Population Intervention Measures to Connect Research Findings to Policy

See also Galea and Vaughan, p. 2091.

Public health research should inform decision-making around programs and policies, either directly or through contribution to the body of evidence. When we study the health effects of green space or access to fruits and vegetables, we hope to inform decisions about distribution of these resources in our cities. However, there can be a disconnection between research and policy decision-making,[1,2] some of which is within the control of researchers.

As an obvious starting place, we should ask questions that have relevance to policy decisions, and engage policymakers who might use the findings. This editorial is about how we present research findings when a relevant question has been asked.

LIMITS OF THE REGRESSION APPROACH

In quantitative research, we present a description of the study population, examine associations of variables with the outcome, and use multivariable regression to address the study question. The multivariable regression is a key step because it allows us to separate the effects of the exposure under study from those of confounding variables. Regression offered an advance on earlier stratification approaches from the perspective that it allowed more thorough and efficient control of confounding.

However, ubiquitous use of regression has led to problems in how we present research findings. First, the form of the regression may dictate the measure used to quantify the association between the exposure and outcome. For example, logistic regression is often employed for binary outcomes. Typically, odds ratios are then used to quantify the association between exposure and outcome, through exponentiation of regression betas. Odds ratios are difficult to explain to a general or policymaking audience. Moreover, they do not capture what we might actually want to know about how exposure and outcome are related, with the exception of specific case–control study designs. Odds ratios muddle our ability to explain our findings to broader audiences, or even understand their magnitudes ourselves.

A second problem is that betas from regressions provide conditional estimates of associations—estimates that are dependent on covariate values. This is most obvious when an interaction between the exposure and a covariate means there are different associations within the same population, depending on individual characteristics. Description of the different associations for subgroups of the population may be an important part of understanding mechanisms behind the association, and may indicate subpopulations with particular vulnerabilities to the exposure. However, policies are typically implemented broadly across a population, and different associations by subgroup are not informative about the population-level overall association. Thus, there is a need to translate from the conditional associations to the population-level association.

Furthermore, the associations we estimate with regressions typically compare extremes of exposure conditions. For example, we might compare the condition of exposure to no exposure. For translation to policy, often the exposure is already experienced in some of the population, and it is an alteration of the current exposure distribution that is of interest. Here, again, there is a need to translate, in this instance from comparison of extremes to shifts in exposure distributions.

MEASURES TO CONNECT FINDINGS TO POLICY

The wider use of population intervention measures would greatly improve the translation of public health research results to policy audiences. Many researchers are familiar with the population-attributable risk—specifically, the difference in the risk of the outcome comparing the exposure as it currently exists in the population to the elimination of the exposure from the population. Thanks to recent work, this type of measure has been generalized so that researchers can compare any distributions of the exposure that might be of interest.[3,4] For example, the outcome under the current exposure distribution can be compared with a specific reduction in the exposure.

In a recent issue of *AJPH*, we illustrated how to estimate measures that compare binge drinking given the observed distributions of alcohol outlet density, to binge drinking if an upper limit were set on alcohol outlet density.[5] Alterations to the exposure that are targeted to certain geographic or demographic subgroups can be compared with alterations that would affect the population overall. Through discussion with policymakers, the researcher can estimate alterations in the exposure that are of

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particular interest as alternatives, or to reflect a range of levels of effectiveness of a policy.

To highlight the difference in the information provided, the standard approach might report that the lack of a nearby source of fresh fruits and vegetables increased the odds of obesity by X. By contrast, through use of population intervention measures, researchers could report that provision of fresh fruits and vegetables everywhere that they are currently lacking would be associated with Y reduction in obesity, and provision of fresh fruits and vegetables in half of the places that they are lacking would be associated with Z reduction in obesity. Simple illustrations of how to estimate these measures are now available in the literature, including sample data and statistical code for implementation, which should facilitate broader accessibility.[5,6]

WHAT COULD THE FUTURE HOLD?

Estimation of population intervention measures will only get us so far. For example, if a study does not draw from the population of interest for policy, the degree to which population intervention measures translate well to another population will not be known. Furthermore, policymakers may prefer to consider the body of evidence rather than relying on a particular study's results. Considering these limitations and extending this basic concept around population intervention measures can generate exciting ideas for the future. Could we imagine a scenario in which our summarization of research goes well beyond meta-analysis? Meta-analysis makes the implausible assumption that different studies are estimating one true underlying effect. Alternatively, we could acknowledge that effects will be different depending on sampling approaches and population characteristics, and use these differences to better anticipate effects in new populations.[7]

For example, as the last step in a research project, we might each contribute associations and sample properties from a project to a centralized database. The database would have a prespecified, standard format to store information on exposures, outcomes, covariates, and associations (both overall and by covariate subgroups), and it could be accessed to address the questions of policymakers. We could take this further and agree on some standardization of exposures and outcomes particularly of interest for policymakers for the purpose of contribution to this database. On the basis of specifics of new populations in which policies or programs are under consideration, we would then be in a position to estimate different potential intervention effects by using the body of evidence to date. There would certainly be challenges to such an endeavor, but it would be a worthwhile effort.

Providing measures that are interpretable, meaningful from a policy perspective, and tailored to the particulars of the population of interest would make a substantial contribution to the effort to translate between research and policy. AJPH

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