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Commentary: On the use of quasi-experimental designs in public health evaluation

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Quasi-experimental designs are often applied in public health research to assess phenomena for which truly experimental studies are not feasible. Recently, investigators have used these tools to examine the association between macro-economic conditions and rates of suicides in specific populations.^{1–3} In this issue of the *International Journal of Epidemiology*, Harper and colleagues have added new evidence to this topic, with an analysis on a large dataset including more than 20 years of data and almost 1 million cases in the USA.⁴ The original analytical approach they propose, combined with the interpretational issues in

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evaluating such a complex multi-factorial phenomenon, provide an excellent opportunity to comment on the benefits and limitations of quasi-experimental designs in public health evaluation studies.

The first issue we would like to discuss pertains to the definition of the research question. This step is straightforward in experimental analyses such as randomized controlled trials, in which the treatment is directly allocated to an intervention group, and a specific health outcome is then measured and compared with a control group. This makes the objective of the analysis, and the scope of the

inference, unambiguous. In contrast, the idea underpinning quasi-experimental studies is to fabricate a natural experiment through the definition of an unobserved counterfactual scenario that mimics the control arm. In these observational investigations, the definition of the counterfactual is rarely stated directly, and the research question and limits of the analysis are not always clear. For example, Harper and colleagues estimate the association between variation in a specific economic index and suicide rates, but then extend their conclusions to the specific effects of the past economic downturn, and compare their results with other studies directly evaluating the suicide burden attributable to this recession period.^{5,6} In fact, the counterfactual the authors apply is likely to describe only a part of the complex pattern of social and economic conditions characterizing periods of protracted stagnation. Other studies cited above have adopted designs more appropriate to this different research question, contrasting specific recessive periods vs non-recessive periods, and it is not surprising that they report higher estimates. In this case, the conclusions and the comparison by the authors extend far beyond the scope of the analysis.

Another problem affecting observational studies is the potential imbalance between the observed and counterfactual states, due to factors external to the association under study. This issue is avoided in experimental studies by the use of randomization. Instead, quasi-experimental analyses address potential imbalances either by design, through comparison with counterfactual scenarios matched for some of these factors, or by controlling for confounding variables in regression models.⁷ The provision of valid estimates of truly causal relationships is therefore dependent on the choice of the design and the specification of the statistical model, which in turn depend on the specific association and type of data collected in the study. For instance, previous studies evaluating suicide rates during the past recession have adopted an interrupted time series design,^{8,9} which is highly dependent on assumptions on the underlying trends.¹⁰ The evaluation of a time-varying economic index allows instead Harper and colleagues to propose an alternative design, where they finely control for temporal trends at national level while assessing state-specific variations in the economic index. This approach exemplifies the flexibility of quasi-experimental designs to be adapted to the specific context of the research investigation.

Nonetheless, the use of complex designs and regression techniques to control for confounders, although providing flexible methods, has its own drawbacks. In the contribution by Harper and colleagues, for instance, the more sophisticated design makes it more difficult for the reader to identify the underlying modelling assumptions. Specifically, the primary approach proposed by the authors presumes

that the national trend, flexibly modelled, is in fact representative of each state. However, when they relax this assumption with the inclusion of state-specific trend components, the estimated rate difference for a 10-unit increase in the economic index substantially rises, from 0.14 per 100 000 person years [95% confidence interval (CI): 0.00–0.28] up to 0.29 (0.12–0.45) in the most complex model. This issue is related to the statistical problem of model selection. When alternative modelling approaches are available and they provide different results, it is not straightforward to select the model that appropriately describes the phenomenon. The authors correctly report results from multiple models as a sensitivity analysis, but fail to offer some explanations about why they base their conclusions on only one of them.

A final comment concerns methods to strengthen the validity observational studies. In particular, the use of controls has been advocated as a powerful tool for extending the analytical armoury of quasi-experimental methods.⁷ Alternative choices for controls are available, depending on the study design. For example, the analysis can be repeated in populations living in geographically similar areas, not affected by a public health intervention to be evaluated. Another option is to apply the same model to a different outcome that is not expected to be influenced by the intervention or factor of interest. Harper and colleagues selected the latter, investigating the association with cancer mortality. The use of controls can be considered as an additional counterfactual scenario, and shares the same pros and cons of the choice of a specific design. In practice, the ideal control should simulate an alternative reality that differs only in terms of the absence of an effect of the intervention or measure. In this case, cancer mortality shares very little with suicides, in terms of outcome definition, common risk factors and, importantly, the lag between potential risk factors and mortality. Alternative choices for the control, such as accidental deaths, would have probably been more appropriate and informative.⁸

In conclusion, quasi-experimental designs represent a useful tool for public health evaluation, as well illustrated in the article by Harper and colleagues. These flexible methods can be adapted to a wide range of public health evaluation studies, and can incorporate assumptions and previous knowledge on the association of interest. However, researchers should be aware of the comparative advantages and limitations of different designs, and be careful in their selection of methods to reinforce the validity of the study, and their interpretation and conclusions.

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