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A methodological framework for model selection in interrupted time series studies

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Abstract

Interrupted time series (ITS) is a powerful and increasingly popular design for evaluating public health and health service interventions. The design involves analyzing trends in the outcome of interest and estimating the change in trend following an intervention relative to the counterfactual (the expected ongoing trend if the intervention had not occurred). There are two key components to modeling this effect: first, defining the counterfactual; second, defining the type of effect that the intervention is expected to have on the outcome, known as the impact model. The counterfactual is defined by extrapolating the underlying trends observed before the intervention to the postintervention period. In doing this, authors must consider the preintervention period that will be included, any time-varying confounders, whether trends may vary within different subgroups of the population and whether trends are linear or nonlinear. Defining the impact model involves specifying the parameters that model the intervention, including for instance whether to allow for an abrupt level change or a gradual slope change, whether to allow for a lag before any effect on the outcome, whether to allow a transition period during which the intervention is being implemented, and whether a ceiling or floor effect might be expected. Inappropriate model specification can bias the results of an ITS analysis and using a model that is not closely tailored to the intervention or testing multiple models increases the risk of false positives being detected. It is important that authors use substantive knowledge to customize their ITS model a priori to the intervention and outcome under study. Where there is uncertainty in model specification, authors should consider using separate data sources to define the intervention, running limited sensitivity analyses or undertaking initial exploratory studies.

Keywords: Interrupted time series; Segmented regression; Modelling; Counterfactual; Evaluation; Intervention Studies; Study design

1. Introduction

Interrupted time series (ITS) has become a core study design for the evaluation of public health interventions and health policies [1]. The design takes advantage of natural experiments whereby an intervention is introduced at a known point in time and a series of observations on the outcome of interest exist both before and after the intervention. The effect of the intervention is estimated by examining any change following the intervention compared with the ‘‘counterfactual’’, represented by the expected ongoing trend in the absence of the intervention (Figure 1) [2]. ITS involves a pre–post comparison, controlling for the counterfactual baseline trend, within the same population; therefore, it can be used in situations where no control population is available [3,4]. This also has the advantage that selection bias and confounding due to group differences, which threaten the reliability of nonrandomized controlled designs, are rarely a problem in ITS studies [2,3]. Furthermore, because ITS incorporates the underlying trend, it controls for short-term fluctuations, secular trends, and regression to the mean [3,4]. The basic ITS design also has limitations; for example, there is the potential for history bias whereby other events concurrent to the intervention may be responsible for an observed effect. In addition, instrumentation effects can occur if there are changes in the way the outcome is measured over time [3]. Previous studies have described these strengths and limitations of ITS in more

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What is new?

Key findings

- Interrupted time series (ITS) is one of the strongest quasi-experimental designs for evaluating the effect of health interventions. However, this design requires careful specification of several modeling features, for which little guidance is offered in the literature

What this adds to what was known?

- We demonstrate how incorrectly modeling either the trend or the type of impact model can generate misleading results and offer a methodological framework for making modeling choices in ITS analyses.

What is the implication and what should change now?

- Researchers must be transparent in providing a clear and objective justification for the choices they make in defining an ITS model which is tailored to the specific intervention and outcome under study.

detail and have provided guidance on its application [2,4,5]. Furthermore, methodological publications have discussed effective approaches for limiting the risk of history bias, including controlled ITS designs and multiple baseline designs [6−8].

One area that has not been covered in detail in the existing literature is how researchers should approach specifying the ITS model used in the analysis. As discussed previously, the ITS design involves making a comparison between the outcome observed following the intervention and the counterfactual. This comparison reduces to two key questions that define the estimated effect of the intervention [2]. First, how is the counterfactual defined? This involves modeling the preintervention trend. Second, how is the impact model of the intervention defined? That is, what type of effect do we hypothesize that the intervention will have on the outcome (such as whether the effect is gradual or abrupt, immediate or lagged)? This involves parameterizing the effect of the intervention relative to the counterfactual. Multiple alternative approaches exist to defining the counterfactual and the intervention impact model and inappropriate model selection could bias results, yet ITS studies often fail to provide a clear justification for their choice of modeling approach [9].

In this article, we suggest approaches to ensure that model specification is objective and appropriate to the intervention and outcome under investigation. The first section discusses the factors that contribute to defining the counterfactual and the second, the factors that contribute

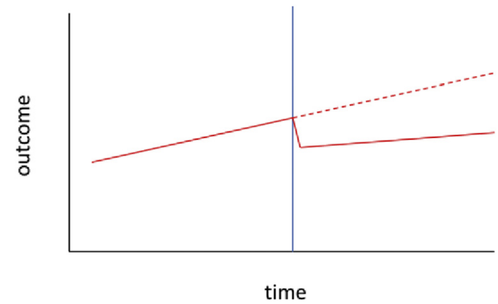

Fig. 1. The interrupted time series design. Solid line = modeled trend; dashed line = counterfactual; vertical line = intervention implementation. This shows a step decrease and decrease in the slope following the intervention.

to defining the impact model. For each of these sections, we use illustrative examples from a recent ITS study of the impact of major reforms to the English National Health Service on hospital activity (described in Box 1) [10] to highlight the pitfalls of incorrect model specification and then provide a framework for a suggested approach to select the model. Finally, we also discuss sensitivity analysis and other approaches to dealing with uncertainty in model specification.

2. Defining the counterfactual

A key step in ITS analysis is to predict how the outcome would have continued over time if no intervention had been implemented, referred to as the "counterfactual" scenario. It is not possible to observe the intervention both being implemented and not being implemented in the same population at the same time. The true counterfactual is therefore never known and therefore inferring causality is rarely possible. Evaluation design centers on creating the best approximation of the true counterfactual. This requires both the study population and the counterfactual to share the same characteristics as far as possible. In ITS studies, this involves modeling the underlying trend in the outcome of interest within a single population. Because the effect of an intervention is a measure of its deviation from the counterfactual, it is essential that the counterfactual is defined as accurately as possible. Incorrect definition of the counterfactual can lead to either overestimation or underestimation of the intervention's effect. When estimating the baseline trend, it is necessary to consider both the data that will be included and the way the trend is modeled.

2.1. The preintervention period

Routine data sources now often span many years; weekly or monthly time series with hundreds of data points are possible. For example, Swedish data on maternal mortality dates back to the mid 18th century [12]. Trends may change over time; therefore, how the counterfactual is predicted can vary depending on the range of data that is