

Interrupted Time Series

An Introduction

What is it?

- Used to retrospectively analysis public health interventions
- Best suited to population level health outcomes over a defined time period.
- Some examples
 - A change in the doctor reimbursement system where doctors receive a payment bonus for targeting specific conditions such as diabetes care, hypertension, and smoking cessation.
 - Introduction of new policy such as a sugar tax which comes into force on a specific date.

When to use it?

- Clear distinction of pre and post intervention period.
- The outcomes of interest can either be a binary variable, continuous, or count data.
- ITS works best with short term outcomes that are likely to change relatively quickly after the introduction of a policy change (Bernal et al. 2017).

Which of the following situations would be appropriate to use ITS

- A) Evaluating women's satisfaction scores after introduction of women being able to choose where they give birth.
- B) Evaluating mental health scores in a prison which introduced park run
- C) Monthly number of asthma attacks after the introduction of a smoking ban
- D) Infant mortality rates over time.

Data

- A time series is a continuous sequence of observations on a population taken repeatedly and usually at equal intervals.
- The data needs to cover a sufficient length of time before a change in policy and data points after the change in policy.
- This span of data is needed to be able to establish a trend in outcomes which is then 'interrupted' by the change in policy.

Estimation

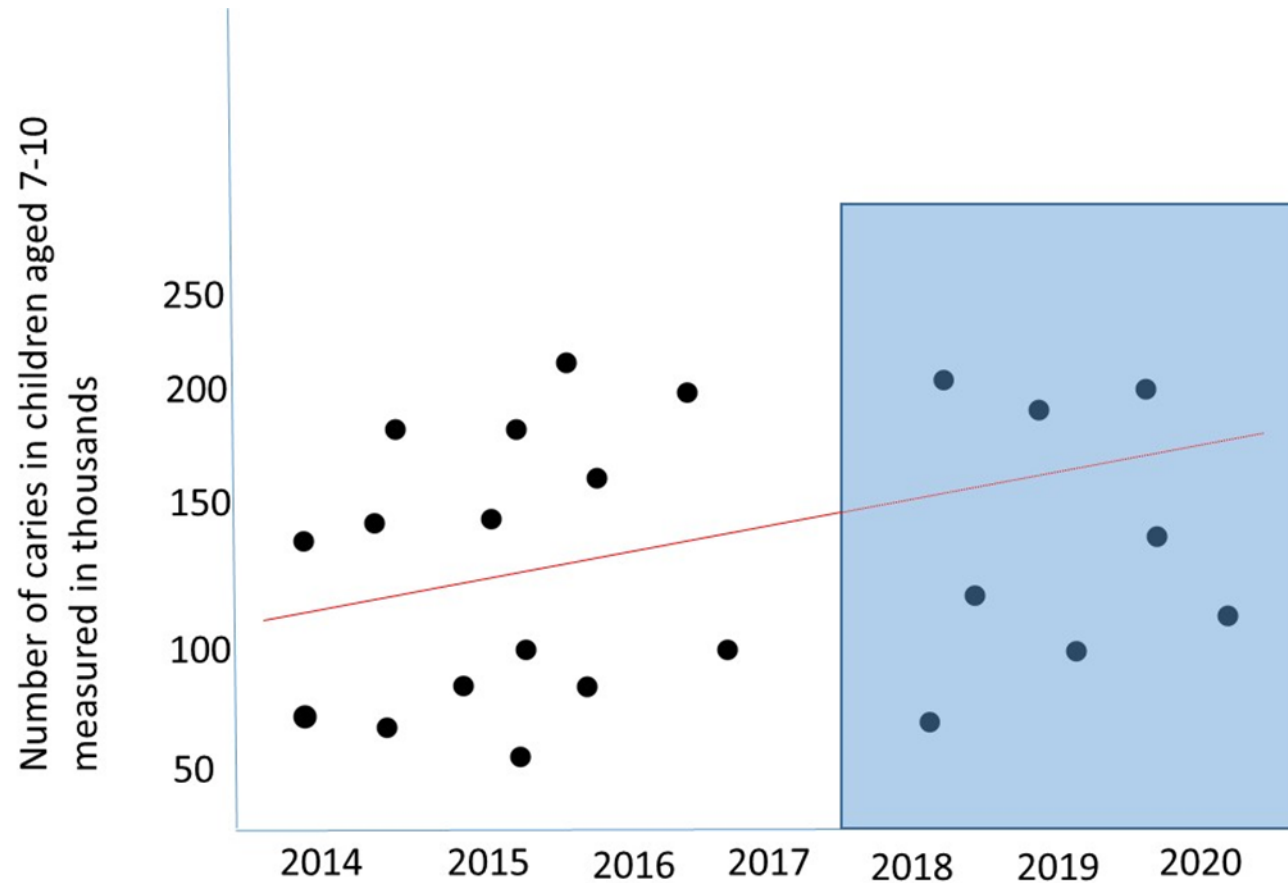
- The basic ITS model is estimated using a regression based model such as linear, logistic or Poisson.
- The basic model would include 3 variables: 1) the pre-intervention slope; 2) the change in level at the intervention point; and 3) and the change in slope between pre and post intervention.
- To improve reliability you can include additional controls. Time constant variables can be added.
- Time varying variable related to the intervention cannot be included.

