## Estimation of causal effects with unobserved confounding: an alternative to instrumental variables

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We consider the problem of identifying causal effects in the presence of unmeasured confounding and two auxiliary instruments that do not qualify as instrumental variables in the usual notion, but nevertheless allow to achieve identification of the effect of interest. Specifically, we compare the classical instrumental variables (IV) estimator to the estimator presented in [2] (KP); see also [3]. The assumptions underlying the KP estimator differ from those typically required by the IV method and can be encoded by directed acyclic graphs (DAGs). It can be shown that the KP estimator reduces to the IV when the two instruments are marginally independent. We evaluate the performances of IV and KP under a number of scenarios. Our simulations show that the KP estimator is generally less prone to misspecification bias than the IV estimator. By exploiting the result in [1], we extend the derivations to all regression graphs that are Markov equivalent to a DAG that satisfies the KP assumption, thereby enlarging the class of models to which the results are of use. The two estimators are applied to the Counterweight Programme Data to evaluate the effect of a binary (hard/soft) treatment on BMI reduction.

## References

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