2): 407-421.
- Jiang, M., et al. (2011). "Breastfeeding and the Child Cognitive Outcomes: A Propensity Score Matching Approach." Maternal and Child Health Journal 15(8): 1296-1307.
- Kim, H. (2019). "Propensity Score Analysis in Non-Randomized Experimental Designs: An Overview and a Tutorial Using R Software." New Dir Child Adolesc Dev 2019(167): 65-89.
- Martín-de-Las-Heras, S., et al. (2022). "Propensity score analysis of psychological intimate partner violence and preterm birth." Sci Rep 12(1): 2942.
- Ruzek, E., et al. (2014). "The quality of toddler childcare and cognitive skills at 24 months: Propensity score analysis results from the ECLS-B." Early Childhood Research Quarterly 29(1): 12-21.
- Wen, X., et al. (2012). "Are two years better than one year? A propensity score analysis of the impact of Head Start program duration on children's school performance in kindergarten." Early Childhood Research Quarterly 27(4): 684-694.

4. Modelling the long-term impacts of childhood interventions
- Skarda, I., et al. (2021). "LifeSim: A Lifecourse Dynamic Microsimulation Model of the Millennium Birth Cohort in England." IJM 14(1): 2-42.
- Skarda, I., et al. (2022). "Evaluating childhood policy impacts on lifetime health, wellbeing and inequality: Lifecourse distributional economic evaluation." Social Science & Medicine 302: 114960.
- Villadsen, A., et al. (2022). "Clustering of adverse health and educational outcomes in adolescence following early childhood poverty: implications for UK's 'levelling up' agenda." medRxiv: 2022.2008.2011.22278671.

Slides and short video presentations for each method are available on our website.

Also learn more about how to apply these methods in our bitesize (12 minute) policy webinars.

Further reading/resources

5. Revised natural experiment guidance

Craig, P., et al. (2012). "Using natural experiments to evaluate population health interventions: new Medical Research Council guidance." Journal of Epidemiology and Community Health 66(12): 1182.

Craig, P., et al. (2017). "Natural experiments: an overview of methods, approaches, and contributions to Public Health Intervention Research." Annual Review of Public Health 38(1): 39-56.

- Bennett, D. L., et al. (2021). "Funding for preventative Children's Services and rates of children becoming looked after: A natural experiment using longitudinal area-level data in England." Children and Youth Services Review 131: 106289.
- Katikireddi, S. V., et al. (2018). "Effects of restrictions to Income Support on health of lone mothers in the UK: a natural experiment study." The Lancet Public Health 3(7): e333-e340.
- Laverty, A. A., et al. (2020). "Impact of banning smoking in cars with children on exposure to second-hand smoke: a natural experiment in England and Scotland." Thorax 75(4): 345.
- Mason, K. E., et al. (2021). "Impact of cuts to local government spending on Sure Start Children's Centres on childhood obesity in England: a longitudinal ecological study." Journal of Epidemiology and Community Health 75(9): 860.

Slides and short video presentations for each method are available on our website.

Also learn more about how to apply these methods in our bitesize (12 minute) policy webinars.

This work is supported by the UK Prevention Research Partnership (MR/S037608/1), which is funded by the British Heart Foundation, Cancer Research UK, Chief Scientist Office of the Scottish Government Health and Social Care Directorates, Engineering and Physical Sciences Research Council, Economic and Social Research Council, Health and Social Care Research and Development Division (Welsh Government), Medical Research Council, National Institute for Health Research, Natural Environment Research Council, Public Health Agency (Northern Ireland), The Health Foundation and the Wellcome Trust.

The Social and Public Health Sciences Unit is core funded by the Medical Research Council (MC_UU_00022/2) and the Scottish Government Chief Scientist Office (SPHSU 17).

Cite as: Stewart, E. on behalf of MatCHNet. 2023. *MatCHNet Methods Briefing 1*, University of Glasgow, Glasgow

For more information, please visit our website: www.gla.ac.uk/matchnet and follow us on Twitter: @MatCHNet_