Estimation continued

- ITS framework is also subject to biases associated with estimating linear and logistic regressions such as serial autocorrelation (when the error term for the previous period is correlated with the error term from the current period).
- Thus, as with any model specification it is suggested to conduct some form of sensitivity analysis to test a range of model assumptions such as different lags or by employing methods to control for potential biases from such factors as serial autocorrelation.

An example-Introduction of a sugar tax on dental caries in 7-10 year old children

Figure 1: Example of Time Series Data on Dental Caries in Children



Basic Model Specifications

$$DC_{it} = \beta_0 + \beta_1 X_{pre} + \beta_2 X_{post} + \varepsilon_{it}$$

- Where DC is a continuous variable for number of dental caries
- β_0 is the intercept or the mean number of dental caries for the sample population if there were no other controls in the model.
- β_1 is the baseline trend in dental caries in children
- X_{pre} is a vector containing child characteristics variables such as socioeconomic status, sugar consumption, etc. This captures trend in dental caries before the introduction of the sugar tax.

Additional things to consider:

- Looking at the intercept is a good way to get a sense check if the estimation model looks sensible in linear regression models. If the intercept is far from the mean then the model may be miss-specified.
- When entering your regression equation in a statistical software package you need to make sure the programme can control for the policy change. To do this you need to make sure the data is clearly divided by pre and post policy period.
- One way to do this is by using [mkspline](#) command in STATA

