# IV Estimators of Causal Effects

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I had never heard of the surrogate instrumental variable or the conditional instrumental variable until reading this chapter. The **surrogate IV** is the case when you have a common unobserved cause $V$ for the treatment $D$ and an instrument $Z$. In this case $Z$ does not cause $D$ but they have an association through the common cause $V$. (Note that $V$ cannot be used as an instrument because it is unobserved). As long as this association produces a strong enough first stage and that there is no relation from $Z$ to the outcome $Y$, we can estimate a causal effect. I'm thinking that the reason why this is never used in the economics literature is that there is rarely a thing that affects your treatment and some other thing that is completely unrelated to the outcome. The **conditional IV** is simply an instrument with a path to $Y$ that can be blocked by an observed set of variables $W$. Again, this is rarely seen in the literature because of the strong assumptions required. If even the cleanest of IVs is often scrutinized, any of these cases would be harder to defend as credible for identifying causal effects.

Another interesting point from this chapter is that **randomization** does not ensure conditional independence. That is, although a lottery assignment of the instrument would mean that $Z$ is randomly assigned, it could still be the case that $Z$ has a causal effect on $Y$ directly or indirectly through a path not crossing through $D$. Researchers often forget to make the argument for conditional independence after they claim that the instrument is randomized.

I had also never made the connection between the Wald estimator and 2SLS. The chapter present **2SLS** as either a way to bolster the homogeneity assumption or to overidentify the model to obtain more precise treatment effects. The former claims that all heterogeneity can be accounted by a vector $X$, requiring a 2SLS estimator in order to condition on X. Apart from the fact that such $X$ is rarely attainable, an OLS estimator may suffice when $X$ is observed. The latter uses several instruments to identify a single causal effect. However, this creates a mixture-of-LATEs challenge because the overidentified causal effect would be an average across two very different groups of compliers, given that different instruments identify different LATEs

Finally, I enjoyed the chapter's discussion on **marginal treatment effects** (MTEs). The idea is to exploit local instrumental variables (LIV), which are small increases in the value of the instrument (e.g., marginal increases in the value of a school voucher). One could theoretically estimate the LATEs for each LIV, which could then be considered MTEs. The advantage of this framework is that one can then think of almost any average causal effect estimate as a weighted average of these MTEs. One should therefore start by defining a policy-relevant treatment effect (PRTE) based on how a proposed policy is assumed to affect selection into treatment in order to determine the type of weights that should be assigned to each MTE. This would then provide policymakers the treatment effect they are looking for rather than some LATE that corresponds to compliers that are not policy relevant.