Evaluating the validity-precision trade-off assuming constancy

Validity is how closely an estimate of an association comes to the ‘truth’ (i.e., the opposite of bias) and we cannot generally know the validity of a measure in observational epidemiology because

- we cannot make measurements in the entire population of the planet (the ‘truth’) because the observed measurements depend on the sample we are studying and the luck of the sample we draw
- measures may change over time (asthma, autism, etc.)

Precision is a measure of the accurately we measure an estimate of association (e.g., a 95% confidence interval), regardless of validity.

Consider a dartboard, where the center (‘cork’ in darts-speak) is the ‘truth’. You might throw 3 darts into the board that are widely spread, but average to the center. This situation is analogous to a valid, but not very precise, measure. On the other hand, you might throw 3 darts into the triple (inner ring) 20 segment. This situation is analogous to a precise, but significantly biased, measure.

There is a trade-off between validity and precision. We control for confounding to reduce bias in our estimate of an association, but the trade-off here is that the precision of an estimate generally decreases as we add variables to a model. The question to address is how to balance validity and precision as we model our system.

So, if the difference between a crude and adjusted main exposure effect estimate is “large”, then the amount of bias due to confounding is “large” and we might be inclined to sacrifice some precision to obtain a less biased estimate.

However, if the difference between a crude and adjusted main exposure effect estimate is “small” but the loss of precision is significant, then we must evaluate whether to adjust for the confounder.

On the other hand, if the difference between a crude and adjusted main exposure effect estimate is “small” and the loss of precision is minor, the penalty for adjustment may be negligible.

We will use a “mean squared error” approach to contrast the “penalty” from reduced precision with the “gain” from increased validity that occurs when we model the minimally sufficient adjustment set of confounders identified using a DAG.

The mean squared error (MSE) of an effect estimate is approximated as ($MSE = bias^2 + variance$), where the “bias” is the difference between an adjusted estimate and a crude (or reduced) estimate.

Here, the component of bias we are considering is just the confounding by one or more adjustment variables in the minimally sufficient conditioning set we identified by analyzing our DAG. We are assuming that our DAG is correct, that we have measured all our variables accurately, and that we have specified them properly in our model.

For the RD, the reduction in bias (i.e., the reduction in confounding) is the change in the RD, $B = RD_{adjusted} - RD_{reduced}$.

We square this value and add it to the change in the variance, $\Delta V = var(RD_{adjusted}) - var(RD_{reduced})$ and call this value M.

For two models, unadjusted model 1 (with $MSE=M1=B1_2 + \Delta V1$) and more-adjusted model 2 (with $MSE=M2=B2_2 + \Delta V2$).

If M1>M2, the validity-precision tradeoff favors adjustment. If M1<M2, the tradeoff favors not adjusting.

For the RR and IOR, we assess the validity-precision tradeoff on the natural log scale.

For the RR: $B = lnRR_{adjusted} – lnRR_{reduced}$ and $\Delta V = var(lnRR)_{adjusted} – var(lnRR)_{reduced}$

For the IOR, $B = lnIOR_{adjusted} – lnIOR_{reduced}$ and $\Delta V = var(lnIOR)_{adjusted} – var(lnIOR)_{reduced}$

The validity-precision tradeoff can be assessed starting with a fully-adjusted estimate from a model that includes all of the covariates in the minimally sufficient adjustment set, and then considering the validity-precision tradeoff for each adjustment variable by deleting them one-by-one from the model. If this approach is taken and more than one adjustment variable is dropped, the tradeoff should be assessed again, this time comparing “full adjustment” with adjustment for the reduced set of covariates. You will be doing this in section B of this lab.

- Note that all change in estimate methods, including the one described above, assume that “adjusted” estimates are less biased than unadjusted estimates; however, “adjustment” can increase bias if the covariate is poorly measured or incorrectly modeled. In addition, change in estimate methods cannot identify covariates that are affected by the outcome or the exposure. Always use prior information to determine whether to adjust and how to adjust for covariates, before using change in estimate methods to assess confounding.
- If confounders are identified (i.e., using a DAG), measured, specified and modeled appropriately, a “fully adjusted” estimate will be the most unbiased; therefore, it should be the standard to which less adjusted estimates are compared.

This may be referred to as “backward deletion” when used to select a subset of confounders for adjustment, since change is assessed as covariates are removed from a fully-adjusted model.

Alternatively, a “forward selection” strategy may be used when it is not possible to model all potential confounders simultaneously (e.g., when data are sparse or covariates are highly correlated), with changes in precision and validity evaluated relative to a crude effect estimate as confounders are added to a model.

These methods apply to the situation where you have a main exposure of interest. If your interest is in prediction or if numerous covariables are of equal interest, there are other considerations involved to evaluate model building.