Results

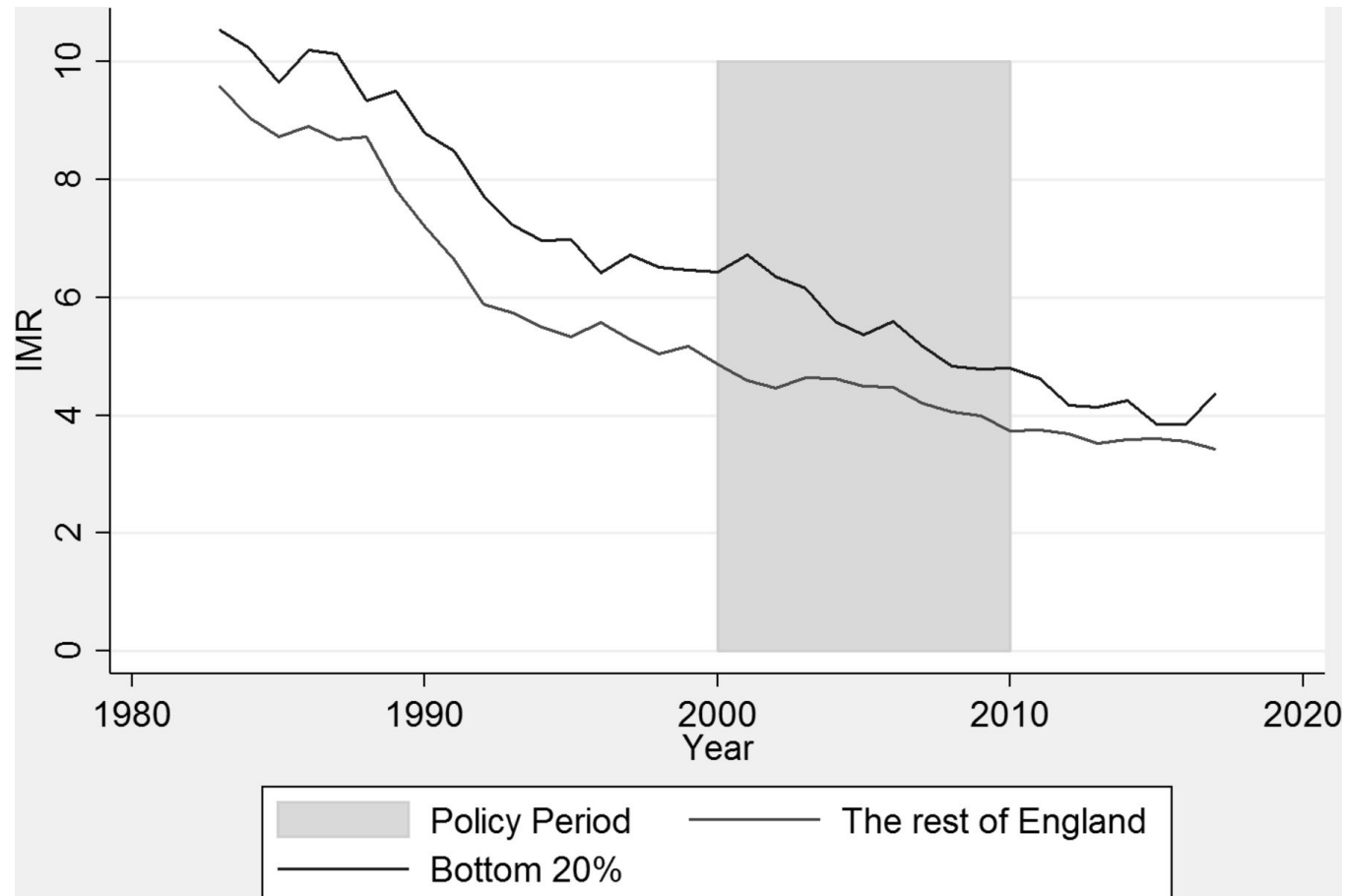
Interpreting results from ITS

Number of dental caries	Coefficient	95% Confidence Intervals
Intercept β_0	0.98	0.23-0.89
Baseline Trend β_1	1.27	1.06-3.75
Trend Change After Introduction of Sugar Tax β_2	0.67	0.13-0.78

*hypothetical results not based on real data

Putting what we learned into practice

- From: The impact of New Labour's English health inequalities strategy on geographical inequalities in infant mortality: a time-trend analysis
- What does the following graph show about trends in infant mortality rates between the most deprived decile and rest of England



How can we interpret these statistics

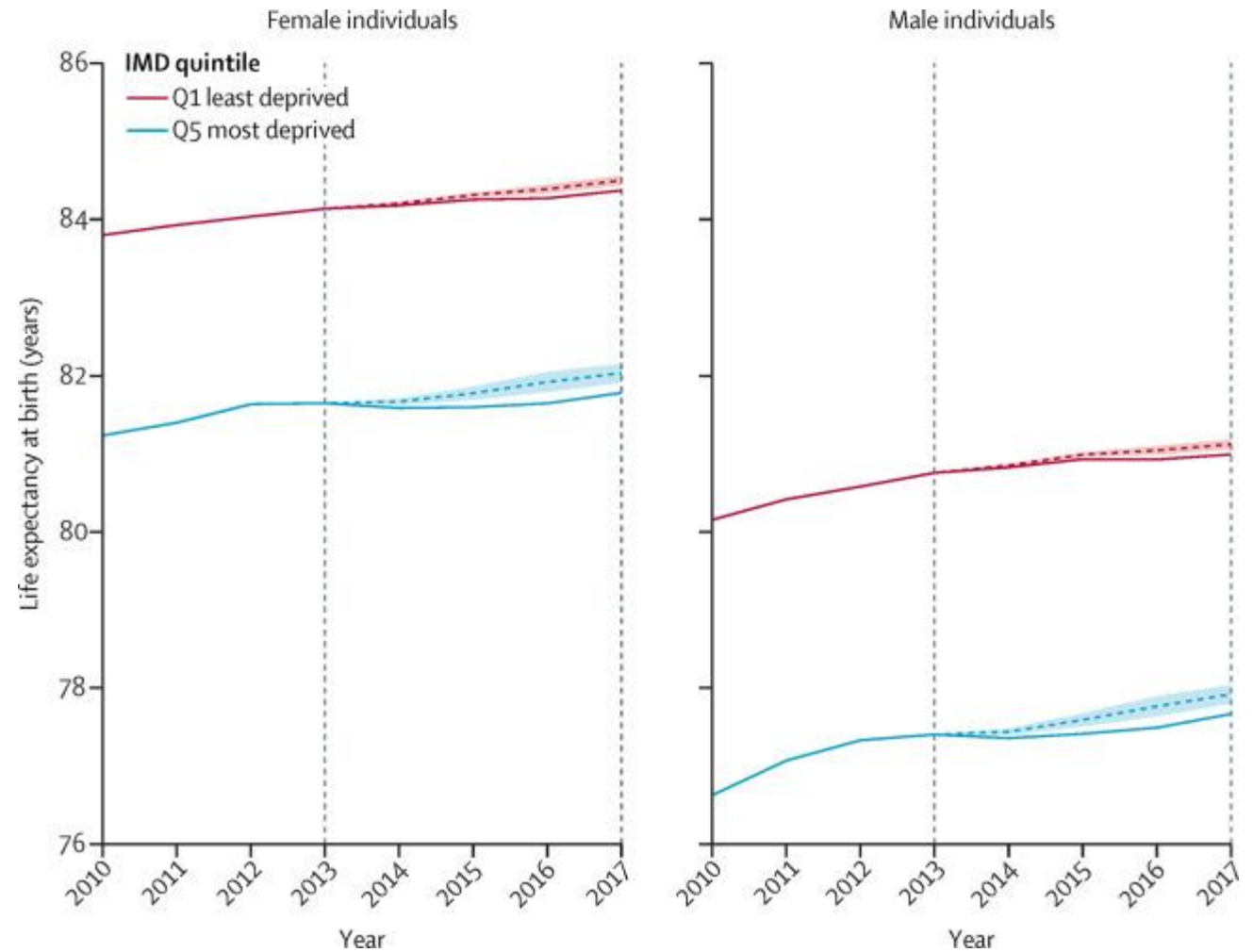
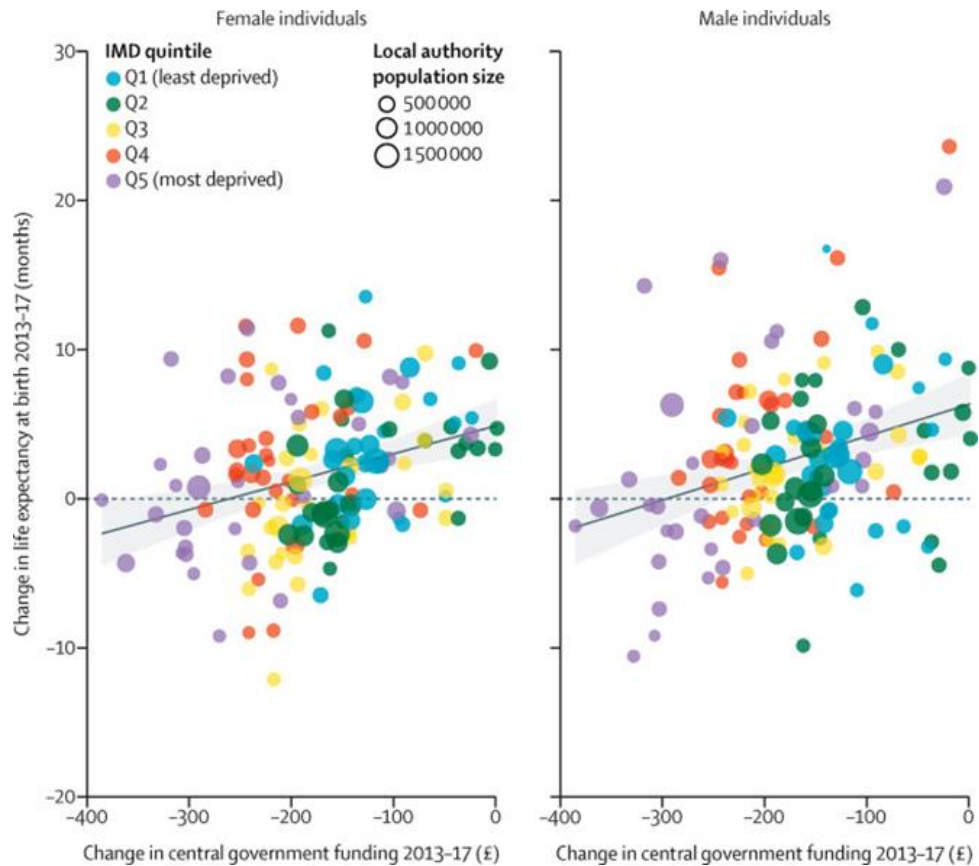
To estimate the changes in the level of absolute inequality over time, we estimated fixed effects (FE) segmented linear regression models, including marginal spline terms to take account of the time trends, with breakpoints at the beginning and end of the health inequalities strategy period. We interacted these time trends with a dummy variable indicating the deprived group of local authorities, allowing the change in the IMR to vary by the level of deprivation

Period	Annual change in absolute gap in the IMR between the most deprived local authorities and the rest of England (95% CI)
Before 1983–1999	0.034 (0.001 to 0.067)
During 2000–2010	-0.116 (-0.178 to -0.053)
After 2011–2017	0.042 (-0.042 to 0.125)

More Examples

- From: Local government funding and life expectancy in England: a longitudinal ecological study
- Investigate whether local authority areas that showed greater reductions in RSG and business rates income, henceforth referred to as central government funding, between 2013 and 2017 had more adverse trends in life expectancy and premature mortality.

Some Figures



- Method: We did a longitudinal ecological study of 147 of the 152 upper-tier local authorities in England, between 2013 and 2017, using fixed-effects regression

Table: Change in life expectancy and premature mortality for each £100 per-capita reduction in annual central government funds allocated to local authorities in England 2013–2017

Life expectancy at birth, months			
Male individuals	-1.28	-1.88 to -0.69	<0.0001
Female individuals	-1.19	-1.73 to -0.65	<0.0001
Life expectancy at age 65 years, months			
Male individuals	-0.81	-1.32 to -0.29	0.0021
Female individuals	-1.09	-1.48 to -0.71	<0.0001
Age-adjusted all-cause mortality for those younger than 75 years, deaths per 100 000			
Male individuals	3.91	6.27 to 1.55	0.0012
Female individuals	2.94	4.61 to 1.27	0.0005

References of papers if you want to have a closer look

- Robinson, T., Brown, H., Norman, P.D., Fraser, L.K., Barr, B. and Bambra, C., 2019. The impact of New Labour's English health inequalities strategy on geographical inequalities in infant mortality: a time-trend analysis. *J Epidemiol Community Health*, 73(6), pp.564-568.
- Alexiou, A., Fahy, K., Mason, K., Bennett, D., Brown, H., Bambra, C., Taylor-Robinson, D. and Barr, B., 2021. Local government funding and life expectancy in England: a longitudinal ecological study. *The Lancet Public Health*, 6(9), pp.e641-e647.

Group Exercise

- What is the difference between RD and ITS?
- Give an example of when you would use RD and when you would ITS?
- How would you convince your team one method is preferred over the other?